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Estimation of current and future distribution of *Ruellia tuberosa* in Java and Madura Island, Indonesia

Estimasi distribusi *Ruellia tuberosa* saat ini dan masa mendatang di Pulau Jawa dan Madura, Indonesia

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Abstrak. *Santika YE, Wardha'adlina WA, Arta YPA, Maheswara VD, Wiraatmaja MF, Setyawan AD. 2024. Estimasi distribusi* Ruellia tuberosa *saat ini dan masa mendatang di Pulau Jawa dan Madura, Indonesia. Pros Sem Nas Masy Biodiv Indon 10: 32-44. Ruellia tuberosa* L. diidentifikasi sebagai tanaman invasif yang dapat mengganggu ekosistem lokal. Distribusi tanaman ini harus diketahui untuk menentukan prioritas pengelolaan guna mengurangi dampaknya. Penelitian ini bertujuan untuk mengetahui sebaran *R. tuberosa* saat ini dan estimasi sebarannya di masa mendatang di Pulau Jawa dan Madura, Indonesia dengan menggunakan perangkat lunak Maximum Entropy (MaxEnt). Oleh karena itu, 21 parameter dalam pemodelan ini terdiri dari 19 variabel bioklimatik, ketinggian, dan radiasi Matahari. Skenario RCP 2.6 dan 8.5 digunakan dalam penelitian ini untuk memprediksi sebaran *R. tuberosa* di masa mendatang. Titik sampel diperoleh dari dua sumber data, yaitu Global Biodiversity Information Facility (GBIF) dan pengamatan langsung. Hasil pemodelan sebaran menggunakan MaxEnt menunjukkan nilai AUC sebesar 0,959. Nilai ini menunjukkan bahwa hasil pemodelan menggunakan MaxEnt memiliki kinerja yang lebih baik dibandingkan dengan metode acak. Pemodelan sebaran pertumbuhan tanaman *R. tuberosa* pada tahun 2030, 2050, dan 2080 menunjukkan adanya penurunan sebaran tanaman tersebut dari tahun ke tahun yang cukup signifikan karena pada tahun tersebut terjadi perubahan iklim yang cukup signifikan yang diakibatkan oleh peningkatan kadar CO_2 yang mengakibatkan terjadinya perubahan iklim global sehingga mempengaruhi pertumbuhan tanaman invasif. Parameter utama yang paling dominan mempengaruhi sebaran *R. tuberosa* adalah BIO 9 (Mean Temperature of Dryest Quarter). Hal ini perlu menjadi perhatian pengelola lingkungan, karena tanaman ini tergolong tanaman invasif.

Kata kunci: Estimasi distribusi di masa depan, spesies invasif, MaxEnt, *Ruellia tuberosa*, pemodelan distribusi spesies

Abstract. *Santika YE, Wardha'adlina WA, Arta YPA, Maheswara VD, Wiraatmaja MF, Setyawan AD. 2024. Estimation of current and future distribution of* Ruellia tuberosa *in Java and Madura Island, Indonesia. Pros Sem Nas Masy Biodiv Indon 10: 32-44. Ruellia tuberosa* L. is identified as an invasive plant that can disrupt local ecosystems. The distribution must be known to determine priority management to reduce the impact. This study aims to determine the current distribution of *R. tuberosa* and its estimated future distribution in Java and Madura Island, Indonesia using Maximum Entropy (MaxEnt) software. Therefore, 21 parameters in this modeling consisted of 19 Bioclimatic Variables, Elevation, and Solar Radiation. RCP scenarios 2.6 and 8.5 were used in this study to predict the future spread of *R. tuberosa.* Sample points were obtained from two data sources, the Global Biodiversity Information Facility (GBIF) and direct observation. The results of distribution modeling using MaxEnt showed an AUC value of 0.959. This value indicates that the modeling results using MaxEnt have better performance than the random method. Modeling the growth distribution of *R. tuberosa* plants in 2030, 2050, and 2080 shows a significant decrease in the distribution of these plants from year to year because there was significant climate change in that year, which was caused by an increase in CO_2 levels, which led to global climate change, thus affecting the growth of invasive plants. The main parameter that predominantly influences the spread of *R. tuberosa* is BIO 9 (Mean Temperature of Driest Quarter). This needs to be of concern to environmental managers, because this plant is classified as an invasive species.

Keywords: Estimation future distribution, invasive species, MaxEnt, *Ruellia tuberosa*, species distribution modeling

INTRODUCTION

Ruellia tuberosa L. is known as Blue-bell, Spearpod, Minnieroot, Snapdragon root, cracker plant, or popping pod, while in Indonesia it is called *pletekan*, *pletikan*, or *ciplukan* (Safitri et al. 2018; Dutta et al. 2020). *Ruellia tuberosa* is a species of the Acanthaceae family whose habitus is perennial herbs (Wati and Anisatu 2023). *Ruellia tuberosa* comes from Central America and spreads to Southeast Asia; and grows in dry, hot, and tropical to subtropical areas, grows fast in humid and shady areas at 150 meters above sea level, and survives in various environmental conditions (Seerangaraj et al. 2021; Putri et al. 2022; Susilo and Farhan 2023). Initially, *R. tuberosa* in Indonesia was known as a weed plant and was not widely used by people in Indonesia as a medicinal plant (Amajida et al. 2019). *Ruellia tuberosa* is widespread in Indonesia because of its tropical climate, so it is a suitable place for *R. tuberosa* plants to grow (Safitri et al. 2019). *Ruellia tuberosa* has benefits in treatment such as anti-diabetic, anti-inflammatory, antinociceptive, antipyretic, antidiuretic, analgesic, diuresis, antihypertensive, antioxidant, insecticide, anticancer, and antidote poison agent (Hepni et al. 2021; Kannan et al. 2021; Annisa et al. 2022).

Java and Madura are two islands in Indonesia experiencing diversity degradation because invasive species are replacing them. One invasive plant often found on Java and Madura Island is *R. tuberosa*, for example, in Balekambang Malang forest (Mukarromah et al. 2020). The Java and Madura islands have a warm climate suitable for *R. tuberosa* to grow compared to other islands. According to Setiawan (2009), climate is important to support plant growth and productivity, sometimes even more important than soil conditions. Therefore, Java and Madura were chosen as research locations for *R. tuberosa* because the potential for distribution is high. Invasive species are species that have a negative impact on the native diversity. Invasive plants are plants that grow outside their natural area and grow in other areas, which have a negative impact on their new habitat and native diversity, as dominating plants in the ecosystem causes species destruction, damage to the environmental or ecosystems, nutrient and hydrological cycles (Susanti et al. 2013; Thapa et al. 2018). Invasive plants have several characteristics: high growth and reproduction, fast adaptation, increased populations quickly, and the ability to live with new food sources (Tjitrosoedirdjo et al. 2016). *Ruellia tuberosa* plant is considered an invasive shrub because it is not native to Indonesia. It threatens the ecosystem because it spreads quickly and disturbs the native vegetation. One way that can be done to determine the current and future distribution of the invasive plant *R. tuberosa* is to model its distribution using MaxEnt software (Putri et al. 2019).

