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## Spatiotemporal influence analysis model for cultural landscapes based on a virtual geographic environment

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A cultural landscape can have a lasting impact on the surrounding region, significantly influencing its culture, customs, and development patterns. It is therefore important to understand the spatiotemporal influence range of a particular cultural landscape. The scope of influence is affected by subjective factors regarding the views, hobbies, communication, and cognitive abilities of all individuals involved in landscape interaction. These factors are difficult to account for using the learning process of traditional methods. To address this problem, we propose a spatiotemporal influence analysis model for cultural landscapes based on a virtual geographic environment (SC-VGE). A virtual geographic environment is constructed to interactively recognize the relationships between individuals and cultural landscapes, forming key parameters of the cultural landscape influence propagation process under various conditions. On this basis, we construct influence propagation agents representing different groups of people. Based on the movement process of the agents in the virtual space, we can determine the spatiotemporal influence range of a specific landscape or landscape object. In experiments, we analyzed two typical cultural landscape examples in the city of Changchun. We conducted a comparative analysis of our approach against several traditional methods, including the Spatial Straight-Line Distance, Spatial Accessible Distance, Cellular Automata, and Multiagent. The SC-VGE method surpassed these traditional methods in overall prediction accuracy, achieving  $89.7 \pm 1.3\%$  and  $87.8 \pm 1.5\%$ . This is more than 9% higher than the highest accuracy among the traditional methods. Higher accuracy enables SC-VGE to more precisely reflect the influence ranges of cultural landscapes, thereby providing better support for the management and analysis of cultural landscape value.

**Keywords** Cultural landscapes, VR, VGE, Spatiotemporal influence, Multiagent

Cultural landscapes are physical entities that have significant social and cultural characteristics; these characteristics not only have a lasting influence on the location of a cultural landscape or landscape object itself but also on the surrounding area<sup>1,2</sup>. Cultural landscapes provide cultural heritage value, play an important role in the cultural ecosystem, and shape a region's culture, customs, and development patterns<sup>3-5</sup>; therefore, it is essential to consider the influence ranges of cultural landscapes in the processes of urban planning, environmental design, and development strategy formulation<sup>6</sup>. Geographic information systems (GISs) are powerful tools that can be used to analyze spatial data; they can be used to identify areas that are likely to be affected by cultural landscapes and provide quantitative data for decision-making<sup>7,8</sup>.

GIS technology has been used to achieve some progress in the analysis of cultural landscape regions, values, and sustainable development strategies<sup>9</sup>; this progress has been achieved through the use of a variety of GIS techniques, including geographical buffer analysis, distance analysis, and the introduction of cellular automata and multiagent methods<sup>10-12</sup>. A key step in these methods is to identify the trend of change for a specific object and build a model on this basis. Then, the constructed model is used to drive the analysis process. However, the influence of cultural landscapes does not derive solely from the physical objects that make them up; it also comes from the subjective experiences and meanings that people attach to them<sup>13,14</sup>. For the description of such subjective phenomena, traditional contrast-based and regression-based methods are often not effective because

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they rely on observable and changing objects, whereas subjective phenomena are often difficult to define and measure and can be influenced by a variety of factors, including an individual's own experiences and biases. As a result, traditional algorithms can often produce inaccurate or misleading results<sup>15,16</sup>.

Virtual geographic environments (VGEs) based on virtual reality (VR) technology offer a promising solution to the problem of analyzing the influence ranges of cultural landscapes. Through VGEs, users can interact with realistic cultural landscape scenes and with people in those scenes. Through these realistic interactions, users can accurately express their inner experience of how cultural landscapes have affected them<sup>17</sup>.

