HABITAT SUITABILITY MODELING FOR ORANGE (CITRUS) CULTIVATION WITH AN ORGANIC AGRICULTURE ORIENTATION UNDER THE IMPACT OF CLIMATE CHANGE IN PHU THO PROVINCE

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Abstract: *Orange is a fruit crop of high economic value in the midland and mountainous region of Northern Viet Nam. In the context of climate change and the orientation toward organic agriculture, identifying areas suitable for orange cultivation is of major importance for sustainable production planning. This study applies the Random Forest (RF) algorithm within the biomod2 platform to assess and predict habitat suitability for orange cultivation in Phu Tho province under CMIP6 climate change scenarios.*

The dataset comprises 14 variables in three groups: climate (WorldClim 2), soil-terrain (SoilGrids, DEM), and anthropogenic factors reflecting production development conditions. The model was trained using RF (ntree = 200, mtry = 2), evaluated by 5-fold cross-validation, and combined into an ensemble model (EMwmean). Future climate data were derived from the MPI-ESM1-2-HR model under two scenarios, SSP2-4.5 and SSP3-7.0, for the periods 2021-2040 and 2041-2060.

The results show that the model achieved high accuracy (AUC = 0.959; TSS = 0.886). Residential density, annual rainfall, and elevation were the factors with the greatest influence on habitat suitability. Under current conditions, 373,445.7 ha (39.89% of the natural area) were classified as suitable or highly suitable. Under the impact of climate change, the suitable area expands under both scenarios but to differing degrees: the expansion is larger and more stable under SSP2-4.5, whereas under SSP3-7.0 the gain is smaller in the early period (2021-2040) and the suitable area subsequently shifts toward higher-elevation areas. The findings provide a scientific basis for planning orange-growing areas oriented toward organic agriculture that are adapted to climate change.

Keywords: *Random Forest, habitat suitability, organic agriculture, CMIP6, Phu Tho.*

1. Introduction

Global agricultural production is facing a dual challenge posed by climate change and the need to shift toward sustainable farming models [1]. In Viet Nam, Decision No. 885/QĐ-TTg dated 23 June 2020 of the Prime Minister, approving the Scheme on Organic Agriculture Development in the period 2020-2030, sets out the orientation of expanding the area under organic farming and developing concentrated organic production zones, thereby improving land-use efficiency and enhancing resilience to climate change.

Orange is one of Viet Nam's key fruit crops, particularly in the midland and mountainous region of Northern Viet Nam, home to well-known production areas such as Cao Phong orange and Sanh orange. However, changing climatic conditions, together with urbanization, land-use conversion, and socio-economic development pressures, are increasing the vulnerability of orange-growing areas [2-4]. In this context, assessing and predicting habitat suitability for orange cultivation oriented toward organic agriculture is of major importance for

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the planning and management of sustainable agricultural production.

Habitat suitability modeling based on Species Distribution Modeling (SDM) has become an effective tool for assessing ecological conditions and predicting spatial change in the object of study [5], [6]. By establishing the relationship between presence data and environmental variables, this approach makes it possible to determine the suitability level of each area and predict changes under future climate scenarios [7]. In recent years, machine-learning algorithms, particularly Random Forest (RF), have been widely used owing to their ability to model nonlinear relationships, handle high-dimensional data, limit overfitting, and provide indices for evaluating the influence of each environmental variable [8], [9]. When integrated within the biomod2 platform, Random Forest also enables the construction of ensemble models, contributing to higher accuracy and stability of the prediction results [10].

Although many studies have applied machine-learning models and SDM to assess habitat suitability for crops, most have focused only on climatic factors or natural ecological conditions. The simultaneous integration of climatic, soil, and terrain factors together with production development conditions to assess habitat suitability for orange cultivation oriented toward organic agriculture under climate change scenarios remains limited, particularly in the midland and mountainous region of Northern Viet Nam [11], [12].

Building on this, the present study was conducted to: (i) Develop a Random Forest model within the biomod2 platform, integrating climatic, soil, terrain, and anthropogenic factors to assess habitat suitability for orange cultivation oriented toward organic agriculture in Phu Tho province; (ii) Determine the influence of environmental factors and production development conditions on habitat suitability; and (iii) Predict changes in the suitable area under CMIP6 climate change scenarios (SSP2-4.5 and SSP3-7.0) for the periods 2021-2040 and 2041-2060, providing a scientific basis for planning the sustainable development of orange-growing areas.

