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Predicting the Habitat Suitability for *Angelica gigas* Medicinal Herb Using an Ensemble Species Distribution Model

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Abstract: The distribution shift of forest species due to the fact of climate change may negatively affect ecosystem services including the production of medicinal resources. Climate change impact assessments of habitat range changes are essential to sustainably manage forest resources. A change in the habitat suitability due to the fact of climate change was predicted for *Angelica gigas*, which has high economic value among forest medicinal resources in South Korea. The habitat suitability was predicted by an ensemble species distribution model that combined the results of nine single algorithm models using the committee averaging method. A total 168 occurrence data and 10 environmental variables were used for the single algorithm models. The area under the receiver operation characteristic curve (AUC) and true skill statistic (TSS) were applied to evaluate the models' performance, and the contribution of the environmental variables was calculated as an important value for each single algorithm model. Climate change scenarios were projected to predict future habitat suitability. The future suitable habitat for *A. gigas* was gradually reduced to the high mountain regions of the eastern part of South Korea regardless of the climate change scenarios. The main environmental variable was the annual mean temperature, and the rise in temperature due to the fact of climate change was found to have a negative effect on the habitat suitability for *A. gigas*. The decline in the habitat suitability for *A. gigas*, a major forest medicinal resource, is expected to result in the reduction in its production. Therefore, it is required to establish adaptation measures to mitigate the negative impact of this decrease, such as protecting the natural habitats of *A. gigas*.

Keywords: climate change scenario; Korean angelica; machine learning; medicinal plant; species distribution model (SDM)

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Citation: Jung, J.B.; Park, G.E.; Kim, H.J.; Huh, J.H.; Um, Y. Predicting the Habitat Suitability for *Angelica gigas* Medicinal Herb Using an Ensemble Species Distribution Model. *Forests* **2023**, *14*, 592. https://doi.org/10.3390/f14030592

Received: 27 February 2023
Revised: 14 March 2023
Accepted: 15 March 2023
Published: 16 March 2023

1. Introduction

The climate is a critical factor that impacts the physiological response and life cycle of forest organisms, and climate change causes habitat range shifts by affecting growth and reproduction [1]. Increases in the elevation or poleward shifts of habitat ranges observed in forest ecosystems clearly demonstrate the impact of climate change on species distribution [2–4]. Consequently, the change in species distribution may exert not only a significant influence on the structure of forest ecosystems, including biodiversity, but also an adverse impact on the provision of ecosystem services [5]. Therefore, predicting changes in species distribution under climate change can be considered a prerequisite for the sustainable management of ecosystem services and the mitigation of adverse impacts [6].

The species distribution model (SDM) involves a series of data processing and an algorithm that predicts the occurrence probability or habitat suitability through the assumption of the relationship between species occurrence and circumstantial environmental variables. The SDM is widely used as a quantitative assessment tool of the impact of climate change [6,7]. However, since predicting habitat suitability includes multiple uncertainties and errors according to the traits of the species, the algorithm, spatial distribution of the occurrence data, sampling method, and collinearity among the explanatory variables, caution in terms of these uncertainties must be taken before interpreting the model results [8–10]. As a practical example, previous research on the future habitat suitability for subalpine evergreen conifers in South Korea showed different results according to the occurrence data, model algorithm, environmental variables, and climate change scenarios [11,12]. Therefore, a methodology that can increase the reliability and reduce the uncertainty of the SDM's results is required [13].

The ensemble approach refers to a statistical agreement method for reducing the model uncertainties caused by the model algorithm and parameters or the climate uncertainties due to the projected climate conditions and, generally, increases the predictive ability compared to a single algorithm model [14,15]. In addition, a consistent agreement can be derived through averaging (e.g., the multimodel inference, arithmetic average, and weighted average), and it is widely applied in decision making for climate change adaptation [16,17]. In South Korea, research that applies the ensemble approach is actively conducted; however, the majority of this research has studied the model uncertainty [12,18,19], and there has been a lack of its application to multiple climate change scenarios for reducing climate uncertainty [20,21]. Wenger et al. [22] documented that in future species distribution prediction, the climate uncertainty was greater than the model uncertainty, and there is an increasing need for an ensemble approach that considers multiple climate conditions during climate change impact assessment [23,24].

Angelica gigas Nakai is endemic to East Asia and mostly lives in the valleys of mountainous area in the Korean Peninsula at an elevation of ≥700 m [25,26]. It is a highly valuable medicinal plant that is traditionally used in Korean herbal medicine, and it is currently produced though local harvesting and cultivation [27]. Although *A. gigas* production heavily relies on cultivation, harvesting remains an important production method. The production of *A. gigas* is closely related to the climate conditions during the growing period [28,29]. Exposure to high temperatures at the onset of growth not only reduces the development of the aboveground and underground parts of *A. gigas* but also decreases the survival rate [30]. In addition, previous research that compared the growth of *A. gigas* for each climate zone and altitude showed that a higher temperature led to the reduced growth of the aboveground and underground parts [31,32]. Poor growth and an increase in mortality are closely related to the species distribution [33]; therefore, temperature increases due to the fact of climate change could induce changes in the distribution of *A. gigas*; however, there is a lack of studies on the change in habitat suitability for *A. gigas* [34].