The aforementioned methods encounter challenges in delineating the influence ranges of cultural landscapes: On one hand, traditional approaches such as cellular automata and multi-agent systems rely on probabilities or models governing their internal behavioral drivers. While these parameters derive from objectively quantifiable metrics (e.g., spatial extent of land-use changes), the inherent difficulty in quantifying subjective factors undermines their foundational validity. On the other hand, VR-based methodologies predominantly emphasize individual experiential dimensions, exhibiting limited capacity to capture collective experiences or simulate group behavioral patterns. This analytical impasse necessitates an integrative approach that combines the strengths of both methodologies. In this article, we propose a spatiotemporal influence analysis model for cultural landscapes based on a virtual geographic environment (SC-VGE). The main innovation of SC-VGE is the use of a VGE to create a digital representation of a cultural landscape or landscape object and its surrounding area. When people interact with the SC-VGE model, they can provide feedback on their experience of the cultural landscape. In this way, their subjective views can be expressed in a data-based and intelligent model-based manner. In turn, a multiagent system can be constructed to simulate people's behaviors and subjective views over a large area, from which the influence range of the cultural landscape can be derived. In experiments, we analyzed two typical cultural landscape examples in the city of Changchun. Compared with traditional distance-based, path-based, cellular automata and multiagent methods, our method produced superior results. In terms of the prediction range, our method was more in line with reality than the other methods. In terms of accuracy, our method was far superior to the other methods. The results of our study show that SC-VGE is able to capture the subjective views of the population interacting with a cultural landscape, which are an important factor in determining its influence. People's subjective views on the influence of landscapes are constantly changing with time and location. Our main method is to collect the opinion of a population, and the output the most likely influence range of a culture landscape on certain group of people. This makes SC-VGE a more accurate and reliable method for analyzing the influence ranges of cultural landscapes.

## Related works

For determining areas and ranges of influence, the most common practices in the GIS field are the use of buffer analysis and path calculation<sup>18–20</sup>. The method of cellular automata (CA) is a typical dynamic method for GIS-based analysis of area and range. By means of the Metronamica model, Markov chain modeling and neural networks, CA can be used to predict the ranges and future change trends of various land use categories<sup>21–23</sup>. Combined with machine learning methods, CA can be used to dynamically analyze the range over which forest fires may spread, which can help in making effective decisions for response<sup>24,25</sup>. CA can similarly be used to model the range of impact of floods<sup>26</sup>. Compared with CA, more dynamic characteristics can be obtained by using multiagent systems, which are suitable for GIS research and analysis focusing on human beings. By combining multiagent systems with CA, various decision rules and models can be formulated to predict the spatial distribution of human beings and accordingly develop suggestions for regional development and infrastructure construction<sup>27–29</sup>. Multiagent systems can be used to simulate both natural and man-made disasters and the human response to such disasters. Through the interactions and activities of individuals and groups, the value and function of the planning and design of relevant facilities can be reasonably analyzed<sup>30,31</sup>. The analysis of dynamic spatiotemporal characteristics in landscapes and terrestrial habitats enables a comprehensive understanding of land-use change processes, thereby providing critical foundations for evaluating land-use patterns and supporting decision-making frameworks<sup>32,33</sup>.

VR can provide a more immersive and realistic way for users to interact with geospatial data. With the incorporation of VR and GIS technology into VGEs, users can gain insight into the characteristics of regions and ground objects, make better decisions, and identify hidden features in the data<sup>34–36</sup>. VGEs can simulate regional, cultural, and natural environments and allow people to interact with virtual objects to reveal the influence of regions on individuals and groups as well as the cognitive process of people's perception of regional environments<sup>37,38</sup>. VR and augmented reality (AR) can be used to collect interactions and perspectives from various groups, which can improve the efficiency of urban planning<sup>39</sup>. VR can also be used to quickly incorporate static and dynamic information when developing a reasonable tourism plan, which can help tourists make decisions faster<sup>40</sup>. Moreover, because VGEs can play a key role in collecting people's subjective opinions about an area, compared to collecting data in the real world, VGEs can minimize the data collection workload and lead to higher accuracy<sup>41–43</sup>. VR-based methodologies demonstrate strengths in enabling individual experiential engagement with authentic geographical environments and capturing subjective feedback. However, our research objective centers on influence analysis for cultural landscapes, which requires collective-level outcomes rather than isolated individual responses. Consequently, integrating group-level statistical analysis and behavioral simulation techniques becomes imperative to achieve the study's goals.