Maximum Entropy (MaxEnt) is software that can estimate the distribution of a species using environmental variables (Phillips and Dudík 2008). MaxEnt modeling is robust and accurate and uses a very small number of data samples (Stalin and Swamy 2015; Chhetri et al. 2018) on the presence of species and environmental variables (Hermawan et al. 2017). MaxEnt can predict current and future invasive plant distribution by including data on environmental variables that have been predicted in the future. This model has proven to be in modeling species distributions with relatively little occurrence data. The distribution model accuracy is analyzed using the Area Under Curve (AUC) value to determine priority areas for controlling *R. tuberosa* (Gunawan Et al. 2023). According to Phillips et al. (2006), if the AUC value is close to 0.5, then the model is no better than random modeling; if close to 1, then the model performs better in determining the suitability of a species' habitat. According to West et al. (2016), the MaxEnt model can be used to predict or estimate land for invasive species management; this modeling can only reflect habitat suitability for invasive species based on previous model comparison studies. Therefore, this study aims to determine the current distribution of *R. tuberosa* and estimate its future distribution in Java and Madura Island, Indonesia using MaxEnt.

MATERIALS AND METHODS

Study area

The area of concentration in this study is Java-Madura Island. Both islands are located in the south of Indonesia (Figure 1). Java-Madura Island has several provinces, including Banten, West Java, DKI Jakarta, Central Java, Yogyakarta Special Region, and East Java. The islands of Java and Madura were formed during the tertiary and quaternary periods, consisting of rhyolitic, dacite-andesite, breccia, and lava tuffs, partly interspersed with sandstones, shales, carbonaceous tuffs, and claystone (Beckford et al. 2023). Java-Madura Island has a tropical climate influenced by the West and east monsoons. This island often experiences *pancaroba* (seasonal changes) due to the rainy and dry seasons. Madura Island itself is a dry land that does not have volcanoes (Muda et al. 2020).

Sample points were obtained from two data sources, the Global Biodiversity Information Facility (GBIF) (53 sampling points) and direct observation (11 sampling points), where a total of 64 point occurences has been used. Sampling points with direct observation were carried out by providing coordinates at locations overgrown with *R. tuberosa* around Surakarta City, Klaten District, Semarang District, and Sampang District using Google Earth. Sample points from GBIF are obtained by downloading a collection of coordinates of the existence of *R. tuberosa* through www.gbif.org. The coordinates of both sources are adjusted to MaxEnt format (Longitude, Latitude), then saved in Excel with CSV format. After the coordinate points are adjusted, they can be used for modeling in MaxEnt software (Zhang et al. 2021).

Ruellia tuberosa

Ruellia tuberosa has striking funnel-shaped purple bracteate flowers on dichotomous plants, thick fusiform tuberous roots, sessile subcylindrical puberulent capsule-shaped fruits with a length of 2 cm, having approximately 20 seeds per loci, linear hypnoid petal lobes 12-20 mm long, purple suborbicular lobes with a width of 12-15 mm and a diameter of 2-2.5 mm, crown tubes 4-6 cm long, erect and broadly branched stems up to 50 cm high, most basal petiolate leaves are ovate smooth to oval with 1.5 cm long alate petioles and pubescent leaf blades measuring 4-6 × 1.5-2.5 cm with cuneate base, blunt apex, and wavy edges (Dutta et al. 2020; Kannan et al. 2021). *Ruellia tuberosa* has a unique characteristic: the dry pods that pop if contacted with water or rubbed with spit (Dutta et al.

2020). *Ruellia tuberosa* is also used by humans as medicinal for treating anti-diabetic, anti-inflammatory, antinociceptive, antipyretic, antidiuretic, analgesic, diuresis, antihypertensive, antioxidant, insecticide, anticancer, and antidote poison agent (Hepni et al. 2021; Kannan et al. 2021; Annisa et al. 2022).

Ruellia tuberosa is suitable to grow in tropical climates (Safitri et al. 2019) and is frequently found in gardens, grasslands, roadsides, or wastelands (Figure 2) (Harika and Radhika 2019; Dutta et al. 2020). *Ruellia tuberosa* is a weed in cultivated fields, xerophiles, and waste ground/ruderal habitats (Dutta et al. 2020). This causes an increase in the potential spread of *R. tuberosa* with drier climate change, while this plant is classified as an invasive species.

Ruellia tuberosa distribution modeling

Species distribution maps are created using MaxEnt modeling, thus enabling the prediction of the spatial distribution of species based on existing environmental data. MaxEnt is a very helpful software for creating maps of the actual distribution of species. Various environmental factors, including topography, soil type, climate data, and other related information, can be used in this method (Asanok et al. 2020). This provides a clearer picture for researchers and conservation practitioners to focus their efforts better. The accuracy of variables related to the phenomenon under study and the completeness and quality of environmental data used as inputs determine how accurate the predictions made by the MaxEnt model are (Kaky et al. 2020). Therefore, a thorough review is needed to ensure the effectiveness and accuracy of the resulting model in forecasting the distribution of observed events. The MaxEnt model generates data in the form of prediction maps, response curves with AUC, and Jackknife analysis results that help the interpretation and understanding of model results by researchers (Muttaqin et al. 2019). Jackknife results are presented in a bar chart. These findings were used to identify the most influencing factors in the MaxEnt model. Based on research by Wei et al. (2020), the model map produced by MaxEnt displays the level of habitat suitability that can be classified into four classes, namely least suitable (0.0-0.2), low suitability (0.2-0.4), medium suitability (0.4-0.6), and high suitability (0.6-1).