This study aimed to assess the impact of climate change on the distribution of *A. gigas* and identify a suitable habitat for *A. gigas*. In detail, this study was purposed to (1) develop an optimal ensemble model for examining habitat suitability for *A. gigas*, (2) determine the relative importance of each environmental variable in predicting the habitat suitability, and (3) identify the change over time in the suitable habitat. In addition, this study used multiple climate change scenarios that can reduce climate uncertainties to increase the reliability of the predicted results.

2. Materials and Methods

2.1. Collection of Species Occurrence Data

Occurrence data for *A. gigas* in South Korea were obtained from the 7th National Forest Inventory (NFI, 2016–2020), the monitoring data on endangered subalpine evergreen conifers of the Korea Forest Service (ESCM, 2017–2018), the 4th National Natural Environment Survey of the National Institute of Ecology (NNES, 2014–2018) [35], the Global Biodiversity Information Facility (GBIF, 1957–2010) [36], and Park (2018) [37] (Table 1). However, if there were occurrences in a cultivated area, they were removed from the occurrence data. This is because the distribution of cultivated populations is influenced not only by environmental variables but also artificial management practices such as fertilization, making it difficult to distinguish the effects of these factors on the distribution. As *A. gigas* is cultivated in open fields rather than forests, where the natural population occurs [25,27], the location of each occurrence was carefully verified using Google satellite imagery, and the occurrences in cultivated areas were excluded from the analysis. To reduce the spatial autocorrelation in the locations of *A. gigas* occurrence, the occurrence data were thinned using a distance of 1 km. Finally, the occurrence data from 168 out of 285 locations were used to construct the species distribution model (Figure 1).

Table 1. Sources and number of occurrence data for *Angelica gigas* in South Korea.

Source	ESCM	GBIF	NFI	NNES	Park (2018)	Total
Original occurrence	150	62	10	46	17	285
Thinned occurrence	65	49	9	40	5	168

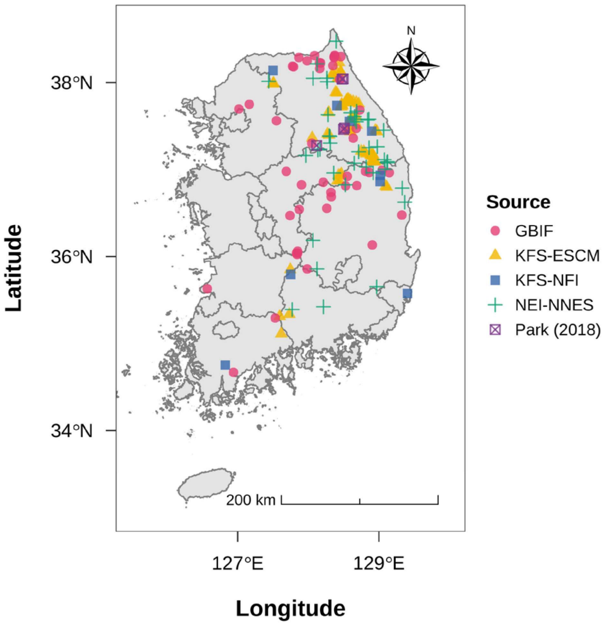

Figure 1. Locations of the thinned occurrence data for *Angelica gigas*.

2.2. Selection of Environmental Variables

A total of 19 bioclimate variables provided by WorldClim version 2.1 were used for the baseline climate (1970–2000) for constructing the species distribution model [38]. The period from 1970 to 2000 was selected because it corresponds to a notable shift in climate regimes that has been evidenced by several studies [39,40]. These studies indicate that changes in both precipitation and temperature began in the mid-1970s, underscoring the importance of this period in understanding the impact of climate change on *A. gigas* distribution. For the future climate, the 19 bioclimate variables of the SSP245 and SSP585 scenarios predicted by ACCESS-ESM1.5 [41], CNRM-ESM2-1 [42], HadGEM3-GC31-LL [43], IPSL-CM6A-LR [44], and MIROC6 [45] among the global climate models (GCMs) of CMIP6 were used. The time ranges of the future climate were 2021–2040, 2041–2060, 2061–2080, and 2081–2100. The mean value of the climate variable of each time range was used in the prediction of future habitat suitability and are indicated in the results as 2030, 2050, 2070, and 2090.

Global Multi-Resolution Terrain Elevation Data (GMTED2010) with a spatial resolution of approximately 1 km^2 (30 arc-second) were used to determine the topographical variables of the altitude, slope, and aspect [46]. In addition, the occurrence characteristics of *A. gigas* that mainly grows near mountain valleys were considered, and the topographic wetness index (TWI) with a 30 arc-second scale, created by the Korea Institute of Geoscience and Mineral Resources (KIGAM), was added [47]. TWI represents the soil moisture variation according to the slope and aspect, and a greater value implies a greater topographical moisture content retention capacity.

Finally, as soil variables, the cation exchange capacity (CEC), which has been found to be closely related with the growth of *A. gigas* [26,28], and bulk density (BOD), which is related to the soil texture and soil porosity, were used among the soil data provided by SoilGrids 2.0 [48]. The collinearity that exists between the explanatory variables of climate, topography, and soil increases the uncertainty of the species distribution model's results [10], and Spearman's rank correlation analysis was performed to remove variables with a correlation coefficient of >0.7 from the analysis [49]. Altitude showed a strong positive correlation (rs = 0.78) with the annual mean temperature (BIO1); therefore, it was eliminated from the final explanatory variable, and 10 environmental variables were selected, as follows, for use in the development of the species distribution model (Figure S1; Table 2). All environmental variables had a spatial resolution of approximately 1 km^2 (30 arc-second). The same topographical and soil variables were used in both the baseline and future projections, as these variables are not expected to change significantly over short time frames.