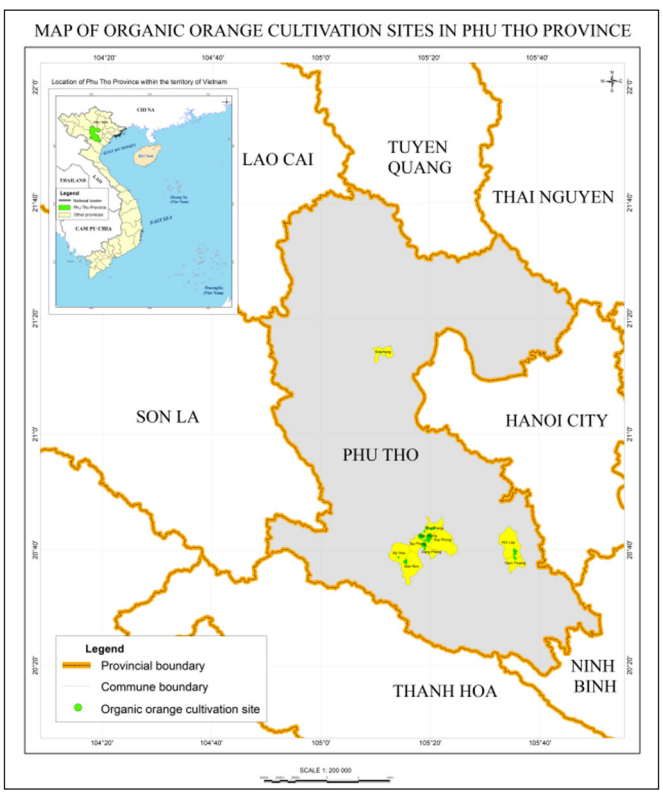


Figure 1. Administrative boundary map of Phu Tho province

2. Study area and data

2.1. Study area

Phu Tho province is located in the midland and mountainous region of Northern Viet Nam. The new Phu Tho province was formed by merging the entire administrative boundaries of the former Phu Tho, Vinh Phuc, and Hoa Binh provinces. After the merger, Phu Tho has a natural area of approximately 9,361.38 km² (936,138 ha) and a population exceeding 4 million, making it one of the largest localities by area and population in the Northern midland and mountainous region. The province's administrative-political center is located in Viet Tri City, the former capital of Phu Tho province. As a Class I urban center, Viet Tri holds a central position in transportation, administration, and culture, and is regarded as a hub that gathers and radiates development momentum for the whole region.

The new Phu Tho province occupies a strategic position as a bridge between the Red River Delta and the Northwest region: it borders Tuyen Quang and Son La provinces to the North; Thai Nguyen province to the Northeast; the capital city of Hanoi to the East; Hung Yen province (across the Red River) to the Southeast; Ninh Binh province to the South; Thanh Hoa province to the Southwest; and Son La province to the West.

Bordering many localities and situated at the midpoint of major transport corridors such as National Highway 2, National Highway 32, and the Noi Bai-Lao Cai Expressway, and being close to Noi Bai International Airport, the new Phu Tho province has favorable conditions for developing trade, industry, logistics services, and tourism.

The province's terrain shows a marked differentiation, from high mountains in the Northwest down to midland hills and river-fringed lowlands in the Southeast. The climate is tropical monsoon with a cold winter, and mean annual rainfall ranges from 1,600 to 2,000 mm. The diversity of soil types (red-yellow Feralit soils, alluvial soils) and microclimates creates ecological sub-zones suitable for a wide range of fruit crops.

2.2. Species occurrence data

Presence data for areas of successful organic orange cultivation were collected through field surveys of concentrated orange-growing areas in May 2025 (Figure 1). To minimize spatial sampling bias, duplicate points falling within the same 100 m × 100 m grid cell were removed, and where two or more points lay less than 1 km apart, a single point was retained at random. All coordinates were standardized to the VN-2000 national coordinate system (EPSG:3405, UTM Zone 48N).