Figure 2. Images of *Ruellia tuberosa*

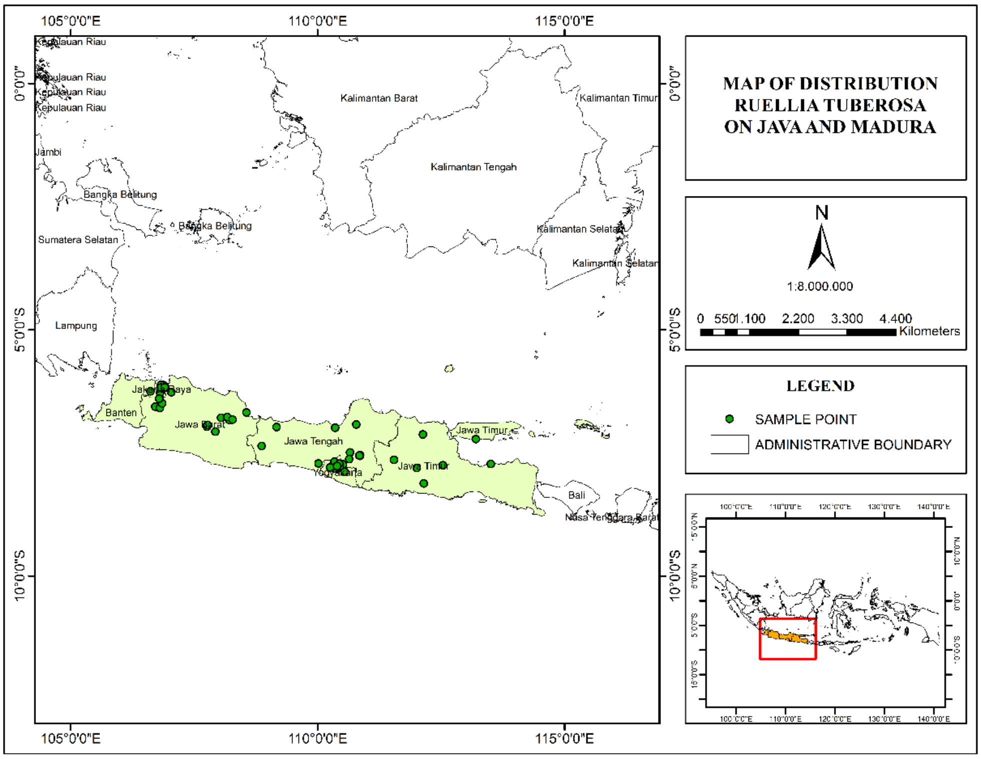


Figure 1. Map of the study area and distribution of *Ruellia tuberosa*

The step of making a species distribution map begins with the collection of environmental parameters and distribution points of related species. Furthermore, environmental parameters and points of presence of species are adjusted in format to the requirements of MaxEnt. Location points must be created with the format species, longitude, and latitude in a Comma-Separated Value (CSV) file. Each environmental parameter is ensured to be a uniform resolution. Parameters with larger resolutions can be downgraded to be the same resolutions as other environmental parameters. According to Merow et al. (2013), in using MaxEnt, the first step is to input environmental data and species presence as inputs for modeling. The MaxEnt model was then run by considering the environmental data provided to predict the spatial distribution of the species studied. The results of this model will provide information on species preferences based on the environmental variables considered. The next process involves analyzing MaxEnt results using ArcGIS, and the resulting data from MaxEnt in ASC format is fed into ArcGIS for further analysis. MaxEnt results are classified at this stage by changing the number of classes and adjusting the limit values according to research needs. In addition, raster data conversion into polygons is carried out to facilitate spatial analysis. The final stage is the visualization and interpretation of the results.

Environmental parameters

This study used 21 parameters of 19 Bioclimatic Variables, Elevation, and Solar Radiation (Table 1). These environmental variables are downloaded from the global climate database WorldClim (www.worldclim.org) (Yiwen et al. 2016); altitude parameters affect habitat types (Matyukhina et al. 2014). The environment variable has a raster format with a spatial resolution of 30s (1 km^2) (Wei et al. 2018). Environmental variables were cut according to the study area under evaluation, to be obtained in raster format but with different resolutions and projections (Wiese et al. 2019). Before model creation, each environment variable must be converted from image file format (.Tiff) to ASC form (Wan et al. 2021). Data Projections in Worldclim must be converted using ArcGIS in CRS projection format: EPSSG:4326 -WGS 84 (Zhao et al. 2021). In the initial model-building process, the Jackknife test in MaxEnt software is used to determine the contribution of environmental variables to the model prediction process and obtain key environmental factors. This is used to eliminate variables that contribute less to the predicted results of the MaxEnt model (Hundessa et al. 2018). Environmental parameters were determined based on contributions to the modeling process with jackknife tests to predict geographic distribution, species abundance distribution patterns, and invasive species distribution (Xu et al. 2019); after modeling the current distribution of *R. tuberosa*, modeling its distribution for the future with future climate change scenarios Representative Concentration Pathway (RCP) (Dong and Gao 2014). The future prediction process is carried out using 2 scenarios, namely in 2030, 2050, and 2080. In this study, we chose to estimate the distribution of *R. tuberosa* in 2030, 2050, and 2080 because there was significant climate change in that year, which was caused by an increase in CO_2 levels, which led to global climate change, thus affecting the growth of invasive plants (Muis 2023). The emergence of CO_2 is caused by population growth every year (Suadnyani et al. 2023); it contributes to air pollution, causes global warming, and triggers climate change (Akhirul et al. 2020). Climate change encourages invasive plants to have high plasticity, which is closely related to the balance of water content to determine the survival of these plants (Rahmadani et al. 2021). The scenarios used are RCP 2 and RCP 8, where RCP 2.6 means minimum greenhouse gas emissions and RCP 8.5 means maximum green house emission (Zhang et al. 2018). Future climate scenarios predict regions that allow *R. tuberosa* to grow in suitable and unsuitable areas (Zeng et al. 2021).

Classification and calculation of *Ruellia tuberosa* distribution area

The classification aims to categorize values according to the suitability of the distribution area of *R. tuberosa*. Classing using Arcgis is done by entering maxent output with ASC format in ArcGIS and then reclassifying ASC raster data into 4 classes, namely, least suitable (0.0-0.2), low suitability (0.2-0.4), medium suitability (0.4-0.6), and high suitability (0.6-1.0) (Gunawan et al. 2023). Convert raster data as a new layer from reclassify into polygon data. Dissolve the resulting raster to the polygon layer via Geoprocessing by checking the "Gridcode" column. In the dissolve result layer, enter all values of type "Gridcode" through the "Symbology" property, then set the color from green to red color, indicating low to high expression of suitability (Tian et al. 2020).

Table 1. Environmental parameters for MaxEnt Modeling

Code	Parameter
BIO 1	Average annual temperature
BIO 2	Daily average forecast
BIO 3	Isothermal,
BIO 4	Seasonal Temperature
BIO 5	Maximum temperature of the hottest month
BIO 6	Minimum temperature of the coldest month
BIO 7	Annual Temperature Forecast
BIO 8	Average temperature in the wettest quarter
BIO 9	Average temperature in the driest quarter
BIO 10	Average temperature in the hottest quarter
BIO 11	Average temperature in the coldest quarter
BIO 12	Annual rainfall
BIO 13	Rainfall in the wettest months
BIO 14	Rainfall in the driest month
BIO 15	Seasonal rainfall
BIO 16	Rainfall in the wettest quarter
BIO 17	Rainfall in the driest quarter
BIO 18	Rainfall in the hottest quarter
BIO 19	Rainfall in the coldest quarter
Elevvasis	Elevation
SRAD	Solar Radiation

The calculation of the area aims to obtain information on the suitability of the distribution area of *R. tuberosa* in units of square kilometers (km^2). The calculation of the area using ArcGIS is done by converting the geographic coordinate system of the data frame into a datum "D_WGS_1984" (Huang et al. 2023). Open the attribute table of the dissolve result layer and create two new columns named "Suitability Index" with the type "Text" and "Area Measurement" with the type "Double." Enter edit mode and input 4 classes of least suitable (0.0-0.2), low suitability (0.2-0.4), medium suitability (0.4-0.6), and high suitability (0.6-1.0) (Gunawan et al. 2023) in the "Suitability Index" column then perform geometry calculations to determining area in geodesy by measuring and calculating area using existing data through plans or maps (Frančula et al. 2021). Geometry calculations are performed in the "Area Measurement" column with the property of "Area," using the corresponding coordinate system and the square kilometer unit (km^2) then save the edits.

