ISSN 2959-6157

Comprehensive Assessment of Invasive Potential: Integrating Growth Simulation and Invasive Factor Indicators for Effective Management Strategies

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Abstract:

Invasive plant species pose a significant threat to ecosystems worldwide. In this study, we developed a comprehensive model to assess the invasive potential of plant species, focusing on dandelions as a case study. Firstly, we simulated the growth of dandelions using a logistic-based model. We predicted the growth dynamics of dandelions throughout the year by considering environmental factors such as temperature, humidity, sunlight, etc. In conclusion, the populations of dandelions varied with higher observations and environmental conditions in a month. Next, we used the Analytic Hierarchy Process (AHP) to evaluate the invasive potential of dandelion from five perspectives: natural energy, environmental impact, reproductive rate, medical use, and practical utility. The results show that reproductive rate and practical utility have more influence on the overall invasive potential of dandelions. To assess the sensitivity of our model, we conducted a sensitivity analysis. The developed model provides a valuable framework for assessing the invasive potential of plant species, which, combining growth simulation and invasive factor indicators, provides a comprehensive assessment of the invasive potential of dandelions. In conclusion, the model's findings contribute to our understanding of invasion dynamics and can guide effective management strategies to mitigate the impacts of invasive plant species on ecosystems.

Keywords: Growth simulation; Analytic Hierarchy Process (AHP); Invasive potential assessment

1 Introduction

1.1 Background

The spread and impact of invasive plant species such as dandelion can lead to a decline in biodiversity, affect human activities and economic sectors, and hurt human health. Despite efforts to control their spread, dandelions' ability to produce large numbers of aeolian seeds allows them to rapidly colonize new areas.

Current management strategies for invasive plants typically involve a combination of chemical, mechanical, and biological control methods. However, the effectiveness of these control strategies varies depending on factors such as the species being targeted, the scale of the infestation, and environmental conditions.

To address the challenges posed by invasive plants like dandelions, we need to develop mathematical models to understand the spread and impact of dandelions; scientists and policymakers can make informed decisions regarding invasive species management, prioritize conservation efforts, and allocate resources effectively.

1.2 Problem Restatement

The problem is to develop a mathematical model to predict dandelion spread and evaluate invasive species' impact. This model should consider factors such as seed dispersal mechanisms, germination rates, growth rates, and competition with other plants to estimate the expansion of dandelion populations over different timeframes. Additionally, the model should incorporate variables to assess the invasiveness of dandelions, including growth rate, reproductive capacity, ability to outcompete native species, and ecological disruptions caused by their presence.

1.3 Assumptions and Justifications

Assumption: Dandelions primarily rely on wind dispersal for seed spread.
Justification: Dandelion seeds possess pappus structures that aid in wind dispersal.
Assumption: Dandelion germination rates are influenced by environmental factors, such as temperature and moisture.
Justification: In many plant species, Germination is influenced by environmental conditions.
Assumption: The growth rate of dandelions is relatively constant across different environments.
Justification: Dandelions are known for their ability to thrive in diverse environments, suggesting a relatively stable growth rate across different habitats.
Assumption: Dandelions exhibit competitive advantages over native species, leading to displacement in invaded areas.
Justification: Various studies have shown that dandelions can outcompete native plant species through rapid growth, early emergence, and effective resource utilization.
Assumption: Ecological disruptions caused by dandelions include reduced biodiversity and altered ecosystem processes.
Justification: Invasive species, including dandelions, have been associated with negative impacts on biodiversity by outcompeting native species for resources. These disruptions can lead to changes in ecosystem processes, such as pollination, seed dispersal, and nutrient cycling.
Assumption: Control measures for invasive species can temporarily reduce dandelion populations but may not eradicate them.
Justification: Invasive species management strategies typically aim to reduce the impact and spread of invasives, but complete eradication is often challenging due to factors such as seed banks, rapid growth, and resilient reproductive strategies of dandelions.
These assumptions provide a foundation for the mathematical model by considering the characteristics of dandelions and their interaction with the environment.