2.3. Input environmental variables

The predictor set comprises 14 spatial data layers, divided into three basic groups comprising two climatic, eight soil-terrain, and four anthropogenic variables:

2.3.1. Climatic variables

Derived from the WorldClim 2 dataset at its native spatial resolution of 30 arc-seconds (~1 km), comprising mean annual temperature (bio_1, °C) and annual precipitation (bio_12, mm) [13]. For future projections, data were extracted from the CMIP6 MPI-ESM1-2-HR model under two emission scenarios, SSP2-4.5 and SSP3-7.0, for two time periods, 2021-2040 and 2041-2060. These climatic variables were selected because temperature and rainfall are the factors that directly determine the growth, yield, and ecological distribution limits of orange trees.

2.3.2. Soil and terrain variables

Extracted from SoilGrids 250 m and a Digital Elevation Model (DEM), including: elevation (DEM), landform (Landform), soil organic carbon content (Soil_Organic_Carbon), sand content (Sand_Content), bulk density (Bulk_Density), soil pH (pH), soil type (Soil_type), and lithology (Lithology) [14]. This group of variables reflects the underlying conditions of the growing environment, influencing water-holding and drainage capacity, soil fertility, root development, and the microclimate of the orange-growing area.

2.3.3. Anthropogenic infrastructure density variables

Constructed using the Kernel Density algorithm in GIS software, including the density

of industrial facilities (CTCN_Den), hydrological network density (Thuyhe_Den), road density (Giaothong_Den), and residential density (KDC). This group of variables is used to reflect the degree of favorability of the conditions for developing organic agricultural production. Among them, hydrological network density represents access to water sources for irrigation; road and residential density reflect access to labor, input supplies, harvesting, and product distribution; while industrial facility density is regarded as an indirect indicator of exposure to industrial activity, helping to assess the risk of impacts on the production environment and agricultural product quality. Incorporating this group of variables allows for a more comprehensive assessment of the suitability of areas for developing orange-growing zones oriented toward organic agriculture.

The anthropogenic variables were assumed to remain unchanged through 2060 because spatially explicit projections of urban/infrastructure development at 100 m resolution for post-merger Phu Tho province are not yet available. Holding these variables constant (ceteris paribus) allows the projected changes in suitability to be attributed directly to climate change, thereby isolating the climate signal from confounding effects arising from highly uncertain socio-economic development trajectories.

3. Research methods

To achieve the stated research objectives, an integrated workflow combining Species Distribution Modeling (SDM), the Random Forest (RF) machine-learning algorithm, and the biomod2 platform was developed to assess the ecological adaptability of orange trees under current and future conditions. The workflow comprises the following main steps: collecting and standardizing occurrence data together with environmental variables; processing and selecting input variables; building, calibrating, and evaluating the RF model; constructing an ensemble model; mapping the current habitat suitability zones; and predicting the spatial change of the suitable area under CMIP6 climate change scenarios. The overall research workflow is presented in Figure 2.

3.1. Spatial pre-processing and multicollinearity control

All raster data layers were converted to the common EPSG:3405 projected coordinate system and resampled to a spatial resolution of 100 m × 100 m. Bilinear interpolation was applied to continuous variables, while the nearest-neighbor method was applied to categorical variables. All suitability classes are reported over the full natural area of the province (936,138 ha, equivalent to 9,361.38 km²); cells lying outside the modelled extent, namely water surfaces and cells without valid predictor values, were assigned to the unsuitable class so that the four classes sum to the total natural area.