Table 2. Environmental variables used in the species distribution model.

Variable	Description	Abbreviation	Source
Climate	Annual mean temperature (°C)	BIO1	WorldClim
	Isothermality (×100)	BIO3	
	Temperature seasonality (standard deviation × 100)	BIO4	
	Precipitation of wettest month (mm)	BIO13	
	Precipitation of driest month (mm)	BIO14	
Topography	Slope (in degree)	SLOPE	GMTED2010
	Aspect (in degree)	ASPECT	
	Topographic wetness index	TWI	KIGAM
Soil	Bulk density (cg/cm^3)	BDOD	SoilGrids
	Cation exchange capacity (mmol$_c$/kg)	CEC	

2.3. Development and Evaluation of the Species Distribution Model

A total of nine algorithms, including artificial neural network (ANN), classification tree analysis (CTA), generalized additive model (GAM), generalized boosting regression model (GBM), generalized linear model (GLM), multiple adaptive regression splines (MARS), maximum entropy (MAXENT), random forest (RF), and surface range envelop (SRE), were used to create the species distribution model [13,50]. Some algorithms require not only presence data but also absence data, for which this research randomly extracted 1000 pseudo-absence data 10 times to generate 10 presence–absence datasets. The training and validation data were distinguished from each dataset at a ratio of 7:3 and were used in the model creation (70%) and model accuracy evaluation (30%), respectively. The single algorithm model was created 10 times for each dataset using the environmental variables, and the contribution of the environmental variables was determined for each model.

Cross-validation was performed five times to assess the accuracy of the single algorithm models. For this purpose, the validation data for each dataset were used to determine the area under the receiver operation characteristic curve (AUC) and the true skill statistic (TSS). The AUC was produced using the true positive rate (i.e., sensitivity) and the false positive rate from the classification table [51]. The sensitivity is the fraction of the actual presence that was correctly predicted as presence, while the false positive rate presents the extent of the false presence among the actual absence. The TSS was determined using the sensitivity and the true negative rate (i.e., specificity), which represents the extent of the prediction as absence among the actual absence, and the calculation of the TSS was as follow [52].

$$\text{True skill statistic (TSS)} = \text{Sensitivity} + \text{Specificity} - 1$$

The prediction performance can be considered good when both the AUC and TSS are close to 1. In this study, the model results were determined to be reliable when the AUC was ≥0.7 and the TSS was ≥0.6 [52,53].

2.4. Prediction of Ensemble Model

Among the single algorithm models, those with a TSS index of ≥0.6 were selected to create an ensemble model with the committee averaging (CA) method [54]. CA is a method of cumulatively adding the occurrence probabilities after the binary conversion of the occurrence probability into 0 and 1 from the single algorithm model and dividing the sum into the total number of models [50]. The final product of the CA ensemble model is not a continuous variable; therefore, it has the advantages of being intuitive and easy for comparison [55]. To reduce the climate uncertainty, two climate change scenarios (SSP245 and SSP585) from five GCMs were projected to determine the mean value of each time range's occurrence probability [21]. To distinguish the suitable habitat, the occurrence probability at the intersection of the sensitivity and specificity at which the TSS is maximized was designated as a threshold value for each climate scenario, and binary conversion was performed. The suitable habitat areas for each time range were determined on the binarized map, and the amount of reduction regarding the habitable area in 1970–2000 is presented in rates (%). In addition, the mean altitudes of the locations distinguished as having the presence of *A. gigas* were calculated to review the tendency of the change in altitude according to the climate change scenario. All analyses were performed using the Biomod2 package [50] in the R program [56].

3. Results

3.1. Performance of the Single Algorithm and Ensemble Model

All algorithms used in this study, excluding SRE, suitably predicted the presence of *A. gigas* (Figure 2A). The AUC and TSS mean values of all single algorithm models were 0.87 ± 0.07 and 0.64 ± 0.10, respectively, and the GBM showed the highest AUC and TSS values among the single algorithm models (AUC = 0.91 ± 0.02; TSS = 0.70 ± 0.05), followed by the GLM, MARS, MAXENT, and RF. The lowest prediction performance was that of SRE (AUC = 0.70 ± 0.03; TSS = 0.40 ± 0.07).