RESULTS AND DISCUSSION

In the current Modeling Map (Figure 3) and the current Conformity and Area Index Data (Table 2), a map of the potential distribution of *R. tuberosa* on Java and Madura Island is known with its area. AUC is a measure of discrimination obtained from a fusion matrix that interprets the model's success in appropriately distinguishing attendance and absence with an AUC value range between 0 and 1, where 0.5 means random discrimination and 1 means perfect and good discrimination (Hao et al. 2020). Based on the AUC value, it is known to be 0.959, where the AUC value is close to number one, which means that the current distribution modeling map results have a very good model and suitability of the area where the plant grows. The most influential parameter is BIO 4 (Temperature Seasonality). The contribution of this parameter is 22.8%, with important permutations worth 23%, indicating that Temperature Seasonality significantly influences the distribution of *R. tuberosa* plants (Table 3). Similar research by Zhang et al. (2023) also showed that parameter BIO 4 (Temperature Seasonality) was the most influential parameter for the potential geographic distribution of *Keteleeria davidiana* (Bertrand) Beissn., with a contribution rate of 34.96% and permutation importance value of 31.72%. Based on the visual map, it is known that areas with very low suitability dominate most of Java and Madura. There are also areas with low suitability in some areas around areas with high suitability, which are more clearly visible than areas with medium suitability. The current modeling map shows that the potential areas for *R. tuberosa* distribution are Jakarta, Depok, Bekasi, Bogor, Yogyakarta, Wonosari, Tegal, South Tangerang, Subang, Karawang, Cirebon, Brebes, Bitung, Slawi, Surakarta, Klaten, Wonogiri, Sukoharjo, Ponorogo, and Sampang (Figure 3). That shows *R. tuberosa* is suitable for growing in densely populated and residential areas. The order of area suitability area of the largest is very low suitability, covering an area of 112,894 km^2; low suitability, covering an area of 10,556 km^2; high suitability, covering an area of 4,491 km^2; and medium suitability, covering an area of 4,452 km^2 (Table 2).

In the estimated distribution map of *R. tuberosa* plants in 2030 using RCP 8.5, the most influential parameter is BIO 9, or the Mean Temperature of the Driest Quarter shown on the AUC curve yield graph (Figure 4). With an AUC value of 0.934, which means the results are accurate. The contribution of this parameter is 17.6%, indicating that the driest quarter temperature significantly influences the distribution of such crops. The effect of environmental variables on the distribution of *R. tuberosa* (Table 3) shows that the parameters BIO 4 and BIO 12 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 4 is Temperature Seasonality and BIO 12 is Annual Precipitation. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in 2030 RCP 8.5 table (Table 2), the order of suitability of the area from the largest is very low suitability of 89581 km^2, then low suitability of 21474 km^2, high suitability of 10472 km^2, and lastly, medium suitability of 10226 km^2

In the estimated distribution map of *R. tuberosa* plants in 2050 using RCP 8.5, the most influential parameter is BIO 19, or Precipitation of Coldest Quarter, with a total contribution of 17.8%, shown in the curve yield graph (Figure 4). With an AUC value of 0.943, which means the results are accurate. The effect of Environmental Variables on the Distribution of *R. tuberosa* (Table 3) shows that the parameters BIO 9 and BIO 2 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 9 is the Mean Temperature of Driest Quarter and BIO 2 is the Mean Diurnal Range. Compared to 2030, the distribution of *R. tuberosa* plants seems to decrease. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in 2050 RCP 8.5 table (Table 2), the order of suitability of the area from the largest is very low suitability of 98258 km^2, then low suitability of 15854 km^2, high suitability of 9035 km^2, and lastly, medium suitability of 86289 km^2.

In the estimated distribution map of *R. tuberosa* plants 2080 using RCP 8.5, the most influential parameter is BIO 9 or Mean Temperature of Driest Quarter, with a total contribution of 16.4% shown in the curve result graph (Figure 4). With an AUC value of 0.942, which means the results are accurate. In the Effect of Environmental Variables on the Distribution of *R. tuberosa* (Table 3), it is shown that parameters BIO 19 and BIO 3 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 19 is the Precipitation of the Coldest Quarter, and BIO 3 is Isothermality. The decline in the distribution of *R. tuberosa* occurred again in 2080. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in the 2080 RCP 8.5 table (Table 2), the order of suitability of the area from the largest is very low suitability of 94155 km^2, then low suitability of 20923 km^2, high suitability of 8487 km^2, and lastly, medium suitability of 8205 km^2.