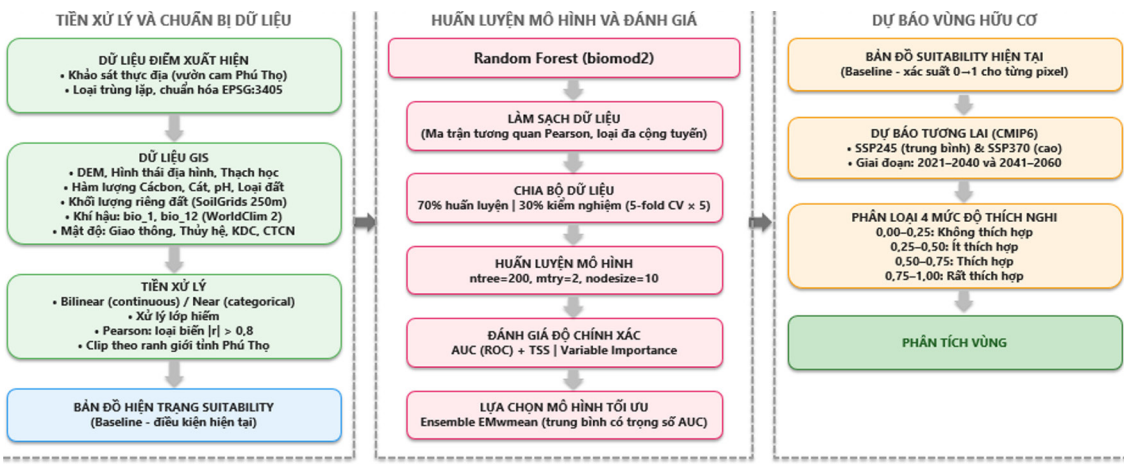


Figure 2. Overall research workflow integrating SDM-RF for orange habitat suitability zoning in Phu Tho province under climate change scenarios

To avoid a decline in model performance caused by multicollinearity, the Pearson correlation matrix (r) was calculated among all continuous variables. If two variables had a correlation coefficient |r| > 0.8, the variable with more direct ecological relevance to orange trees was retained [15].

3.2. Random Forest and biomod2 configuration

The study used the biomod2 package in the R environment. Pseudo-absence (PA) sampling was performed randomly, generating 1,000 PA points, repeated 3 times (PA.nb.rep = 3) [16]. The Random Forest algorithm was configured with the following optimal hyperparameters [9]:

Number of decision trees (n_{tree}) = 200.

Number of randomly selected variables at each split node (m_{try}) = 2.

Minimum node size (nodesize) = 10.

Reliability testing was carried out using 5-fold cross-validation repeated five times, yielding 25 model runs. The ensemble model (EM_{wmean}) was constructed by computing the weighted average of the component models based on their AUC values.

3.3. Model accuracy assessment

Classification performance was evaluated using two standard statistical indices:

Area Under the ROC Curve (AUC): values range from 0.5, corresponding to random discrimination, to 1.0, corresponding to perfect discrimination; values above 0.9 indicate excellent discriminatory ability.

True Skill Statistic (TSS): Calculated as TSS = Sensitivity + Specificity − 1. TSS is independent of prevalence, and a value > 0.6 indicates a highly reliable model.

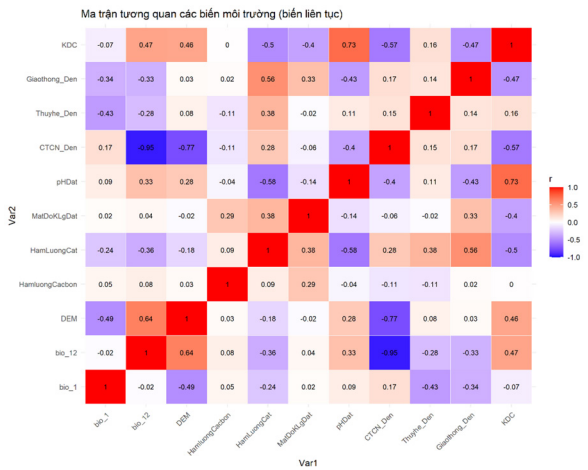


Figure 3. Pearson correlation matrix among the variables

4. Results and discussion

4.1. Correlation matrix and multicollinearity removal

The Pearson correlation matrix computed on 11 continuous variables at orange occurrence points showed that most variable pairs had low-to-moderate correlation coefficients (|r| < 0.7), indicating a low risk of multicollinearity.

However, the pair of industrial facility density (CTCN_Den) and annual rainfall (bio_12) showed a very strong negative correlation (r = -0.95), exceeding the permissible threshold (|r| > 0.8). According to the variable-selection criterion, annual rainfall (bio_12) was retained and industrial facility density (CTCN_Den) was removed, so that 13 predictor variables were used in the final model; this limits the effect of multicollinearity and improves model stability. This strong negative correlation arises from spatial confounding related to terrain/elevation. Industrial facilities in Phu Tho are concentrated in low-elevation delta and midland zones with favorable transport access (along the Red River and major arterial roads), while these same zones receive lower annual rainfall than the mountainous Northwest as a result of

topographic effects. CTCN_Den and bio_12 are therefore not directly causally related; rather, both correlate strongly with a shared underlying factor - elevation/terrain. This represents a typical case of indirect multicollinearity mediated by landscape structure.