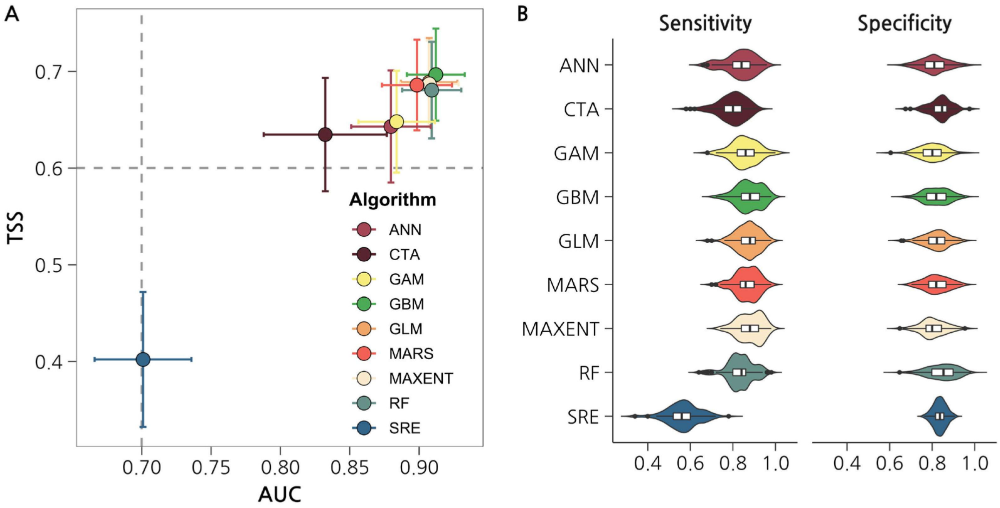

Figure 2. Validation metrics for the single algorithm models: AUC and TSS (**A**) and sensitivity and specificity (**B**). The points and crosses represent the mean and standard deviation of the AUC and TSS metrics for 100 models of each algorithm. The boxplots show the mean and interquartile range of the sensitivity and specificity, while the violin plots show the distribution of the sensitivity and specificity for 100 models of each algorithm.

In the ensemble model that was created with the models that had a TSS of ≥0.6 among the single algorithm models, 98 GLM models were included and accounted for the greatest number of models, followed by 97 GBM and MARS models, 96 MAXENT models, 94 RF models, 83 GAM models, 78 ANN models, and 74 CTA models, which contributed to the ensemble model. In contrast, all SRE models were excluded from the ensemble model. The AUC and TSS of the ensemble model were 0.96 and 0.78, respectively, and showed a superior prediction ability compared to the single algorithm models. The sensitivity of each single algorithm model was highest in the MAXENT (0.88 ± 0.06), and the specificity was 0.85 ± 0.07 in the RF, which was higher than that in the other algorithm models (Figure 2B). The specificity of the SRE was lower than the sensitivity, and the overall prediction ability was low.

3.2. Habitat Suitability and Environmental Variable Contribution

The suitable habitat area for *A. gigas* predicted by the ensemble model under the baseline climate conditions (1970–2000) was 25,130 km^2, and the habitat suitability was high in the eastern regions and the high-altitude areas of some mountains in the southern regions of South Korea (Figure 3A). The single algorithm models showed similar spatial tendencies to the ensemble model; however, there was a difference in the habitat suitability (Figure S2). Among the nine algorithms, the MAXENT and RF predicted a low probability of the habitat being suitable, and the SRE showed a relatively higher habitat suitability than the other algorithms (Figure 3B).

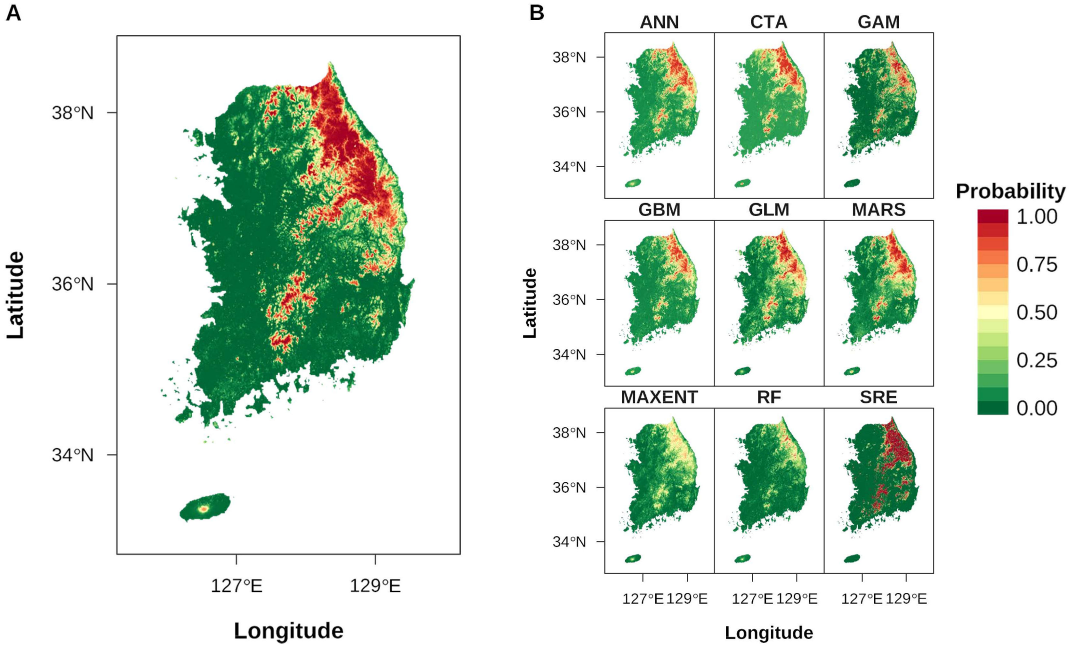

Figure 3. Habitat suitability for *Angelica gigas* predicted by the (**A**) committee averaging ensemble model and (**B**) single algorithm models under the baseline climate conditions (1970–2000).

The environmental variable that related most to the occurrence of *A. gigas* was the annual mean temperature (BIO1) (Figure 4). The variable importance of the annual mean temperature identified from 900 single algorithm models was 0.66 ± 0.45, and it best described the occurrence of *A. gigas* among the environmental variables used in the species distribution model. The variable importance of the annual mean temperature was the highest at an average of 0.92 ± 0.12 in the CTA algorithm model, and it showed the lowest value (0.24 ± 0.07) in the SRE algorithm model. After the annual mean temperature, the importance value of the CEC was high, with the total model average being 0.14, and it had a greater impact on the occurrence of *A. gigas* than the topographical variables. Among the topographical variables, the TWI showed a greater contribution than the slope and aspect.