1.4 Our Approach Overview

In this study, we aimed to assess the invasive potential of different plant species by integrating a growth simulation model, invasive factor indicators, and a multi-criteria decision-making method. The following steps were undertaken to achieve our objectives:
Logistic Regression-Based Growth Simulation: We collected data on various growth-related factors, including temperature, humidity, sunlight, soil moisture, and other relevant variables. Logistic regression models are also used to predict the probability of dandelion growth.
Temperature Mapping and Growth Prediction: We employed a sine polynomial function to map the temperature values from the optimal range of 15-25 degrees Celsius to a normalized range of 0-1. By applying the temperature mapping to the logistic regression model, we predicted the probability of dandelion growth based on the normalized temperature values. We collected five indicators to evaluate the invasive factors of the plant species under consideration, including the number of natural enemies, environmental impact, reproductive rate, medicinal use, and practical utility.
Analytic Hierarchy Process (AHP) for Weight Determination: A group of experts evaluated pairwise comparisons of the indicators, establishing their relative priorities. Based on these comparisons, a judgment matrix was constructed and processed through AHP to obtain the weights of the indicators.
Integration of Invasive Factors and Growth Prediction: To obtain a comprehensive assessment of the invasive potential of plant species, we combined the invasive factor indicators and the growth predictions. We assigned weights to each invasive factor indicator based on the AHP results and calculated an overall invasive factor score for each plant species using a linear weighting approach.
By following this approach, we aimed to provide a comprehensive understanding of the invasive potential of different plant species by considering multiple factors and incorporating growth simulations based on logistic regression.

2 The Model of Question1

2.1 Optimal Temperature Range for Dandelion Growth and Mapping of Temperature Indicator

The optimal temperature range for dandelion growth is between 15°C and 25°C. Dandelions exhibit their highest growth rates within this range, allowing them to thrive and compete with other plant species.
To evaluate temperature conditions in a specific location, such as Ningbo, we can use weather data to assess whether the temperatures fall within the optimal range for dandelion growth. In this case, we will map the temperature from an interval-based to a peak-based indicator.
The interval-based indicator represents a temperature range, such as the daily maximum and minimum temperatures. However, for simplicity, we will focus on the maximum temperature. Let's denote the maximum temperature as T_{max}.
To map the interval-based indicator to a peak-based indicator, we can calculate the peak temperature index (T_{peak}) as follows:

$$M = max\left\{a - min\left\{x\ \right\}\left\{, max_i\right\} - b\right\}, x_i = \begin{cases} 1 - \frac{a - x_i}{M}, x_i < a \\ 1, a \leqslant x_i \leqslant b \\ 1 - \frac{x_i - b}{M}, x_i > b \end{cases} \tag{1}$$

In this equation, x_i re represents the peak temperature index, which ranges from 0 to 1 if the maximum temperature is below 15℃.

By mapping the temperature indicator to a peak-based index, we obtain a single value representing the temperature conditions relative to the optimal range for dandelion growth. This index can be used to assess the suitability of the temperature for dandelion growth and compare different periods or locations.

In the case of Ningbo, we can utilize historical weather data to calculate the peak temperature index (x_i) for each day. By analyzing the variations in x_i over time, we can gain insights into the suitability of temperature conditions for dandelion growth in the region.

It is important to note that a comprehensive assessment of the environmental conditions is necessary to understand the complete picture of dandelion growth dynamics.

2.2 Fitting Temperature-Time Relationship Using a Sinusoidal Model

A sinusoidal model can be employed to represent the relationship between time (*t*) and temperature (*T*). The equation derived from the fitting algorithm is given by:

$$T(t) = -0.2 \times sin\left(4.2\pi \bullet \frac{t}{365}\right) + 0.8 \tag{2}$$

In this equation, $T(t)$ represents the temperature at time t. The term $-0.2 \times sin\left(4.2\pi \bullet \frac{t}{365}\right)$ captures the sinusoidal variation in temperature over time, while the constant term 0.8 represents the mean temperature value.

By adjusting the amplitude, phase, and mean value of the sinusoidal function, the model can fit different temperature patterns Fig.2. In this case, the amplitude of the sinusoidal function is 0.2, and the phase is controlled by the term $\frac{t}{365}$, which scales the time variable to fit within one year.

The sinusoidal model is often used in environmental and climate studies to represent seasonal temperature variations. It can capture the cyclical nature of temperature changes, such as the higher temperatures in summer and lower temperatures in winter.