In a study focusing on the spatial range of objects, particularly in the investigation of real-world entities such as the degradation range of forests and the expansion range of cities, we encounter clearly defined and verifiable objects. Consequently, these studies can be considered "explicit and accurate." However, when examining the influence range of cultural landscapes, though similar to objective studies, the focus shifts to the subjective thoughts of individuals. These thoughts, unlike objective entities, cannot be validated by a "visible" object and are challenging to represent through geographic methods such as "spatial distance" and "spatial accessibility."

Furthermore, in numerous instances, the validation of “subjective thoughts” proves difficult. Even for the same individual in the same location, perspectives may change over time, making this dynamic nature challenging to comprehend. Thus, the essence of our research lies in gathering subjective viewpoints and mapping their “potential” rather than “explicit” scope in spatial terms. Therefore, it is necessary to capture the influence ranges of cultural landscapes from two directions. On the one hand, a VGE should be introduced. Through this VGE, people’s subjective views on cultural landscapes can be collected. On this basis, predictive models can be built. On the other hand, intelligent agents should be used to convert these predictive models into actions, from which the influence ranges of the cultural landscapes of interest can ultimately be derived.

## Methodology

### Overall design of the method

Traditional studies measuring areas of development or change using GIS technology typically rely on finding physical objects (such as specific vegetation or buildings). The definition of “influence range of cultural landscapes” is:

Definition: In a spatial range, the influence range of cultural landscapes refers to the population’s identification with the impact of a specific cultural landscape on the overall atmosphere, regional style, group habits, and behavioral patterns within that range.

However, the influence range of a cultural landscape is difficult to measure because it is not a solely physical entity but rather a combination of impressions, senses, and ideas that are experienced by people in a specific space. To measure this subjective range, we need to quantify the relationship between cultural landscape features and people’s subjective views and then build models of human activities in the cultural landscape space.

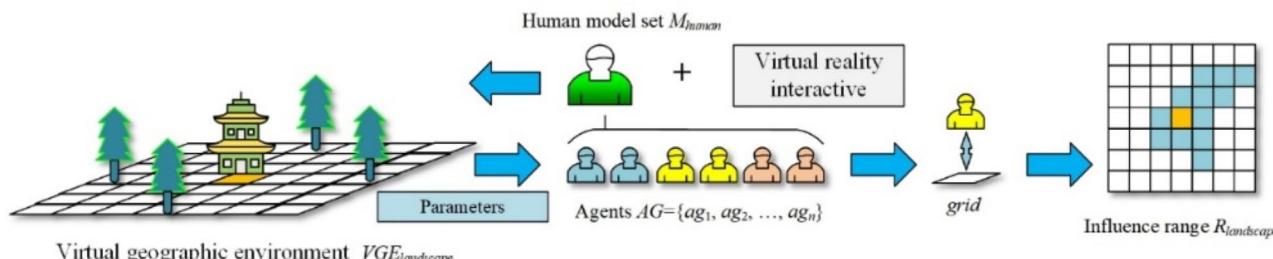
Since it is not practical to conduct large-scale surveys of people in the surrounding areas of cultural landscapes to construct a large training sample set, we propose the use of a VGE to achieve this goal, as shown in Fig. 1.

As illustrated in Fig. 1, the core design idea of our method is as follows. First, a VGE that corresponds to a certain cultural landscape is built, denoted by  $VGE_{landscape}$ . Then, a virtual human model set,  $M_{human}$ , is established in  $VGE_{landscape}$ . This model set contains knowledge of the subjective features of  $VGE_{landscape}$  as perceived by a specific population (such as a group of college students) and is used to form agents  $AG=\{ag_1, ag_2, \dots, ag_n\}$  that can simulate the diffusion process of the cultural landscape’s influence in this population. Then, the influence range of the cultural landscape,  $R_{landscape}$ , can be inferred from the agents’ spatiotemporal actions in  $V_{landscape}$ . From the perspective of method input and output, the input of SC-VGE includes two contents: (1) Input cultural landscape and its surrounding geographic information, which is used to construct  $VGE_{landscape}$ . (2) Users interact in  $VGE_{landscape}$  using VR equipment to obtain input of group opinions, which will obtain a series of key data related to landscape influence. Through a series of iterations and processing of SC-VGE, the method finally outputs a map of the cultural landscape influence range  $R_{landscape}$ , which clearly marks which locations are within the influence range of the cultural landscape.