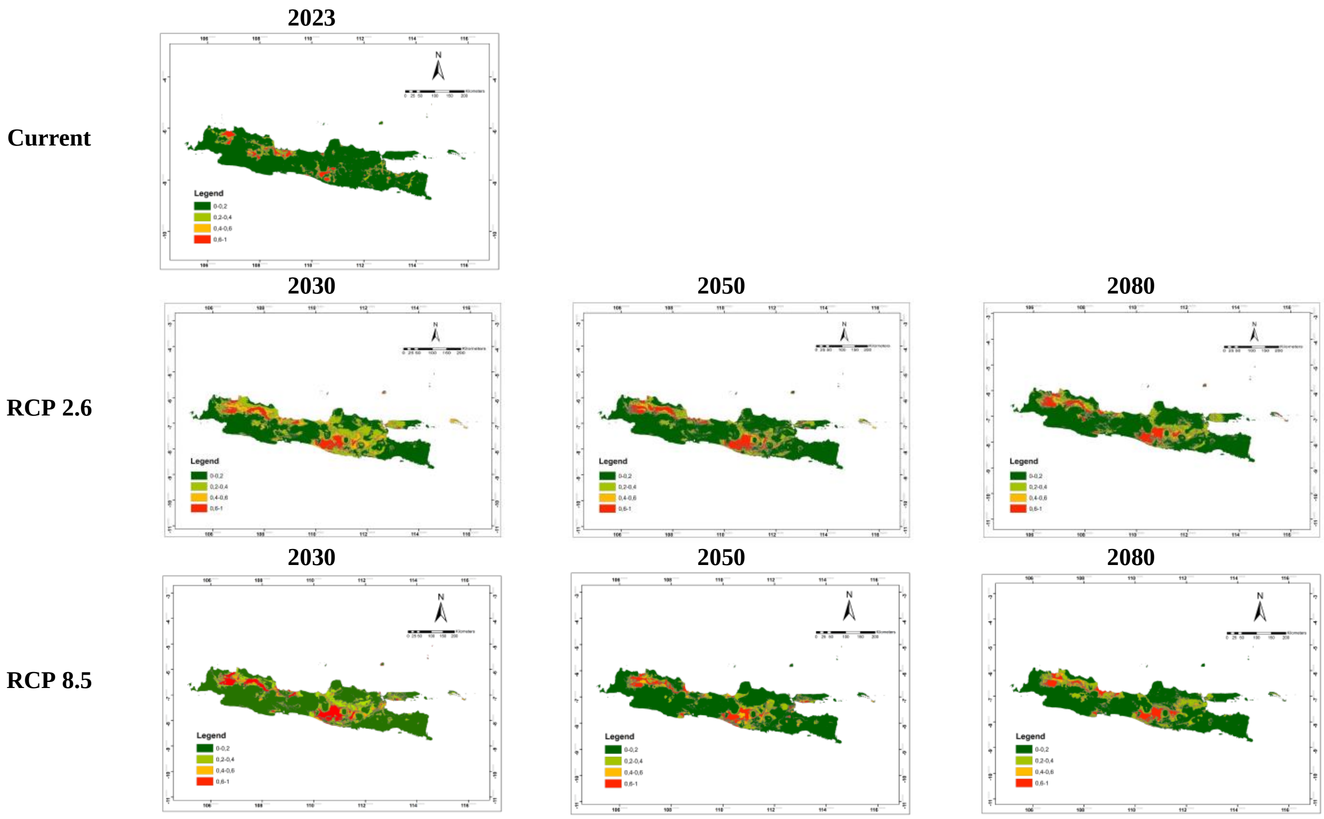


Figure 3. Distribution of *Ruellia tuberosa*

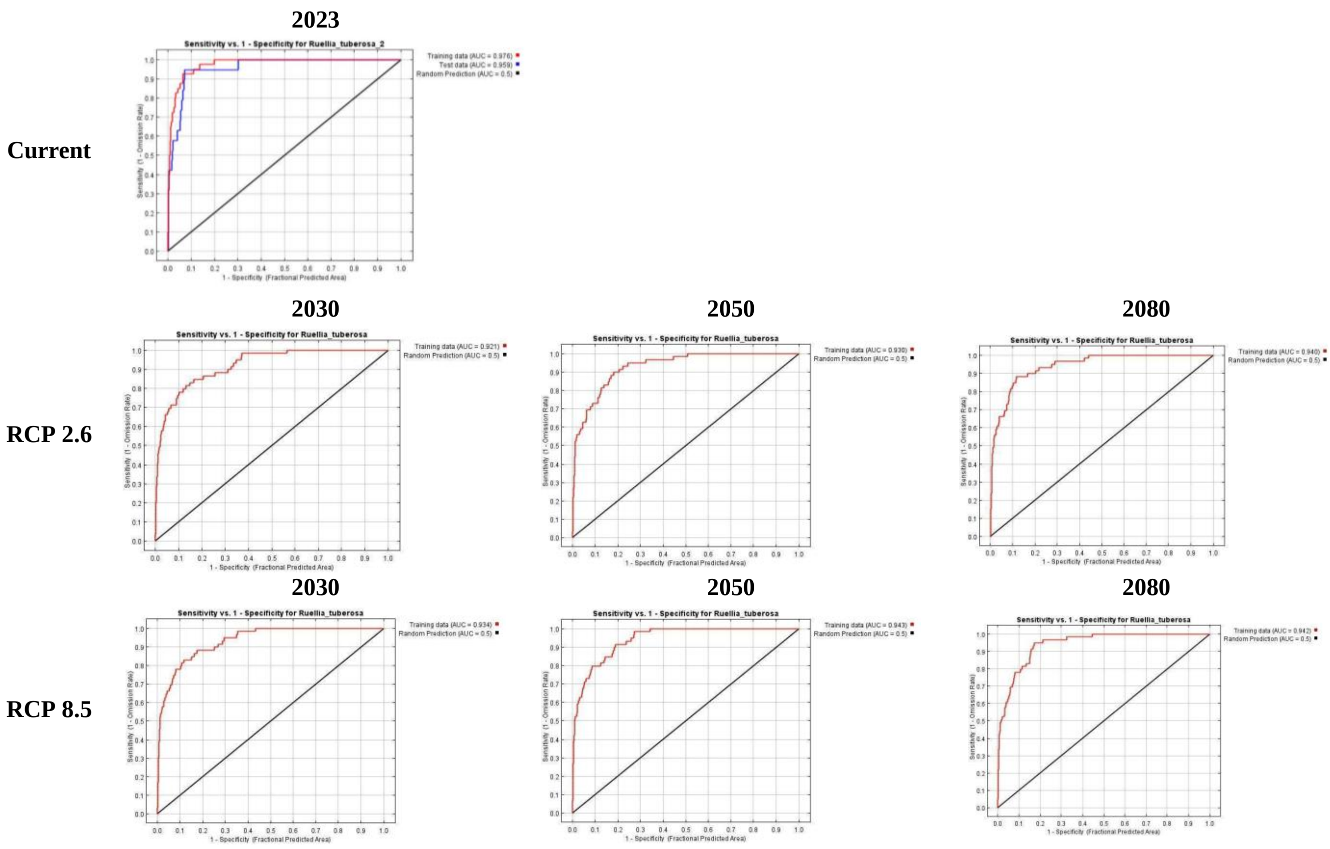


Figure 4. The result of AUC curves

Table 2. Suitability Index and area of distribution of *R. tuberosa*

Index Name	Suitability Index	Area (km^2)						
		Current	2030 RCP 8.5	2050 RCP 8.5	2080 RCP 8.5	2030 RCP 2.6	2050 RCP 2.6	2080 RCP 2.6
Very Low Suitability	0-0.2	112894	89581	98258	94155	74142	92046	91229
Low Suitability	0.2-0.4	10556	21474	15854	20923	32129	19020	21037
Medium Suitability	0.4-0.6	4452	10226	8628	8205	16460	9451	9441
High Suitability	0.6-1	4491	10472	9035	8487	8978	11205	10059

In the estimated distribution map of *R. tuberosa* in 2030 using RCP 2.6, the most influential parameter is BIO 6, or Minimum Temperature of The Coldest Month, with a total contribution of 15% shown on the curve yield graph (Figure 4). With an AUC value of 0.921, which means the results are accurate. The effect of Environmental Variables on the Distribution of *R. tuberosa* (Table 3) shows that the parameters BIO 9 and BIO 4 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 9 is the Mean Temperature of Driest Quarter and BIO 4 is Temperature Seasonality. This parameter highlights the importance of minimum temperatures during the coldest months in forming the distribution pattern of *R. tuberosa*. A decrease in minimum temperature in the coldest months, as indicated in BIO 6's contribution to the RCP 2 scenario, can change environmental conditions and create a more suitable space for the growth of these plants. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in 2030 RCP 2.6 table (Table 2), the order of suitability of the area from the largest is very low suitability of 74142 km^2, then low suitability of 32129 km^2, medium suitability of 16460 km^2, and lastly, high suitability of 8978 km^2.

In the estimated distribution map of *R. tuberosa* plants in 2050 using RCP 2.6, the most influential parameter is BIO 4 or Temperature Seasonality, with a total contribution of 21.1%. With an AUC value of 0.930 shown in the curve result (Figure 4), the result is accurate. The effect of Environmental Variables on the Distribution of *R. tuberosa* (Table 3) shows that the parameters BIO 9 and BIO 12 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 9 is the Mean Temperature of Driest Quarter and BIO 12 is Annual Precipitation. This parameter describes temperature fluctuations between seasons of the year in a region. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in 2050 RCP 2.6 table (Table 2), the order of suitability of the area from the largest is very low suitability of 92046 km^2, low suitability of 19020 km^2, high suitability of 11205 km^2 and lastly, medium suitability of 9451 km^2.

In the estimated distribution map of *R. tuberosa* plants 2080 using RCP 2.6, the most influential parameter is BIO 9 or Mean Temperature of Driest Quarter, with a total contribution of 14.6%. With an AUC value of 0.940 shown in the curve result (Figure 4), the result is accurate. The effect of Environmental Variables on the Distribution of *R. tuberosa* (Table 3) shows that parameters BIO 4 and BIO 17 also have a considerable influence on the distribution of *R. tuberosa* plants, where BIO 4 is Temperature Seasonality and BIO 17 is Precipitation of Driest Quarter. Based on the Suitability Index and Area of Distribution of *R. tuberosa* in the 2080 RCP 2.6 (Table 2), the order of suitability of the area from the largest is very low suitability of 91229 km^2, low suitability of 21037 km^2, high suitability of 10059 km^2, and medium suitability of 9441 km^2.