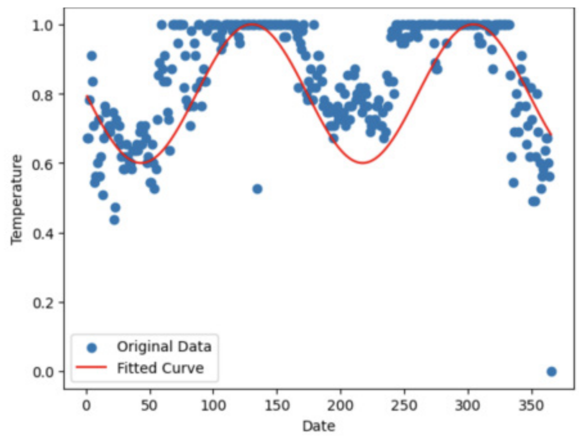

Fig.1 Fitting Temperature-Time Relationship using a Sinusoidal Model.

To obtain equation (1) through a fitting algorithm, a dataset of temperature measurements at different time points is required. The algorithm aims to find the best-fitting parameters that minimize the difference between the observed temperature values and the values predicted by the model.

The fitting process involves adjusting the amplitude, phase, and mean value of the sinusoidal function to optimize the fit to the data. Various optimization techniques can be employed to estimate the best fit parameters.

Once the parameters are determined, the fitted equation can estimate the temperature at any given time point within the observed time range. This allows for the interpolation and extrapolation of temperature values, providing valuable insights into the temperature fluctuations over time.

It is important to note that the sinusoidal model assumes a cyclical pattern in temperature variations. However, it may not capture all the complexities of temperature dynamics, especially in the presence of non-periodic factors such as weather events or long-term climate trends. Therefore, the model's accuracy and applicability should be assessed in the context of the specific dataset and research objectives.

2.3 Dandelion Growth Simulation with Temperature Requirements

To understand and simulate the growth of dandelions, we will employ a logistic model that considers the influence of temperature, an important factor affecting their growth and development. By incorporating temperature requirements, we can gain insights into how different temperature regimes impact the population dynamics of dandelions.

The logistic growth equation provides a mathematical representation of population growth that is common in ecological modeling. It is given by:

$$P(t) = \frac{K}{1+\left(\frac{K-P_0}{P_0}\right)\bullet e^{-r\bullet t}} \quad (3)$$

In this equation, $P(t)$ represents the dandelion population size at time t, P_0 is the initial population size, *K* is the carrying capacity, *r* is the growth rate, and *t* denotes time.

To incorporate the influence of temperature on dandelion growth, we introduce a temperature factor, denoted as T_f, that modifies the growth rate, *r*. The growth rate (*r*) is the rate at which the population increases without limiting factors. The modified growth rate is given by:

$$r = r_0 + r_0 \bullet T_f \quad (4)$$

Here, r0 represents the baseline growth rate, and Tf is the temperature factor. The temperature factor is a dimensionless value that quantifies the influence of temperature on dandelion growth. It is calculated by considering the difference between the current temperature (Tc) and the optimal temperature (To), normalized by the optimal temperature:

$$T_f = \frac{T_c - T_0}{T_0} \quad (5)$$

The optimal temperature (T_0) represents the temperature at which dandelions experience the highest growth rate, while T_c denotes the current temperature. Calculating the temperature factor using Equation (3) allows us to determine how much the growth rate is modified under different temperature conditions.

To simulate the growth of dandelions using the logistic model with temperature requirements, we can iteratively calculate the population size, $P(t)$, at different time points. Starting with the initial population size, P_0, we can use the logistic growth equation (Equation 1) and the modified growth rate (Equation 2) to obtain the population size at each time step. By repeating this process for multiple time points, we can observe the population dynamics of dandelions over time, considering the temperature requirements.

It is important to note that the logistic growth equation‘s carrying capacity (K) represents the maximum population size that the environment can support. In the context of dandelions, the carrying capacity is influenced by various factors, including resource availability, competition with other plant species, and environmental conditions. The logistic model assumes that the population growth rate gradually decreases as it approaches the carrying capacity.