4.2. Model predictive performance

Both the individual Random Forest model and the ensemble model (EM_{wmean}) showed excellent classification accuracy.

The validation AUC of 0.959 and TSS of 0.859 confirm the strong capability of the RF algorithm to distinguish between suitable and unsuitable areas for orange cultivation. Combining the models into the EMwmean ensemble raised the TSS to 0.886, optimizing the spatial reliability of the output map.

4.3. Variable importance and ecological-physiological interpretation

Variable importance analysis showed that residential density (KDC ≈ 0.30), annual rainfall (bio_12 ≈ 0.28), and elevation (DEM ≈ 0.25) were the three factors with the greatest influence on habitat suitability for orange cultivation (Figure 4).

The results indicate that the development of orange-growing areas depends not only on natural ecological conditions but is also significantly influenced by factors related to production organization. Rainfall and elevation determine the thermal, moisture, and terrain conditions for orange tree growth, while residential density reflects the availability of labor, production infrastructure, services, and market access for product distribution.

Table 1. Performance of the Random Forest and Ensemble models

Model configuration	Evaluation dataset	TSS	AUC
RF (Individual)	Calibration (Training)	0.893	0.924
RF (Individual)	Validation (Testing)	0.859	0.935
EM_{wmean} (Ensemble)	Combined	0.886	0.959

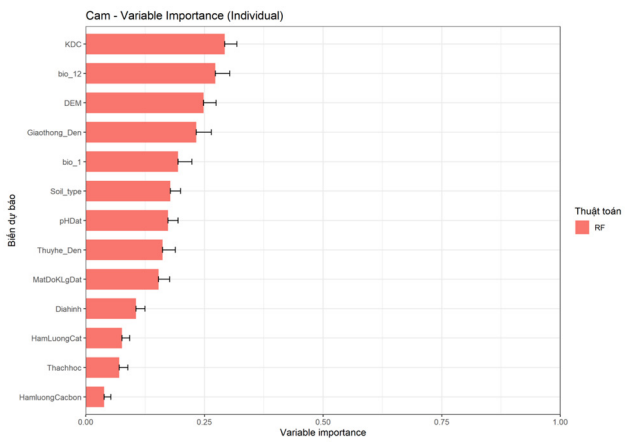


Figure 4. Relative influence of the variables

Unlike conventional cultivation, which can be highly mechanized and operated with low on-site labor density, organic cultivation requires substantially greater labor intensity - from manual weeding and composting/application of organic fertilizer to biological pest control - and is therefore closely tied to the frequent presence of farming households in the orchard. The relationship between residential density and habitat suitability thus reflects the labor-intensive nature inherent to organic production, rather than contradicting the organic orientation of this study.

The anthropogenic variables were constructed using the Kernel Density algorithm, which measures the degree of concentration

(density) of these factors within a search radius around each location, rather than the distance from that location to the nearest such factor. A high KDC value therefore reflects the labor and infrastructural favorability of the surrounding area as a whole, rather than directly measuring the degree of exposure of a specific cultivation site to an adjacent domestic pollution source - a factor that should instead be assessed using a distance-based variable (e.g., distance to the nearest residential boundary or pollution source). The current lack of distinction between density-based and distance-based variables in the input dataset is a limitation in variable design, and the authors identify this as a necessary addition for future studies, in order to clearly separate the roles of "favorability for production organization" and "local pollution risk," which are currently combined within a single density variable.

On the ground, areas of high residential density in Phu Tho province are mainly distributed in the midland and low-lying delta zones along the rivers, where natural conditions are favorable and specialized fruit-growing areas have already become established over many years. This indicates a convergence between suitable ecological conditions and production development orientation, contributing to the formation of areas with strong potential for orange cultivation oriented toward organic agriculture.

4.4. Habitat suitability distribution under current conditions

The current suitability map indicates that the total suitable area for organic-oriented orange cultivation in Phu Tho reaches 373,445.7 ha (39.89% of the natural area).