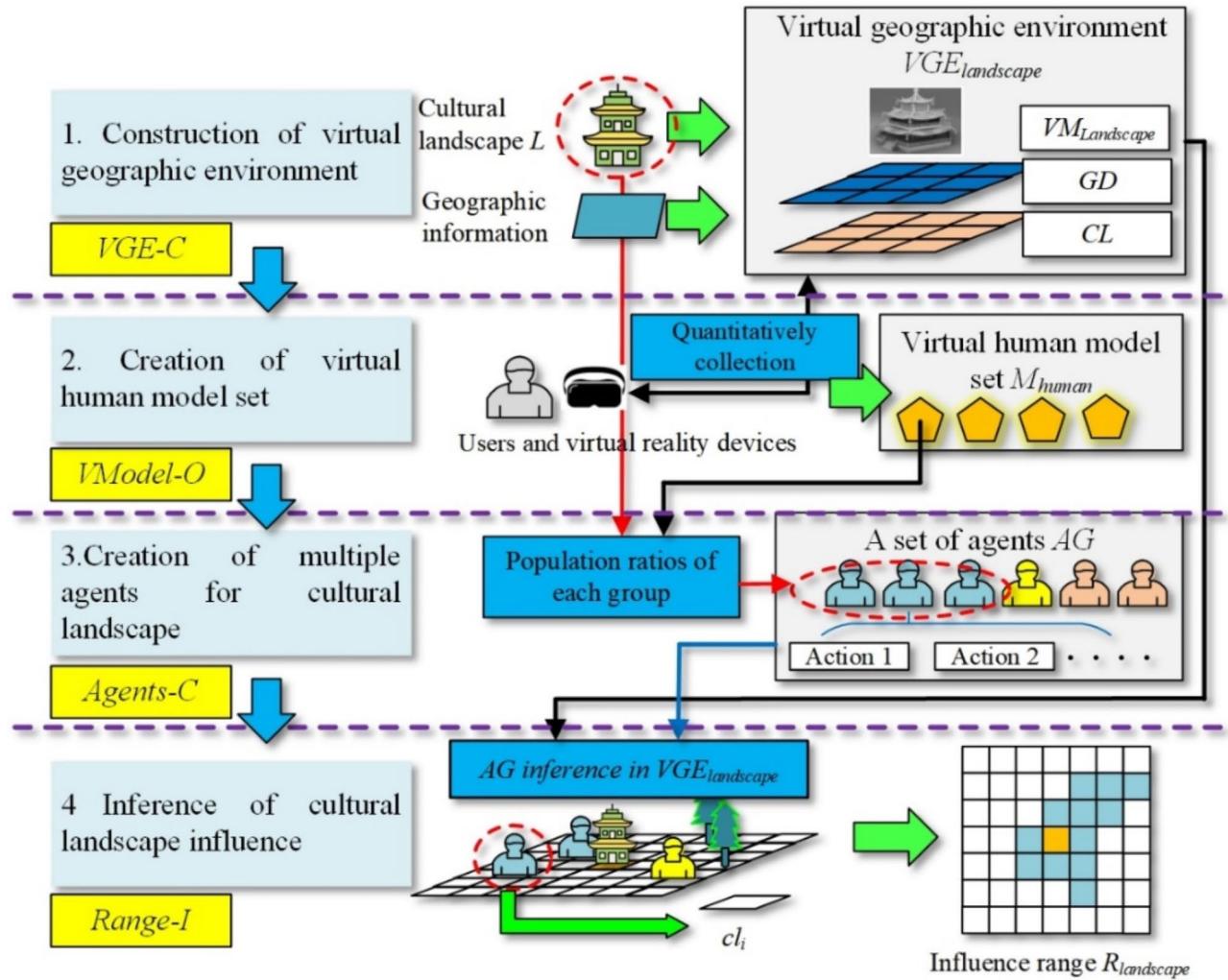
Based on the above core idea, the overall process of our method is shown in Fig. 2.