By adjusting the temperature factor (T_f) based on the temperature conditions, we can explore how different temperature regimes affect dandelions‘ growth and population dynamics. For instance, if the current temperature (T_c) is below the optimal temperature (T_0), the temperature factor will be negative, indicating a reduction in the growth rate compared to the baseline. On the other hand, if the current temperature exceeds the optimal temperature, the temperature factor will be positive, suggesting an increase in the growth rate.

By simulating dandelion growth under different temperature scenarios, we can gain insights into how temperature influences population dynamics, including the rate of population increase, time to reach the carrying capacity, and potential fluctuations in population size over time. This information assists in guiding management strategies for invasive dandelion populations [3].

2.4 The Simulation Results

By incorporating the temperature coefficient into the model, we could observe the impact of temperature variations on the growth dynamics of dandelions.

Initially, as the temperature increased from the initial reference temperature (T_0), the dandelion population responded positively, exhibiting accelerated growth. This positive response was evident as the population size increased rapidly, approaching the environment‘s carrying capacity (*K*). The population‘s intrinsic growth rate (*r*) facilitated this rapid initial growth phase [2].

However, as the temperature continued to rise, the dandelion population‘s growth rate gradually slowed. This deceleration occurred because the temperature coefficient(*k*) dampened growth (Fig 2). The sensitivity of dandelion growth to temperature variations became apparent as the population approached its carrying capacity.

Furthermore, when the temperature exceeded a certain threshold, the growth of the dandelion population started to decline. This negative response indicated that extremely high temperatures adversely affected dandelion growth. The inhibitory effect of temperature on growth became dominant, leading to a decrease in the population size.

Overall, the results demonstrated the complex relationship between temperature and dandelion growth. The model captured the initial positive response of the population to temperature increases, followed by deceleration and eventually a decline in growth with excessively high temperatures.

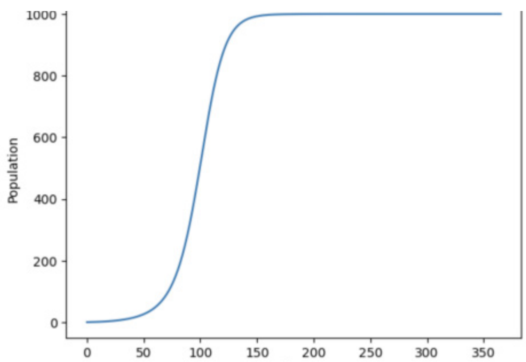

Fig.2 Dandelion Growth Simulation with Temperature Requirements.

It is important to note that the simulated results are based on the assumptions and parameter values of the logistic model with a temperature coefficient. The accuracy and applicability of the results depend on the validity of these assumptions and the representation of temperature-growth relationships.

3 The Model of Question2

3.1 Mathematical Model for Evaluating the Impact Factor of Invasive Species

Invasive species pose significant threats to ecosystems worldwide. A mathematical model can be developed by integrating multiple variables to assess their impact. This model applies the Analytic Hierarchy Process (AHP) to determine the relative importance of different factors contributing to the invasiveness of a plant species.

Let me represent the impact factor, which quantifies the severity of the invasion. The impact factor can be computed as a weighted sum of various factors pertaining to different aspects of the invasive species. These factors include:

1. Predator/Prey Ratio (*P*): The number of natural predators or competitors of the invasive species relative to its population size. This factor assesses the potential for natural control mechanisms to limit the invasiveness.
2. Environmental Impact (*E*): The extent to which the invasive species disrupts the local environment, such as altering the nutrient balance, reducing biodiversity, or outcompeting native species. This factor captures the ecological consequences of the invasion.
3. Reproductive Rate (*R*): The rate at which the invasive species reproduces and spreads. Higher reproductive rates contribute to faster population growth and potential expansion into new areas.
4. Medicinal/Culinary Use (*M*): The value of the invasive species in terms of its medicinal or culinary properties. This factor acknowledges potential benefits derived from the species despite its invasiveness.

A pairwise comparison matrix is constructed to determine the relative importance of these factors. The matrix represents the relative weights of each factor concerning one another. A group of experts or stakeholders assign values to pairwise comparisons based on their judgment and expertise. The values range from 1 (equal importance) to 9 (extreme importance).