Within this total, the “highly suitable” zone covers 189,279.8 ha (20.22%) and the “suitable” zone covers 184,165.9 ha (19.67%). The “marginally suitable” zone covers 166,877.3 ha (17.83%), located mainly in the transitional areas between the delta and the midland, while the “unsuitable” zone covers 395,815.0 ha (42.28%), concentrated in the high mountainous areas in the Northwest of the province and in areas lying outside the modelled extent.

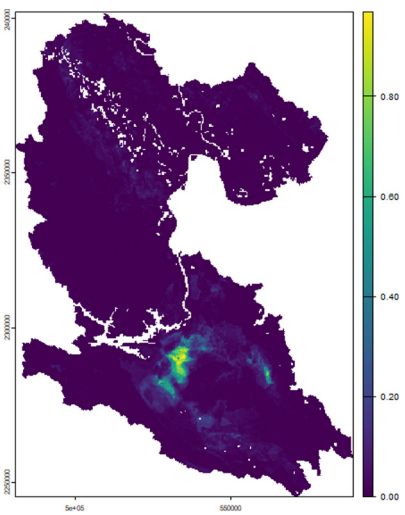


Figure 5. Current orange habitat suitability map in Phu Tho province

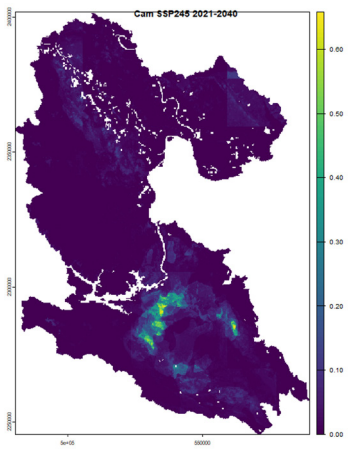
Table 2. Area by current habitat suitability class

Suitability class	Area (ha)	Proportion (%)
Unsuitable area	395,815.0	42.28
Marginally suitable area	166,877.3	17.83
Suitable area	184,165.9	19.67
Highly suitable area	189,279.8	20.22

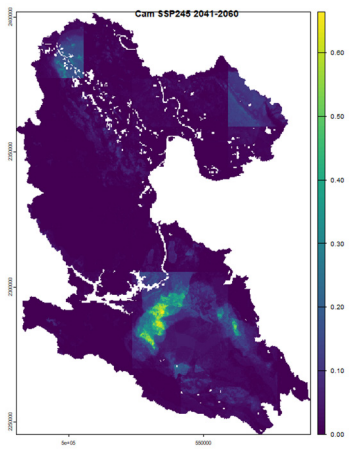
4.5. Predicted spatial dynamics under future climate change scenarios (CMIP6)

Changes in climatic factors under the MPI-ESM1-2-HR model generate complex spatial shifts in the suitable area.

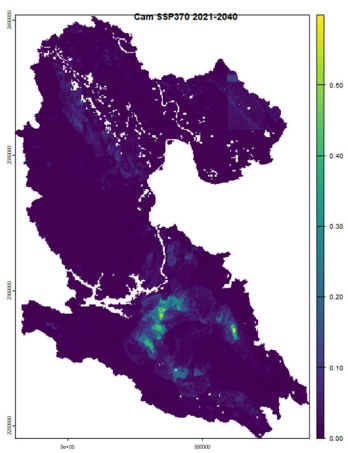
SSP2-4.5 scenario: The total suitable area for organic-oriented orange cultivation (comprising the "Suitable area" and "Highly suitable area" classes) tends to increase in the 2021-2040 period, reaching 447,231.0 ha (47.77% of the natural area), an increase of approximately 73,785 ha compared with the current condition. This indicates that, under the medium-emission scenario, projected changes in climatic conditions favor an expansion of the suitable area into low-hill zones with favorable natural conditions. By the 2041-2060 period, the suitable area decreases slightly to 441,551.1 ha (47.16%) but remains at a high level, indicating that the potential for developing organic orange-growing areas is relatively stable under climate change.