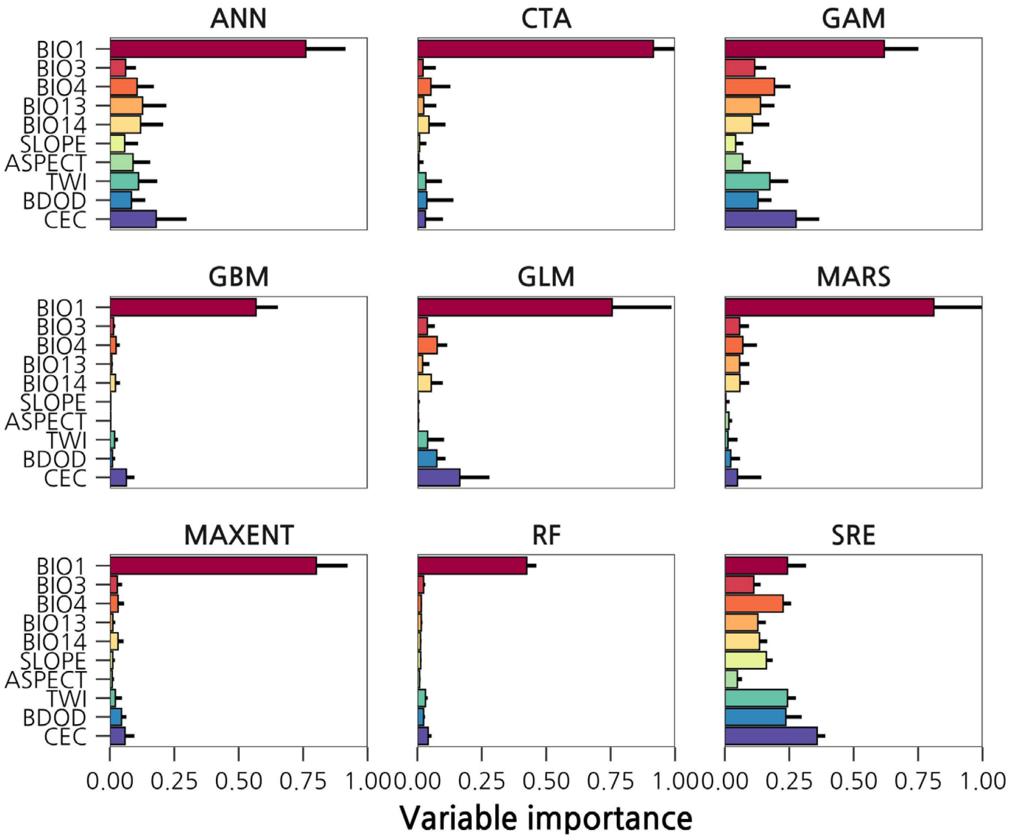

Figure 4. Importance values of the 10 environmental variables on the prediction of the occurrence of *Angelica gigas* by the single algorithm models. The bars and error bars represent the mean and standard deviation of the importance value for 100 models of each algorithm.

3.3. Future Changes in Suitable Habitat

The habitat suitability predicted by reflecting five GCMs and two SSP combinations with the climate change scenarios decreased in the low-altitude regions, and the suitable habitat areas gradually narrowed down to the high-altitude regions, such as mountainous areas (Figure 5). The mean habitat suitability was lower in the SSP585 scenario than the SSP245 scenario for all time ranges. The mean suitable habitat areas of *A. gigas* in 2030 were 8967 ± 3170 km^2 for SSP245 and 7358 ± 2931 km^2 for SSP585, which were reductions of 64 ± 13% and 71 ± 12%, respectively, compared to the habitat areas under the baseline climate conditions (Table 3; Figure 6A). In approximately 2090, *A. gigas* occurrence was predicted only from a mean area of 9 km^2 in SSP585 and of 1074 km^2 in SSP245. The greatest decrease in the suitable habitat area was observed in HadGEM3-GC31-LL, followed by that in ACCESS-ESM1.5, IPSL-CM6A-LR, CNRM-ESM2-1, and MIROC6. In the case of HadGEM3-GC31-LL, the decreases in the area in the SSP245 scenario were 81.1% in 2030 and 99.7% in 2090, and the reductions were 86.8% in 2030 and 100% in 2090 in the SSP585 scenario. In contrast, for MIROC6, with the lowest predicted decrease in the area, the SSP245 scenario showed decreases of 51.0% in 2030 and 87.3% in 2090. The reductions were 57.4% and 99.8% in 2030 and 2090, respectively, in the SSP585 scenario. The mean altitude of suitable habitat was 671 m under the baseline climate conditions; however, according to SSP585, it tended to increase from 907 m in 2030 to 1089 m in 2050, 1315 m in 2070, and 1225 m in 2090, and a suitable habitat for *A. gigas* gradually reduced to mountainous areas with a high altitude (Figure 6B). The annual mean temperature is expected to increase from 11.3 °C in 1970–2000 to 13.1 °C for SSP245 and 13.3 °C for SSP585 by 2030 (Figure S3). By 2090, the annual mean temperature is expected to rise to 15.0 °C for SSP245 and 17.5 °C for SSP585.