Let W = [w_{ij}] be the pairwise comparison matrix, where w_{ij} represents the weight of factor i compared to factor *j*. The matrix should be consistent, satisfying the condition $w_{ij} = 1/w_{ij}$.

Using the AHP, the weights of the factors can be derived by calculating the priority vector, P = [*p1, p2, p3, p4*], where pi represents the weight of factor *i*.

Next, the impact factor, I, is computed as the weighted sum of the factors:

$$I = p_1 \times P + p_2 \times E + p_3 \times R + p_4 \times M \quad (6)$$

The impact factor provides a quantitative measure of the overall invasiveness of a species, considering its predator/prey ratio, environmental impact, reproductive rate, and medicinal culinary use.

3.2 Calculation of Weights using the Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a decision-making technique that enables the determination of relative weights for different factors based on pairwise comparisons. A pairwise comparison matrix is constructed to begin the AHP process. The matrix represents the relative importance of each factor compared to the others. W = [w_{ij}] is a pairwise comparison matrix, where w_{ij} represents the weight of factor *i* compared to factor *j*. The values in the matrix are assigned based on the judgments of experts or stakeholders, who assess the relative importance of the factors [4].

The pairwise comparison matrix should adhere to the following guidelines:

1. Reciprocity: The matrix should be reciprocal, meaning that the weights should satisfy the condition $w_{ij} = 1/w_{ij}$ for all *i* and *j*.
2. Scale: The values in the matrix should follow a scale that reflects the relative importance of the factors. A common scale assigns values from 1 (equal importance) to 9 (extreme importance), with intermediate values indicating intermediate levels of importance.

To ensure the reliability of the pairwise comparison matrix, a consistency check is performed using the concept of consistency ratio (CR). CR measures the consistency between the judgments made in the pairwise comparisons. The consistency ratio is calculated as follows:

$$CR = \frac{\lambda_{max} - n}{n-1} \tag{7}$$

Where λ_{max} represents the maximum eigenvalue of the matrix, and n is the number of factors being compared. ACR value less than 0.1 indicates an acceptable level of consistency.

Once the consistency of the matrix is verified, the weights of the factors can be calculated.

The geometric mean method calculates the weights by taking the geometric mean of each column in the pairwise comparison matrix. The geometric mean of a column j is computed as:

$$GM_j = \left(\prod_{i=1}^{n} w_{ij}\right)^{\frac{1}{n}} \tag{8}$$

Where n is the number of factors being compared. The weights for each factor are then normalized by dividing each geometric mean by the sum of all geometric means:

$$p_i = \frac{GM_j}{\sum_{j=1}^{n} GM_j} \tag{9}$$

The arithmetic mean method calculates the weights by taking the arithmetic mean of each column in the pairwise comparison matrix. The arithmetic mean of a column j is computed as:

$$AM_j = \frac{1}{n}\sum_{i=1}^{n} w_{ij} \tag{10}$$

Similarly, the weights for each factor are then normalized by dividing each arithmetic mean by the sum of all arithmetic means:

$$p_i = \frac{AM_i}{\sum_{j=1}^{n} AM_j} \tag{11}$$

The eigenvalue method calculates the weights by determining the principal eigenvector of the pairwise comparison matrix. The principal eigenvector represents the weights of the factors. To obtain the eigenvector, the matrix is first normalized by dividing each element in a column by the sum of the columns. Then, the eigenvalues and eigenvectors of the normalized matrix are computed. The principal eigenvector corresponds to the largest eigenvalue. Finally, the weights are obtained by normalizing the principal eigenvector so that the sum of all weights is equal to 1.

After calculating the weights using one of the averaging methods, the impact factor (I) can be computed as the weighted sum of the factors:

$$I = p_1 \times P + p_2 \times E + p_3 \times R + p_4 \times M \tag{12}$$

Pi represents the weight of the factor I obtained from the AHP process.

The pairwise comparison matrix is first constructed based on expert judgments to apply the model. The consistency of the matrix is checked using the consistency ratio. If it meets the acceptable level of consistency, the weights of the factors are calculated using one of the averaging methods mentioned above.