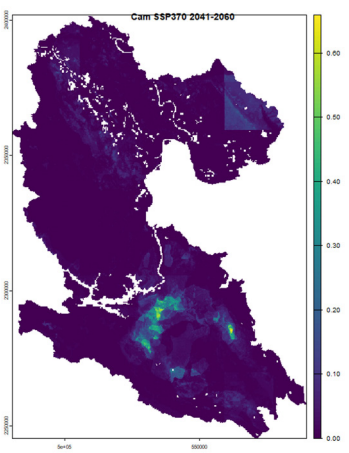
a) SSP2-4.5 scenario, 2021-2040



b) SSP2-4.5 scenario, 2041-2060



c) SSP3-7.0 scenario, 2021-2040



d) SSP3-7.0 scenario, 2041-2060

Figure 6. Predicted orange habitat suitability under climate change scenarios

SSP3-7.0 scenario: Under the high-emission scenario, the suitable area for orange cultivation also expands relative to current conditions but shows more pronounced fluctuations between periods. In the 2021-2040 period, the total suitable area reaches 418,784.6 ha (44.73% of the natural area), an increase of approximately 45,339 ha compared with current conditions. This gain is, however, markedly smaller than that projected under SSP2-4.5 for the same period, indicating that a higher emission level attenuates the climatic benefit in the near term. By the

2041-2060 period, the suitable area increases to 445,466.0 ha (47.58%), with an emerging trend of expansion toward higher-elevation areas. These results show that, under the impact of climate change, the suitable area for orange cultivation tends to shift spatially, indicating that planning for organic production zones should take future climate scenarios into account.

Table 3. Area and proportion of orange habitat suitability zones oriented toward organic agriculture in Phu Tho under future climate scenarios

Suitability class	SSP2-4.5 (2021-2040)	SSP2-4.5 (2041-2060)	SSP3-7.0 (2021-2040)	SSP3-7.0 (2041-2060)
	ha / %	ha / %	ha / %	ha / %
Unsuitable area	356,589.0 / 38.10	324,209.7 / 34.64	379,533.5 / 40.55	336,692.4 / 35.97
Marginally suitable area	132,318.0 / 14.13	170,377.2 / 18.20	137,819.9 / 14.72	153,979.6 / 16.45
Suitable area	227,333.9 / 24.28	220,207.1 / 23.52	201,369.5 / 21.51	219,742.1 / 23.47
Highly suitable area	219,897.1 / 23.49	221,344.0 / 23.64	217,415.1 / 23.22	225,723.9 / 24.11

5. Conclusions

This study successfully applied a Random Forest model within the biomod2 platform to assess and predict habitat suitability for orange cultivation oriented toward organic agriculture in Phu Tho province under the impact of climate change. The model achieved high accuracy, with AUC = 0.959 and TSS = 0.886, demonstrating a strong ability to capture the relationship between the distribution of orange-growing areas and both natural conditions and production development conditions.

The results show that residential density (KDC), annual rainfall (bio_12) and elevation (DEM) are the three factors with the greatest influence on habitat suitability for orange cultivation. Climatic and terrain factors determine the trees' growth conditions, while the anthropogenic factor reflects the favorability of infrastructure and production organization, helping to guide planning for growing areas oriented toward organic agriculture. Under the CMIP6 climate change scenarios, the suitable area tends to change in size and shift toward higher-elevation areas, particularly under the high-emission SSP3-7.0 scenario.

The results provide a scientific basis for planning and developing orange-growing areas oriented toward organic agriculture, contributing to improved land-use efficiency and strengthened resilience to climate change in Phu Tho province.

The study still has certain limitations, including the assumption that anthropogenic variables remain unchanged under future scenarios; the use of only a single global climate model (MPI-ESM1-2-HR); and the use of only two climate variables - temperature and rainfall - for future scenarios. Future studies should incorporate land-use change (LUCC) scenarios, use a multi-GCM ensemble, include additional climatic variables (e.g., maximum and minimum temperature), and consider changes in socio-economic factors to improve the reliability of the predictions and their capacity to support decision-making in organic agriculture development planning.

Author contribution statement: *Conceptualization: Nguyen Thi Huyen Trang; Methodology: Tran Dang Hung; Data collection and processing: Pham Quang Hiep; Data analysis: Nguyen Thi Minh Hang, Le Phuong Ha, Dao Thi My Linh, Nguyen Thi Kim Thanh; Writing-original draft preparation: Nguyen Van Ha; Writing-review and editing: Nguyen Thi Huyen Trang. All authors have read and approved the final manuscript.*

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Declaration: *The authors declare that this manuscript is an original work, has not been published previously, is not under consideration for publication elsewhere, and that there are no conflicts of interest among the authors.*

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