The influence of environmental variables on *R. tuberosa* habitat was a suitability modeling based on operational results from Jackknife. This graph is a method used to determine the influence of environmental variable factors on the modeling system (Putri et al. 2019). Based on the results of Jackknife operations today (2023) (Figure 5), the factor that most influences the growth of *R. tuberosa* plants is BIO 4 (Temperature Seasonality). The environmental variable that influences the current growth of *R. tuberosa* is seasonal temperature. Jackknife's predictions for 2030, 2050, and 2080 have 2 modeling scenarios: RCP 2.6 and RCP 8.5. RCP 2.6 is used for minimum greenhouse gas emissions, and RCP 8.5 means maximum greenhouse gas emissions. Based on the predicted results of Jackknife modeling operations in 2030 using RCP 2.6 (Figure 6), the environmental variable that has the most influence on the growth of the invasive plant *R. tuberosa* is BIO 19 (Precipitation of Coldest Quarter). In contrast, in 2030 modeling using RCP 8.5 (Figure 6), there are 4 environmental variables that influence the growth and development of *R. tuberosa* plants, namely BIO 19 (Precipitation of Coldest Quarter), BIO 4 (Temperature Seasonality), BIO 6 (Min Temperature of Coldest Month), and BIO 9 (Mean Temperature of Driest Quarter). Based on the results of the Jackknife 2050 modeling prediction operation using RCP 2.6 (Figure 6), the most influential environmental variable in *R. tuberosa* plant breeding process is BIO 4 (Temperature Seasonality), whereas using RCP 8.5 (Figure 6), the most influential variable in the plant breeding process *R. tuberosa* is BIO 19 (Coldest Quarter Precipitation). Based on the results of the Jackknife 2080 modeling prediction operation using RCP 2.6 (Figure 6), the environmental variables that have the most influence in *R. tuberosa* plant breeding process are BIO 19 (Precipitation of Coldest Quarter) and BIO 6 (Min Temperature of Coldest Month), while using RCP 8.5 (Figure 6) The most influential variable in the reproduction process of *R. tuberosa* is BIO 6, namely (Min Coldest Month Temperature).

Table 3. Contribution of environmental parameters to the distribution of *Ruellia tuberosa*

Current		2030 RCP 8.5		2050 RCP 8.5		2080 RCP 8.5		2030 RCP 2.6		2050 RCP 2.6		2080 RCP 2.6	
Variable	**Percent Contribution**	**Variable**	**Percent Contribution**	**Variable**	**Percent Contribution**	**Variable**	**Percent Contribution**	**Variable**	**Percent Contribution**	**Variable**	**Percent Contribution**	**Variable**	**Percent Contribution**
BIO 4	22.8	BIO 9	17.6	BIO 19	17.8	BIO 9	16.4	BIO 6	15	BIO 4	21.1	BIO 9	14.6
BIO 2	17.2	BIO 4	13.7	BIO 9	14.1	BIO 19	15.2	BIO 9	12.9	BIO 9	15.1	BIO 4	13.7
BIO 3	6.8	BIO 12	9.6	BIO 2	10.3	BIO 3	15.2	BIO 4	12.9	BIO 12	12.6	BIO 17	12.1
BIO 16	6.6	BIO 17	9	BIO 18	9.2	BIO 7	8.1	BIO 17	12.4	BIO 17	10.4	BIO 6	11.1
SRAD1	6.3	BIO 19	8.5	BIO 12	8.4	BIO 17	5.4	BIO 19	11.3	BIO 6	9.5	BIO 3	9.3
BIO 11	5.7	BIO 16	7.6	BIO 6	8	BIO 6	5.2	BIO 16	8.1	BIO 15	6	BIO 16	7.3
BIO 12	5	BIO 2	6.5	BIO 17	7.6	BIO 18	5.2	BIO 12	5.6	BIO 16	5.4	BIO 15	7.1
BIO 19	4.8	BIO 15	4.9	BIO 15	5	BIO 15	5.1	BIO 15	5.5	BIO 2	4.9	BIO 19	5.9
SRAD7	4.6	BIO 8	4.4	BIO 7	4.8	BIO 16	4.8	BIO 3	4.8	BIO 19	4.8	BIO 12	5.5
BIO 8	3.8	BIO 6	4	BIO 3	3.5	BIO 2	4	BIO 7	3.9	BIO 3	2.7	BIO 2	4.1
SRAD3	3	BIO 18	3.7	BIO 8	3.4	BIO 8	3	BIO 10	2.5	BIO 14	1.8	BIO 14	3.6
BIO 7	2.3	BIO 3	2.8	BIO 16	3.3	BIO 10	3	BIO 8	1.9	BIO 5	1.4	BIO 8	1.4
BIO 15	1.9	BIO 7	2.1	BIO 4	2.9	BIO 13	2.7	BIO 5	1.2	BIO 8	1.4	BIO 13	1.4
BIO 5	1.7	BIO 11	2.1	BIO 11	1.1	BIO 5	2.6	BIO 14	1	BIO 18	1.4	BIO 18	1.3
BIO 6	1.3	BIO 13	1.3	BIO 1	0.3	BIO 4	2.1	BIO 11	0.6	BIO 7	0.7	BIO 7	1.1
Elevation	1.2	BIO 1	1.1	BIO 13	0.3	BIO 11	1.7	BIO 1	0.2	BIO 11	0.4	BIO 11	0.4
BIO 17	1.2	BIO 14	0.6	BIO 5	0	BIO 12	0.1	BIO 13	0.1	BIO 1	0.2	BIO 10	0.1
BIO 13	1.1	BIO 10	0.4	BIO 14	0	BIO 1	0.1	BIO 18	0	BIO 10	0	BIO 5	0.1
SRAD9	0.9	BIO 5	0.1	BIO 10	0	BIO 14	0	BIO 2	0	BIO 13	0	BIO 1	0
SRAD4	0.4												
SRAD2	0.3												
SRAD5	0.3												
SRAD10	0.3												
BIO 14	0.2												
BIO 18	0.2												
SRAD12	0.1												
BIO 9	0												
SRAD11	0												
BIO 1	0												
SRAD6	0												
SRAD8	0												
BIO 10	0												