For example, let's consider the impact factor of dandelions. Experts assess the pairwise comparisons and construct the matrix. They assign values to each element based on the relative importance of the factors. The consistency of the matrix is checked, and if it passes the consistency test, the weights are computed using the chosen averaging method.

Table 1: The Comparison Matrix of AHP model

	Enemies	Environment	Reproductive Rate	Medicinal	Edible
Natural Enemies	1	3	2	5	4
Environment	1/3	1	2	3	2
Reproductive Rate	1/2	1/2	1	4	3
Medicinal Use	1/5	1/4	1/4	1	1/2

Table 2: The Weight of Invasion Factor

Criterion	Weight
Natural Enemies	0.2446
Environment	0.1934
Reproductive Rate	0.2573
Medicinal Use	0.0924
Edible Use	0.2123

Similarly, the model can be applied to determine the impact factors for two other invasive plant species in specific regions of interest. The pairwise comparison matrices are constructed, consistency is checked, and weights are calculated using the chosen averaging method.

The model provides a rigorous and systematic approach to evaluating the impact of invasive species by considering multiple factors and their relative importance. By quantifying the impact factors, decision-makers can prioritize management strategies and allocate resources effectively to mitigate the negative consequences of invasive species.

3.3 The Application of the Model

3.3.1 Dandelion

Number of Natural Enemies: The dandelion has seven natural enemies, including rabbits, cows, horses, sheep, birds, pigs, and humans.

Environmental Impact: The dandelion has several environmental impacts, including soil conservation, protection of water sources, photosynthesis, attraction of insects and butterflies, and aesthetic appeal.

Reproductive Rate: With multiple heads producing 150-200 fruits each, a dandelion plant easily produces 1000-2000 seeds yearly, indicating a high reproductive rate.

Medicinal Use: The dandelion has two medicinal uses, known for its properties in clearing heat and toxins and diuretic effects.

Edible Parts: All parts of the dandelion plant, including stems, leaves, flowers, fruits, seeds, and roots, are edible.

3.3.2 Yellow Daisy

Number of Natural Enemies: The yellow daisy has seven natural enemies (Fig 4), including the daisy leaf beetle, large green leafhopper, wireworms, aphids, red spider mites, leaf miners, and thrips.

Environmental Impact: The yellow daisy contributes to air purification but can also lead to soil impoverishment, affect aesthetics, and influence photosynthesis.

Reproductive Rate: Yellow daisies have a very high reproductive rate, with each plant producing 100,000 seeds per year.

Medicinal Use: Yellow daisies have various medicinal uses, including lowering blood pressure, promoting liver health and vision, providing energy, and clearing heat and toxins.

Edible Parts: The yellow daisy's flowers, leaves, roots, stems, seeds, and fruits are all edible.

3.3.3 Forsythia

Number of Natural Enemies: Forsythia has six natural enemies Fig3, including parasitic flies, parasitic wasps, aphids, red spider mites, ladybugs, and wild rabbits.

Environmental Impact: Forsythia plays a role in preventing decay, enhancing aesthetics, stabilizing soil, and protecting water sources.

Reproductive Rate: Forsythia has a moderate reproductive rate, with each plant producing around 10 seeds per year.

Medicinal Use: Forsythia has multiple medicinal properties, including clearing heat, detoxification, reducing swelling, dispersing nodules, antibacterial effects, and strengthening the heart.

Edible Parts: All parts of the forsythia plant, including fruits, leaves, stems, roots, seeds, and flowers, are edible.

To calculate the invasive factors for each plant species, we can assign a numerical value to each factor and calculate the overall invasive factor score using a weighted average approach. Here is the calculation for each plant species.

Fig.3 The Image of Yellow Daisy and Forsythia

Now, we can substitute each factor's values and calculate the dandelion's invasive factor score (Table 3).

