Supplementary materials

1. Parameter configurations of the street view comparison model across various dimensions.

Tables S1 to S5 illustrate the parameter configurations of the street view comparison model across five dimensions. Each table includes five distinct parameter settings, specifically learning rate and decay factor, which are evaluated based on the corresponding loss, accuracy, and overfitting conditions to determine the impact of these parameter combinations.

(1) *Wealthy*

Table S1. Model parameter setting of wealthy dimension.

Option	Learning rate	Decay factor	Loss	Accuracy	Overfitting or not
1	0.085	0.500	0.442	0.809	×
2	0.100	0.500	0.629	0.652	×
3	0.050	0.500	0.452	0.801	×
4	0.085	0.600	0.462	0.797	×
5	0.085	0.400	0.446	0.802	×

In the wealthy dimension, with the configuration of Option 1 (learning rate 0.085, decay factor 0.500), the model exhibits the lowest loss (0.442), the highest accuracy (0.809), and does not suffer from overfitting.

(2) *Lively*

Table S2. Model parameter setting of lively dimension

Option	Learning rate	Decay factor	Loss	Accuracy	Overfitting or not
1	0.085	0.250	0.575	0.734	×
2	0.100	0.250	0.693	0.506	×
3	0.050	0.250	0.617	0.747	√
4	0.085	0.500	0.592	0.721	×
5	0.085	0.100	0.689	0.551	×

In the lively dimension, Option 1 (learning rate 0.085, decay factor 0.250) is the optimal choice. Although Option 3 (learning rate 0.050, decay factor 0.250) achieves the highest accuracy (0.747), it suffers from overfitting. Comparatively, Option 1 offers the lowest loss (0.575) and a relatively high accuracy (0.734) without encountering overfitting.

(3) *Habitable*

Table S3. Model parameter setting of habitable dimension

Option	Learning rate	Decay factor	Loss	Accuracy	Overfitting or not
1	0.085	0.200	0.546	0.734	×
2	0.100	0.200	0.691	0.541	×
3	0.050	0.200	0.567	0.721	×

4	0.085	0.500	0.673	0.742	√
5	0.085	0.100	0.694	0.481	×

In the habitable dimension, Option 1 (learning rate 0.085, decay factor 0.200) is the optimal choice. Although Option 4 (learning rate 0.085, decay factor 0.500) achieves the highest accuracy (0.742), it suffers from overfitting. Option 1, on the other hand, does not encounter overfitting, exhibits the lowest loss (0.546), and maintains a relatively high accuracy (0.734), making it the most favorable choice.

(4) *Tidy*

Table S4. Model parameter setting of tidy dimension

Option	Learning rate	Decay factor	Loss	Accuracy	Overfitting or not
1	0.085	0.250	0.512	0.762	×
2	0.100	0.250	0.531	0.742	×
3	0.050	0.250	0.522	0.753	×
4	0.085	0.500	0.595	0.751	√
5	0.085	0.100	0.541	0.735	×

In the tidy dimension, Option 1 (learning rate 0.085, decay factor 0.250) is the optimal choice. This configuration achieves the lowest loss (0.512) and the highest accuracy (0.762), without encountering any overfitting issues.。

(5) *Terroir*

Table S5. Model parameter setting of terroir dimension

Option	Learning rate	Decay factor	Loss	Accuracy	Overfitting or not
1	0.085	0.650	0.648	0.646	×
2	0.100	0.650	0.671	0.614	×
3	0.050	0.650	1.637	0.618	√
4	0.085	0.500	1.231	0.645	√
5	0.085	0.800	0.724	0.561	×

In the terroir dimension, Option 1 (learning rate 0.085, decay factor 0.650) is the optimal choice. This configuration achieves the lowest loss (0.648) and the highest accuracy (0.646), without encountering any overfitting issues.

2. Introduction of the TrueSkill algorithm

TrueSkill is a multi-player competitive ranking algorithm based on Bayesian theory, initially proposed by Microsoft for the ranking system of online multiplayer games (Microsoft 2005, Graepel et al. 2007). This algorithm iteratively updates the ranking scores of participants after each match, generating dynamically adjusted ranking results for winners and losers in two-player matches (Minka et al. 2018).

In this study, pairwise comparison is regarded as a two-player competition, with the two images in each sample comparison defined as “participants,” and the winner being the image that volunteers are more inclined to choose. Initially, all images have the same score. After each comparison, the TrueSkill algorithm adjusts the scores of the two images based on the comparison result: the winning image’s score increases, while the losing image’s score decreases. Through multiple comparisons, the scores of all images gradually converge to stable ranking values. The following are the update rules for the scores of winners and losers in each match, where each player's skill distribution is modeled as a random variable $N\ (\mu, \sigma^2)$:

$$\mu_{winner} \leftarrow \mu_{winner} + \frac{\sigma_{winner}^2 + \gamma^2}{c} \cdot f(\frac{\mu_{winner} - \mu_{loser}}{c})$$

$$\mu_{loser} \leftarrow \mu_{loser} - \frac{\sigma_{loser}^2 + \gamma^2}{c} \cdot f(\frac{\mu_{winner} - \mu_{loser}}{c})$$

$$\sigma_{winner}^2 \leftarrow [\sigma_{winner}^2 + \gamma^2] \cdot [1 - \frac{\sigma_{winner}^2 + \gamma^2}{c} \cdot g(\frac{\mu_{winner} - \mu_{boxr}}{c})]$$

$$\sigma_{loser}^2 \leftarrow [\sigma_{loser}^2 + \gamma^2] \cdot [1 - \frac{\sigma_{loser}^2 + \gamma^2}{c} \cdot g(\frac{\mu_{winner} - \mu_{loser}}{c})]$$

$$c^2 = 2\beta^2 + \sigma_{winner}^2 + \sigma_{loser}^2$$

$$f(x) = \frac{N(x)}{\Phi(x)}$$

$$g(x) = f(x) \cdot [f(x) + x]$$

where μ is the mean of the score, σ^2 is the variance of the score, $N(x)$ is the probability density of the normal distribution, $\Phi(x)$ is the cumulative normal distribution, β^2 is the performance variance, and γ^2 is the dynamic variance.

3. Data sources for objective socio-economic indicators

The data for various indicators used in this study primarily originates from the 2023 statistical yearbooks provided by the provinces of China as well as the “China Rural Statistical Yearbook” (2023). Certain specific indicators are sourced from survey data published by government departments. For instance, data on the proportion of land used for cultivated and water conservancy facilities (X24) is sourced from the main data results of the third national land survey published by the Ministry of Natural Resources, PRC (Ministry of Natural Resources, PRC 2021). The number of traditional villages (X34) is compiled from the list of Chinese traditional villages issued by the Ministry of Housing and Urban-Rural Development, PRC (Ministry of Housing and Urban-Rural Development, PRC 2023).

References

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