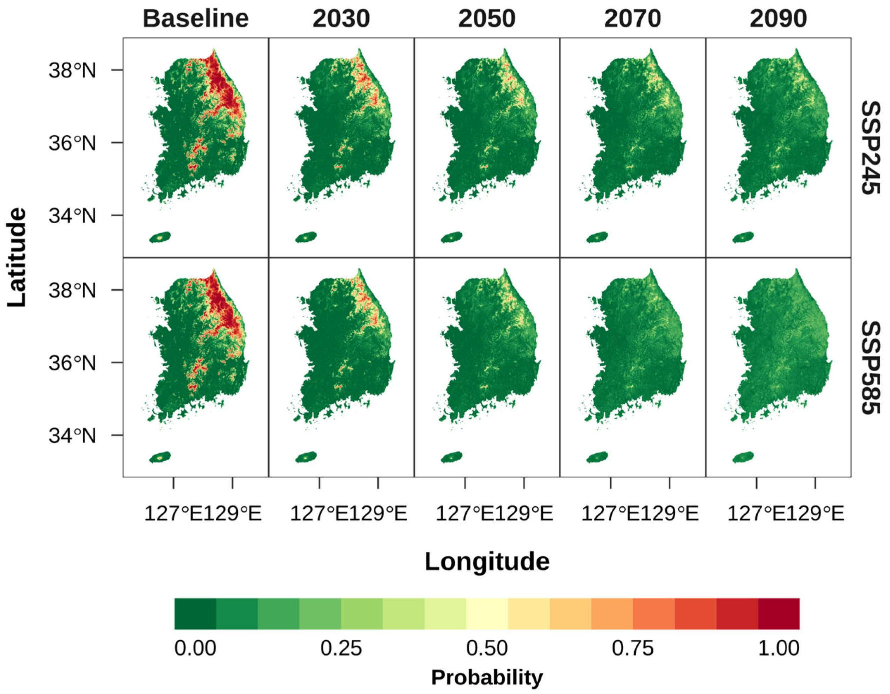

Figure 5. Mean habitat suitability for *Angelica gigas* under the SSP245 and SSP585 scenarios of multiple GCMs using the committee averaging ensemble approach.

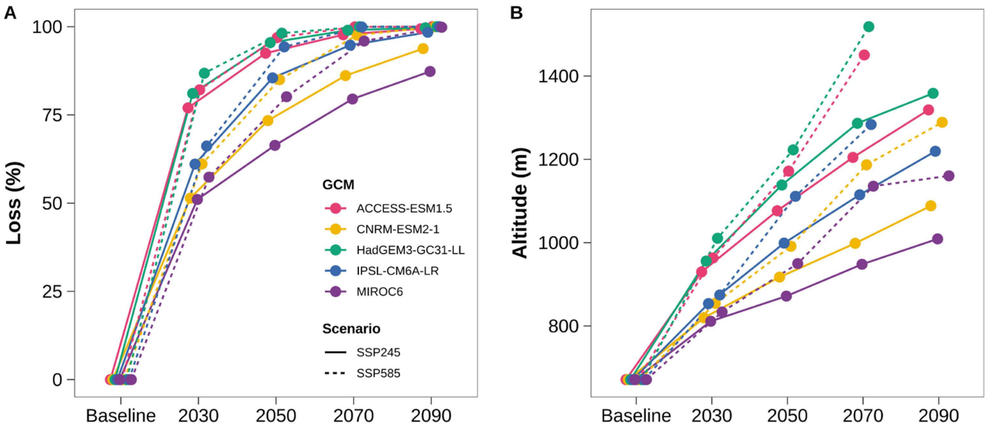

Figure 6. Future suitable habitat area loss (%) compared to the area under the baseline climate conditions (1970–2000) (**A**) and the mean altitude (**B**) of suitable habitat for *Angelica gigas* under the SSP245 and SSP585 scenarios of multiple GCMs using the committee averaging ensemble approach.

Table 3. Predicted area (km^2) of suitable habitat for *Angelica gigas* under the SSP245 and SSP585 scenarios of multiple GCMs using the committee averaging ensemble approach. The numbers in parentheses are future suitable habitat area loss (%) compared to the area under the baseline climate conditions (1970–2000).

	SSP245				**SSP585**			
GCM	**2030**	**2050**	**2070**	**2090**	**2030**	**2050**	**2070**	**2090**
ACCESS-ESM1.5	5780 (77.0)	1887 (92.5)	572 (97.7)	146 (99.4)	4491 (82.1)	773 (96.9)	16 (99.9)	- (100)
CNRM-ESM2-1	12,210 (51.4)	6687 (73.4)	3483 (86.1)	1561 (93.8)	9773 (61.1)	3769 (85.0)	603 (97.6)	7 (99.9)
HadGEM3-GC31-LL	4753 (81.1)	1135 (95.5)	252 (99.0)	76 (99.7)	3314 (86.8)	462 (98.2)	2 (99.9)	- (100)

Table 3. *Cont.*

	SSP245				SSP585			
GCM	**2030**	**2050**	**2070**	**2090**	**2030**	**2050**	**2070**	**2090**
IPSL-CM6A-LR	9787 (61.1)	3646 (85.5)	1316 (94.8)	398 (98.4)	8499 (66.2)	1434 (94.3)	23 (99.9)	- (100)
MIROC6	12,303 (51.0)	8450 (66.4)	5148 (79.5)	3188 (87.3)	10,712 (57.4)	4988 (80.2)	1021 (95.9)	40 (99.8)
Mean	8967 (64.3)	4361 (82.7)	2154 (91.4)	1074 (95.7)	7358 (70.7)	2285 (90.9)	333 (98.7)	9 (99.9)