Table 3 Invasive Factor Score for The Dandelion

Plant Species	Invasive Factor Score
Dandelion	0.211
Yellow Daisy	0.342
Forsythia	0.617

4 The Sensitivity and Robustness Analysis

To analyze the sensitivity and robustness of our model,

we utilized logistic regression to simulate the growth of dandelions and employed a sine polynomial to fit the temperature data. Subsequently, we predicted the growth of dandelions using this temperature mapping.
Logistic Regression for Growth Simulation: Logistic Regression for Growth Simulation is a suitable approach for simulating the growth of dandelions. It models the probability of growth as a function of predictor variables.
Sine Polynomial for Temperature Mapping: We utilized a sine polynomial function to map the temperature from the optimal range of 15-25 to a normalized range of 0-1. This function captures the periodic nature of temperature variations throughout the year.
Predicting Dandelion Growth: We applied temperature mapping for each temperature value within the optimal range to obtain the normalized temperature value (between 0 and 1). Then, we used this normalized temperature value as an input to the logistic regression model to predict the probability of dandelion growth. A higher probability indicated a higher likelihood of growth.
To analyze the sensitivity and robustness of our model, we conducted several sensitivity tests and evaluated the impact of variations in input parameters on the predicted growth outcomes. Additionally, we performed robustness analysis by introducing uncertainties and noise into the temperature data and assessed the stability of our growth predictions.

5 Strengths and Weakness of the Model

5.1 Strengths of the Model

Firstly, the model captures a holistic understanding of the invasion process by considering various indicators and incorporating growth dynamics.
Secondly, AHP allows for a systematic and objective assessment of the importance of each indicator, enhancing the accuracy and reliability of the model‘s evaluations.
The logistic regression-based growth simulation enables the model to predict the growth dynamics of dandelions under different conditions, and it can provide insights into the influence of environmental variables on the invasive potential of plant species. Incorporating a sine polynomial function for temperature mapping can effectively assess the impact of temperature variations on dandelion growth, providing a more realistic representation of their invasive potential.
Finally, consideration of Multiple Perspectives: The model incorporates expert judgments through the AHP process, enabling the consideration of multiple perspectives in determining the weights of invasive factor indicators. This approach ensures a more comprehensive and balanced evaluation of the invasive potential of plant species.

5.2 Weaknesses of the Model

Firstly, the model relies on a set of predefined invasive factor indicators, which may not encompass the full range of factors that contribute to the invasive potential of plant species, which could limit the model‘s ability to capture the complete invasive profile.
Secondly, the logistic regression-based growth simulation assumes a linear relationship between predictor variables and the probability of growth, which may not fully capture the complex interactions and literariness in dandelions‘ growth dynamics.
Thirdly, the model‘s growth predictions are based on historical data, which may not fully capture the future growth patterns of dandelions. Changes in environmental conditions or introducing new management practices could lead to deviations from the predicted growth outcomes.
Next, the AHP process relies on expert judgments for pairwise comparisons and weight determination. The subjectivity of these judgments introduces uncertainty and potential bias in the model‘s weight assignments.
Finally, the model’s applicability may be limited to the specific plant species and environmental conditions for which it was developed. Extrapolating the model’s findings to different species or regions would require careful consideration of the variations in growth dynamics and invasive factors across different contexts.
While the model possesses several strengths, such as its comprehensive assessment, quantitative weighting, and growth simulation capabilities, it also has limitations related to the scope of invasive factors, assumptions in the logistic regression, reliance on historical data, subjectivity in AHP weighting, and limited generalization.
6 Conclusion
In this study, we developed a comprehensive model to assess the invasive potential of different plant species. By integrating invasive factor indicators, logistic regression-based growth simulation, and AHP, we gained valuable insights into the factors influencing invasion dynamics and provided a quantitative assessment of invasive potential.
Firstly, by considering indicators such as natural enemies, environmental impact, reproductive rate, medicinal use, and practical utility, we captured various aspects of inventiveness and accounted for their relative importance through AHP-based weight determination [1].
Secondly, by considering factors such as temperature, humidity, sunlight, and soil moisture, we could assess environmental variables‘ influence on plant species‘ invasive potential using logistic regression-based growth simulation.

However, our model has the limitations of our model. Nonetheless, our model provides a valuable framework for assessing invasive potential and can serve as a basis for developing effective management strategies for invasive species. By understanding the relative importance of invasive factors and their interactions with growth dynamics, policymakers, and land managers can prioritize their efforts and allocate resources accordingly.

Future research endeavors should focus on expanding the scope of invasive factors considered, refining the growth simulation model, and validating the model's findings across different plant species and environmental contexts. Regular updates and re-calibrations using new data will be crucial to maintain the model's accuracy and relevance.

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