As shown in Fig. 2, our method is divided into four stages:

1. Construction of the VGE: For a cultural landscape  $L$ , a three-dimensional VR model  $VM_{Landscape}$  is established based on its real geographic scale; a set of geographic information grid cells  $GD=\{gd_1, gd_2, \dots, gd_n\}$  with width =  $P_{grid}$  is obtained for the area where  $L$  is located, and a set of geographic cells for agent interaction,  $CL=\{cl_1, cl_2, \dots, cl_n\}$ , is established based on  $GD$ . Then,  $VGE_{landscape}=(VM_{Landscape}, GD, CL)$  is formed, which contains the three-dimensional model, geographic information, and geographic cells. The function of this stage is implemented by the VGE construction algorithm (VGE-C).
2. Creation of the virtual human model set: VR devices are used to allow participants representative of a certain population to view the environment corresponding to  $VGE_{landscape}$  and to collect information through their interactions with this environment. During interaction, the subjective viewpoints of the participants are quantitatively collected in the geographic information grid  $GD$ . When collection work is performed with a certain group, a corresponding subjective behavior dataset  $VI=\{vi_1, vi_2, \dots, vi_n\}$  can be formed. A regression neural network model is then introduced to learn the relationship between the behavior of the group and the geographic features of the environment. By repeating this collection process with multiple groups  $Group=\{gp_1, gp_2, \dots, gp_n\}$ , a virtual human model set  $M_{human}=\{m_1, m_2, \dots, m_n\}$  can be formed, where each  $m_i$  can predict the behavior of individuals belonging to a certain group at a specific location. The function of this stage is implemented by the virtual human model set obtain algorithm (VModel-O).



**Fig. 1.** Core design idea of the proposed method.



**Fig. 2.** Overall process of the proposed method.

3. Creation of multiple agents interacting with the cultural landscape: Based on the population ratios of each group in the surrounding area of  $L$ , a set of agents  $AG=\{ag_1, ag_2, \dots, ag_n\}$  is established, where each  $ag_i$  is an instance of a model  $m_i$  in  $M_{human}$ . Under certain spatiotemporal conditions,  $ag_i$  can use  $m_i$  to perform a variety of actions in the virtual environment that have an impact on itself, other agents, and the environment. The function of this stage is implemented by the agent creation algorithm (Agents-C).
4. Inference of the cultural landscape's influence: All elements in  $AG$  are run simultaneously with an interval  $P_{interval}$  and each  $ag_i$  records the accumulated cultural influence in the specific cell  $cl_i$ . The cultural influence is recorded based on the results recorded for all elements in  $CL$ , and the influence range  $R_{landscape}$  of the cultural landscape can be inferred from  $CL$ . The function of this stage is implemented by the range inference algorithm (Range-I).

By following the above four steps, the proposed SC-VGE method can be used to establish models to quantitatively measure the influence of cultural landscapes on people and infer the scope of that influence. In the entire system, the grid parameters of the  $P_{grid}$  and the time interval of the  $P_{interval}$  determine the flexibility of the system; the determination of these two parameters is closely related to the size of the relevant region and the number of available samples. Since our goal is to collect and simulate subjective opinions of the population, the principle of the entire parameter selection is to express features and make the method easy to train under a limited amount of data and sample size (Data collection is affected by the time of user interaction with the operating environment and the number of devices, making it difficult to obtain sufficiently large datasets). Parameters that are too small or too detailed would prevent us from providing an effective magnitude of samples to statistically derive patterns, while parameters that are too large would result in the entire output being too coarse and losing its decision-making value.