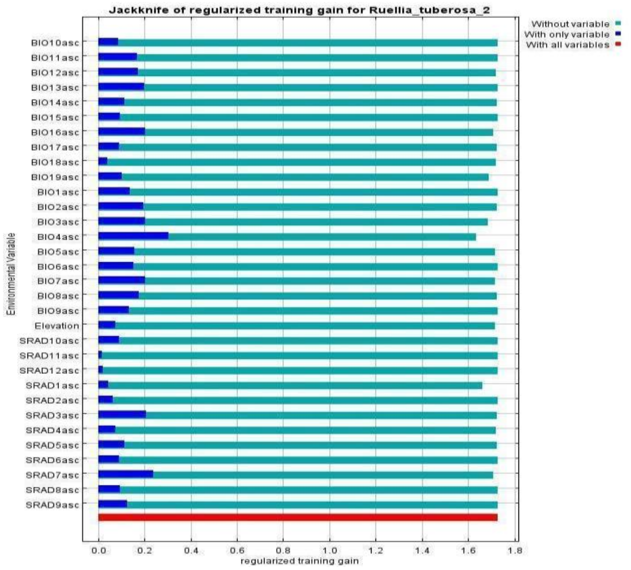
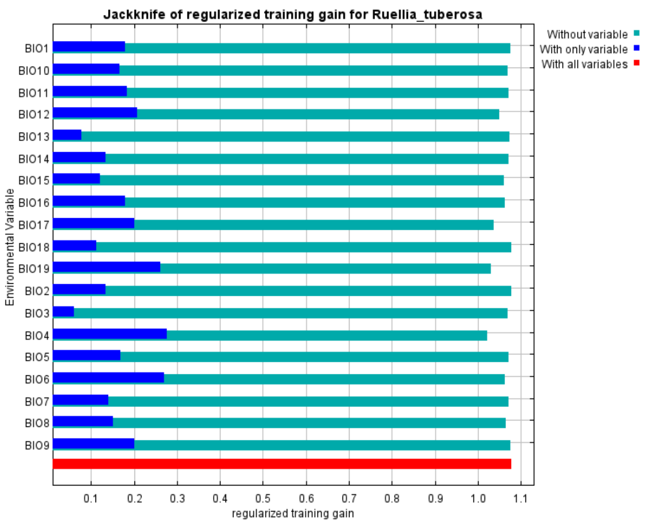
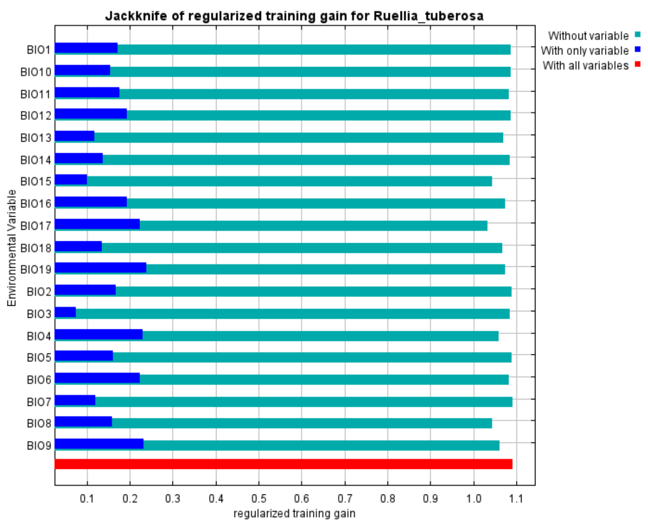


Figure 5. The results of the Jackknife of variable's contributions in 2023



A



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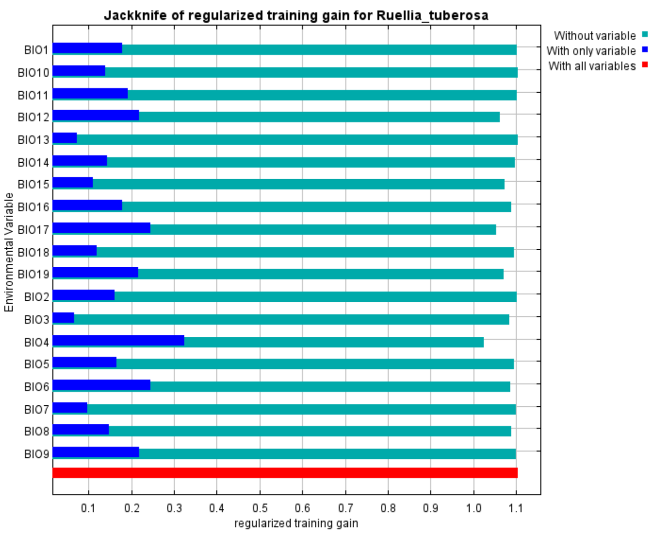

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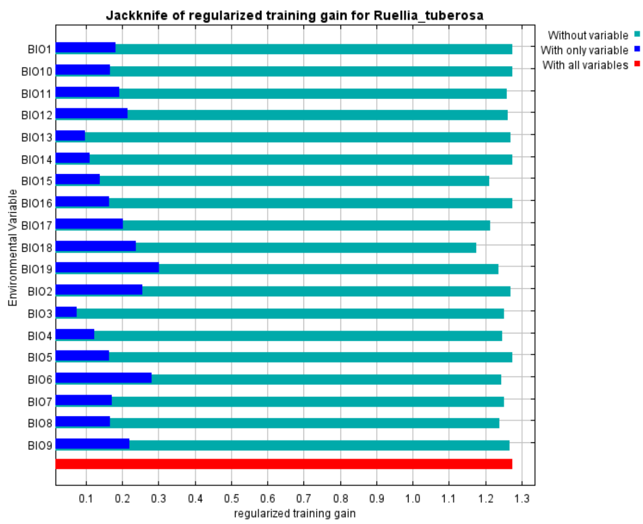
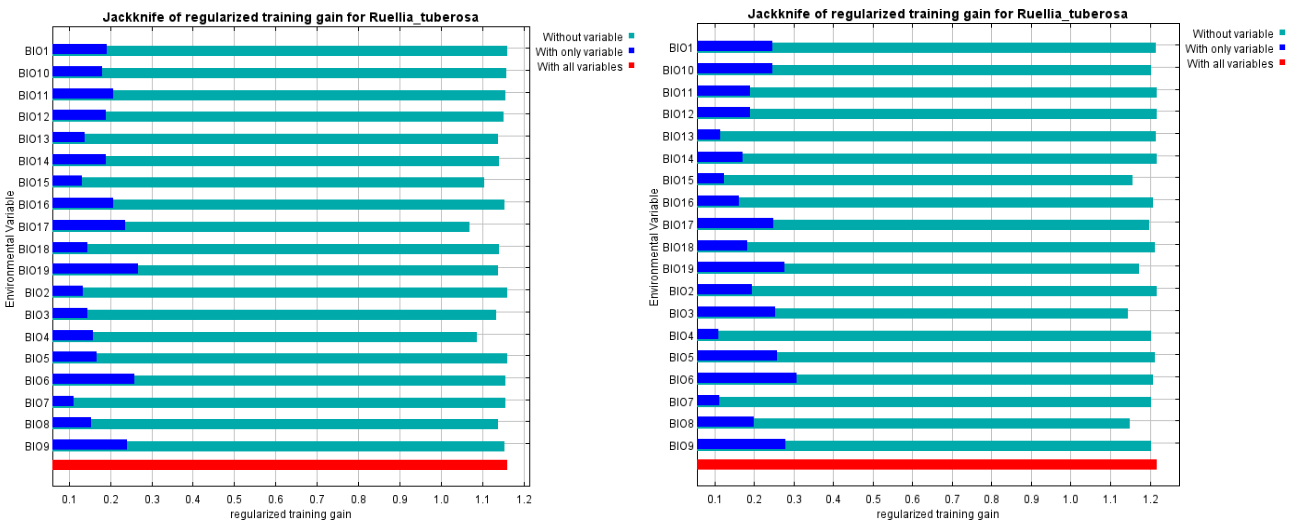


D



E F

Figure 6. The influence of environmental variables on the distribution of *Ruellia tuberosa*: A. In 2030 using RCP 2.6; B. In 2030 using RCP 8.5; C. In 2050 using RCP 2.6; D. In 2050 using RCP 8.5; E. In 2080 using RCP 2.6; F. In 2080 using RCP 8.5

Based on research from Putri et al. (2019), who used jackknife operations to determine the suitability of frog habitat on Java Island, the results obtained were that land cover, temperature, and drought had a big influence on modeling, namely jackknife modeling. As in the modeling carried out by Putri et al. (2019), to determine the influence of environmental variables on jackknife operation, the test AUC value and the regularized training gain value obtained due to the treatment of environmental variables that have been determined are needed. The greater the AUC test value and regularized training gain resulting from using certain environmental variables, the higher the classification of these environmental variables as factors that influence the modeling created.