4. Discussion

An ensemble species distribution model was used to predict the future habitat suitability for *A. gigas* under multiple climate change scenarios. The AUC and TSS values of the ensemble model created with the committee averaging method were 0.96 and 0.78, respectively, and showed a relatively higher prediction ability than the single algorithm models and contributed to reducing the model uncertainty of the prediction by merging the different results for each algorithm into one [14,15]. Therefore, the results of this study that predicted the distribution of *A. gigas* using the ensemble model are applicable as preliminary data for selecting suitable habitats for *A. gigas*. However, the ensemble model evaluation used validation data from an identical dataset; hence, the ensemble model's performance may deteriorate when the model is transferred into the independent temporal and spatial ranges from the training data [57]. Further, in the case of optimizing the model through mediation of the parameters, the performance of the single algorithm model could be higher than that of the ensemble model, which used the defaults, for which the use of an ensemble model requires the accurate assessment of the ensemble model performance through additional procedures, such as the null model or external validation aside from internal validation [58,59]. Therefore, in future research, it seems reasonable to validate the model using spatial blocking or independent validation data [58]. In addition, preventing overfitting of the single algorithm model through mediation of the model parameters could support the improvement of the accuracy and overall transfer capacity of the ensemble model.

Among the nine algorithms used in this research, the GBM showed the highest accuracy in predicting the occurrence of *A. gigas*. This high prediction ability of the GBM can be identified in several previous studies that compared the model algorithms [60,61], and a study in South Korea on subalpine evergreen conifers demonstrated the high predictive performance of the GBM along with the RF [12]. The GBM not only has the strengths of the boosting technique, such as machine learning and regression tree, but also the advantage of being able to consider the nonlinear relationship and interaction between explanatory variables, which is not possible in regression analysis algorithms, such as GLM or GAM [62]. The GBM is sensitive to the number of occurrence data and is known to have a higher accuracy compared to other algorithms in the case of having a significant number of occurrence data ($\geq$100) [63]. Therefore, if the results from the GBM algorithm model are given preference along with the ensemble model when selecting an appropriate habitat for *A. gigas*, this can increase the reliability of decision making.

The other algorithms, excluding SRE, were also found to have a suitable prediction ability based on the AUC and TSS, and they were referenced for the prediction of suitable habitats for *A. gigas*. This could contribute to the complementation of erased or missing ecological information from the ensemble model by preserving the ecological relationship assumed by each algorithm. On the contrary, the TSS value of the SRE algorithm was low, and some research in South Korea has verified the low accuracy of the SRE compared to other algorithms; therefore, the use of the SRE algorithm appears to require caution during the creation of the ensemble model [18,21].

The natural habitats of *A. gigas* are found in the valleys or gentle slopes of high mountains, and these habitats form on altitudes of ≥700 m in the eastern regions and ≥1000 m in the southern regions of South Korea [25,26]. In this study, it was observed that the suitable habitats for *A. gigas* exist at altitudes above the mean value of 671 m, as determined by the baseline conditions. This is attributed to the intrinsic correlation between altitude and temperature, wherein altitude indirectly affects the growth, reproduction, and distribution of *A. gigas* by influencing the prevailing environmental conditions, including temperature [31,32]. Temperature, especially during summer, significantly impacts the growth of *A. gigas* [34,37]. Furthermore, this study discovered that the mean temperature during the warmest quarter (BIO10) of the baseline climate conditions (1970–2000) at the location of the occurrence data was 19.3 °C, which closely aligns with the optimal growth temperature in July–August of approximately 20 °C reported in earlier research [27,37]. Based on the given scenario, it is highly probable that the impact of temperature on growth will intensify alongside the rise in the average annual temperature. Previous research shows that as the altitude of the cultivation site increases and the climate becomes cooler, the survival rate of transplanted *A. gigas* increases, and there is also a noticeable increase in the underground biomass [31,64]. In contrast, high temperatures adversely affect *A. gigas* growth, and the biomass of the aboveground and underground parts decrease when the temperature increases to above 20–25 °C, which is the optimal growing temperature for *A. gigas* [27,28]. Jeong et al. [30] showed that the extent of the reduction of the aboveground and underground biomasses increased as the temperature increased with regard to the optimal growing temperature. The highly significant effect of the annual mean temperature (BIO1) on the prediction of the habitat suitability for *A. gigas* may have reflected the changes in the growth characteristics according to the optimal growing temperature.

Temperature is not only related to vegetative growth but also to reproductive growth and regeneration. *A. gigas* is a long-day plant, which forms the flower stalk when the photoperiod elongates, and the rate of flower stalk formation is highest at 20 °C regardless of the photoperiod conditions, followed by that at 15 °C and 25 °C [27]. Meanwhile, Cho and Kim [65] studied the *A. gigas* germination rate, and stated that the rate decreased from 62.7% to 22.3% when the temperature increased from 20 °C to 30 °C. Choi and Yun [66] also reported that the germination rate was the highest at the optimal temperature for growth, and that a temperature increase from that level decreased the germination rate. Overall, an increase in temperature appears to impede the dispersion of *A. gigas* by negatively affecting its growth and regeneration.