The areas of Java Island and Madura Island have environmental characteristics suitable for the growth of *R. tuberosa*, especially in certain areas with warm or hot climates. Geographical conditions Java island has an average annual temperature of 22-29°C; this condition causes the growth of *R. tuberosa* so fast on the island of Java, especially in urban areas such as Jakarta and Surakarta, as shown by the red map. Environmental conditions that tend to be warm are favored. Therefore, the spread of this plant is very fast. Likewise, in the Madura Island area, some areas have a temperature climate suitable for overgrowth and the development of *R. tuberosa*.

Discussion

From the map analysis of the estimated distribution of *R. tuberosa* growth in 2030, 2050, and 2080 using the RCP 8.5 scenario, there is a significant decrease in the distribution of this plant from one year to another. Through the analysis, the main parameters that dominantly affect the distribution of *R. tuberosa* are BIO 9 or Mean Temperature of Driest Quarter, BIO 2 or Mean Diurnal Range, BIO 3 or Isothermality, BIO 4 or Temperature Seasonality, BIO 12 or Annual Precipitation, and BIO 19 or Precipitation of Coldest Quarter. BIO 9 describes the average temperature of a region's hottest year. Changes in elevated temperature and precipitation totals in the Driest quarter in the RCP 8.5 scenario are key factors leading to a sharp decline in the distribution of this crop. This indicates that extreme temperatures in summer, or the quarter with the highest temperatures of the year, have major implications for the availability of suitable habitats for the growth of *R. tuberosa* (Seerangaraj et al. 2021). *Ruellia tuberosa* also has tuberous roots and an intelligent seed dispersal system to help it survive the dry season and multiply (Singh et al. 2023). In comparison, in the rainy season, it often grows as a weed (Kathiravan et al. 2018). Besides temperature, climate change also has the potential to disrupt other parameters that support plant growth, such as air humidity, rainfall, and interactions with other flora and fauna (Tram and Quach 2022). Warmer temperature conditions and total rainfall in the quarter are believed to be the main factors forming a more conducive habitat for the growth and spread of *R. tuberosa* (De Freitas et al. 2020). Increasingly unsuitable environmental conditions, ever-increasing temperatures, the coldest cold weather, and too great a difference in mean highest and lowest temperatures could lead to a further decline in its distribution range (Arun et al. 2022). Drastic changes occur because climatic conditions, which include very high temperatures and overall ecosystem changes, can cause a significant decrease in the habitat that supports the growth of this plant (Ernakovich et al. 2014).

The estimated distribution map of *R. tuberosa* plant growth in 2030, 2050, and 2080 using the RCP 2.6 scenario illustrates a consistent increase from one decade to the next. Many parameter changes strongly influence this in key environmental parameters that play a role in forming suitable habitats for the growth of these plants. The most influential parameters in each year are different. Through this analysis, the main parameters that dominantly affect the distribution of *R. tuberosa* are BIO 6 or Minimum Temperature of the Coldest Month, BIO 4 or Temperature

Seasonality, BIO 9 or Mean Temperature of Driest Quarter, BIO 12 or Annual Precipitation, and BIO 17 or Precipitation of Driest Quarter. All three parameters highlight the role of temperature in influencing the distribution and growth of *R. tuberosa*. Plant adaptation to temperature conditions that vary from month to month, season to season, and quarter to quarter is key in exploiting or utilizing climate change for the future expansion of these plant-growing areas. The minimum temperature in the coldest months is a critical factor affecting the adaptation and growth of this plant. Temperature conditions during this period can determine the availability of supportive habitat for *R. tuberosa* (Harika and Radhika 2021). Relatively stable temperatures between seasons reduce extreme fluctuations, providing more predictive and suitable environmental conditions for these plants to multiply (Wulandari and Tamam 2021). The increase in temperature in the warmest quarter of the year expands the distribution area suitable for the growth of *R. tuberosa*. Warmer temperature changes in the warmest quarter allow this plant to grow in areas that may not have previously supported its growth well (Harinath et al. 2019).

Ruellia tuberosa is one species of plant that has the ability to grow invasively, so it has the potential to cause significant disturbance in some areas. Therefore, effective control of the spread of *R. tuberosa* is needed to minimize negative impacts and protect other biodiversity. One of the effective and affordable ways that can be done to control the spread of *R. tuberosa* is to utilize it for various useful purposes. One of the benefits of *R. tuberosa* is that it can be used as a diabetes medicine. This plant contains various pharmacological benefits such as antioxidants, anti-inflammatory, and anticancer, antinociceptive, antipyretic, antidiuretic, analgesic, diuresis, antihypertensive, antioxidant, insecticide, anticancer, and antidote poison agent (Ko et al. 2019; Hepni et al. 2021; Kannan et al. 2021; Annisa et al. 2022). The use of *R. tuberosa* plant in Indonesia for medicine is not without reason, because *R. tuberosa* plant contains many phytochemicals that can be used to treat diabetes (Wati and Anisatu 2023). According to research from Rahmi et al. (2014), extracts from *R. tuberosa* leaves have hypoglycemic activity which can be used to treat diabetes mellitus. Compounds such as alkaloids, flavonoids, triterpenoids, steroids and saponins which can be used as medicine are found in *R. tuberosa* plant. These compounds may contribute to lowering blood sugar levels by increasing insulin sensitivity or involving mechanisms that inhibit glucose absorption in the gastrointestinal tract (Ko et al. 2018).

Predicted future changes in temperature and rainfall will also influence the distribution of local species. Species performances and survival are expected to change in a non-uniform manner across the landscape (Barton et al. 2019). Predicted future changes in temperature and rainfall will also influence the distribution of local species. Local species that are unable to adapt to climate change cannot compete with invasive foreign species that have higher adaptability. As species may be unable to disperse, establish, or adapt quickly enough to keep up with a warming climate (Aitken and Whitlock 2013). Ways to mitigate invasive foreign species include controlling or eradicating them to prevent the entry and development of invasive species (Orapa 2017). Efforts to eradicate invasive species can use several methods, including functional eradication involving clear and dominant ecological mechanisms. Many predators can attack invasive species for functional eradication, as prey for consumption. In addition, several attributes of the recipient ecosystem configuration will support the success of functional eradication, giving rise to resistance that creates dependence on the state of the invasive species ecosystem which is influenced by stressors such as habitat degradation and exploitation (Green and Grosholz 2021). Not only controlling their invasive growth, but also providing added value to health and natural resource utilization. Through innovative approaches, we can turn a plant that was initially considered a weed into something useful for society and the environment. While the use of *R. tuberosa* can be used for a variety of purposes including medicinal, its use as a dispersal control is only temporary. While this plant can provide benefits as a substitute in some situations, its role tends to be substitutive and unreliable in the long term (Chothani et al. 2010). These limitations emphasize the importance of developing more effective and reliable alternatives (Sharma et al. 2023). Further research and development is needed to fully understand the potential and limitations of this plant so that it can be optimally used in various applications.

In conclusion, the distribution of *R. tuberosa* is currently seen in most of Java and Madura, which dominate areas with very low suitability. Some areas also have low suitability, which is more obvious than areas with medium suitability. From the analysis of the map of the estimated distribution of *R. tuberosa* plant growth in 2030, 2050, and 2080, there is a significant decrease in the distribution of this plant from one year to year because there was significant climate change in that year, which was caused by an increase in CO_2 levels, which led to global climate change, thus affecting the growth of invasive plants. The main parameter that predominantly influences the spread of *R. tuberosa* is BIO 9 (Mean Temperature of Driest Quarter).

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