A. gigas naturally inhabits regions with high moisture conditions such as valleys [25]; however, the results of this study showed that the TWI or aspect had a lower variable importance than that of the other climate variables. Interestingly, a study conducted on Mt. Hallasan, Jeju Island, found that the height of *A. gigas* on the north-facing slope was higher than that on the south-facing slope [67]. Additionally, Park et al. [28] reported the high growth of the underground parts at a high air humidity. These findings suggest that moisture conditions may play a role in the growth and distribution of *A. gigas*, but their impact may be more complex than previously thought. One possible explanation of the low variable importance of the TWI and aspect in this study is that the spatial resolution of these variables may be too coarse to adequately capture the microscale soil moisture variations. Therefore, further research is needed to understand the growth and distribution of *A. gigas* in relation to the moisture conditions.

The CEC was used as the explanatory variable for the model in this study to indicate the content of exchangeable cations, and the results showed that CEC had the strongest relationship to the distribution of *A. gigas*, after the annual mean temperature. This result agrees with the results of a study that showed that *A. gigas* mainly inhabits soils with high organic matter content, total nitrogen content, CEC, and exchangeable cations content [25]. According to Park et al. [28], the biomass of *A. gigas*'s roots increased with a higher CEC, and the Ca^+, Mg^{2+}, and Na^+ contents were positively correlated to root growth [26]. Chang and Choi [68] inferred that exchangeable cations or CEC positively impacted the growth of *A. gigas*, since potassium fertilizer increased the growth of its aboveground and underground parts. In addition, vigorous root development could be considered to impact the spatial distribution of individual *A. gigas* indirectly and directly by contributing to increasing the survival rate and resistance to physical disturbances that occur frequently in valley and boulder areas (as the main habitats).

In the ensemble model, the predicted suitable habitat area for *A. gigas* tended to gradually shift towards the high-altitude areas of mountainous areas as time progressed from the near future to the distant future in both the SSP245 and SSP585 scenarios. Further, according to the SSP585 scenario, there would be no suitable habitat in South Korea in 2090, and the consistent decreasing trend shown for all GCMs validated the change in the suitable habitat. Meanwhile, the future habitat suitability differed according to the projected GCM. For example, when applying the SSP245 scenario to a near future prediction, the predicted suitable habitat area for *A. gigas* showed a significant decrease (by 30%) in the HadGEM3-GC31-LL model compared to the MIROC6 model. This suggests that the use of multiple GCMs and the ensemble model are essential to reduce the prediction uncertainty that occurs due to the choice of a single GCM projection and that the ensemble model presented in this study could contribute to an increase in the reliability of the prediction of the habitat suitability for *A. gigas*.

According to the Ministry of Agriculture, Food, and Rural Affairs of South Korea, the amount of *A. gigas* produced over the past 10 years decreased by 34% (i.e., from 1857 tons in 2012 to 1225 tons in 2021) and the cultivation area decreased by approximately 27% (i.e., from 625 ha in 2012 to 457 ha in 2021) [69]. This future decrease in habitat suitability is estimated to deteriorate the conditions for the production of *A. gigas*, for which adaptation measures for climate change are urgently needed for sustainable *A. gigas* production. Therefore, the management of their natural habitats is considered important. However, *A. gigas* could easily suffer damage from overexploitation and habitat loss due to the fact of its high medicinal value [70], and methods for obstructing artificial disturbances to the naturally growing population, including the setting of protection areas for medicinal plant resources, must be considered.

Meanwhile, the suitable habitat predicted by this study and the actual distribution may differ, because the species distribution model did not consider the interspecies interaction or other environmental factors that interfere with the growth and reproduction of *A. gigas*. For example, various insects pollinate *A. gigas*, and the phenological mismatch with these insects bears the risk of negatively impacting the distribution of *A. gigas* [71,72]. Thus, future research must also consider various ecological processes.

5. Conclusions

Under climate change, the suitable habitat for *A. gigas* is expected to gradually be restricted to high-altitude mountainous areas where the temperatures are suitable. This decrease in the habitat suitability is strongly linked to the projected rise in the annual mean temperature. Furthermore, stress from elevated temperatures can not only restrict the range of *A. gigas* but also impair its overall vegetative and reproductive growth, highlighting the significant impact of climate on the species. The production of *A. gigas* is expected to decrease as a result of the decline in suitable habitat area. To adapt to climate change, protective measures such as conserving the natural habitats of *A. gigas* may be necessary. The ensemble model created in this study can help to reduce model and climate uncertainties, and its future application as a basis for sustainable *A. gigas* production is expected to contribute to the establishment of climate change adaptation measures.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f14030592/s1, Figure S1: Spearman's rank correlation coefficients for selected environmental variables; Figure S2: Zoomed-in plot of the habitat suitability for *Angelica gigas* predicted by the single algorithm models under the baseline climate conditions (1970–2000); Figure S3: Change in the annual mean temperature under the SSP245 and SSP585 climate change scenarios of multiple GCMs.

Author Contributions: Formal analysis, J.B.J. and G.E.P.; Methodology, J.B.J. and G.E.P.; Visualization, J.B.J.; Writing—original draft, J.B.J., G.E.P., H.J.K., J.H.H. and Y.U.; Writing—review and editing, J.B.J. and G.E.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Institute of Forest Science (NIFoS) (grant number: FE0100-2018-11).

Data Availability Statement: The data from the current study are available from the corresponding author upon reasonable request.

Acknowledgments: We would like to thank Won Il Choi for his valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

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