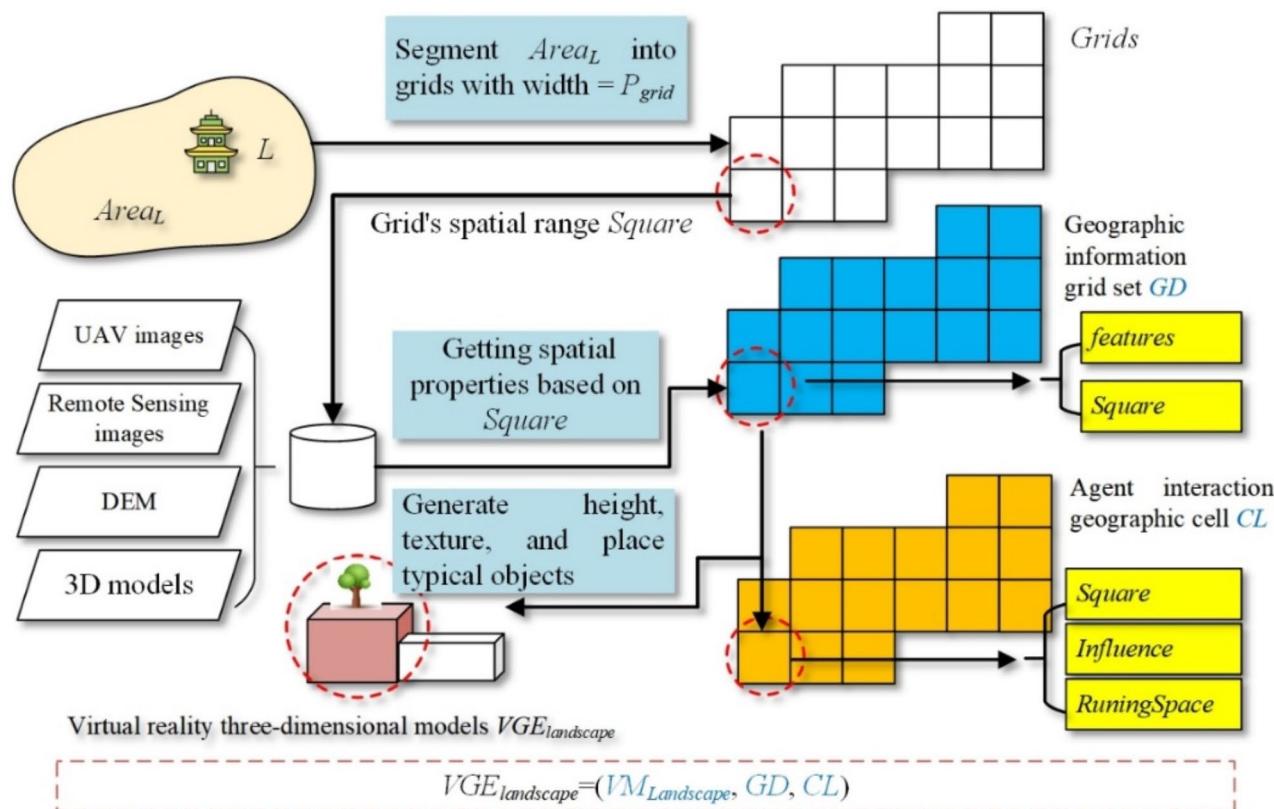
### Construction of the VGE

The VGE of the cultural landscape of interest needs to have three functions:

1. Provide a 3D model of the landscape  $L$  and the surrounding geographic environment to provide a virtual space for interacting models.
2. For a specific spatial location, provide a series of basic geographic data for subsequent analysis and calculation.
3. Accommodate a certain number of agents at a specific location for the inference process and store their results.

Based on the above requirements,  $VGE_{landscape} = (VM_{Landscape}, GD, CL)$  is defined in the SC-VGE method. The construction process is shown in Fig. 3.

As shown in Fig. 3, for the area  $Area_L$  corresponding to landscape  $L$ , the first step of the SC-VGE method is to collect remote sensing images, digital elevation model (DEM) data, and models of typical vegetation and typical objects in the study area to construct the regional feature dataset  $DB_{area}$ . Based on  $DB_{area}$ ,  $Area_L$  is separated into a set of geographic information grid cells  $GD$  based on the width parameter  $P_{grid}$ , where each grid cell stores corresponding spatial data in  $DB_{area}$ . A spatial visualization model of  $Area_L$  is then generated using the elements in  $GD$ ; at the same time,  $CL$  is also generated using the elements in  $GD$ . The corresponding process is shown in Algorithm 1.



**Fig. 3.** Overall process of the proposed method VGE construction process.

**Input:**  $DB_{area}$ ,  $Area_L$ ,  $P_{grid}$ **Output:**  $VGE_{landscape}$ **Begin** $VM_{Landscape} = \emptyset$ ;  $GD = \emptyset$ ;  $CL = \emptyset$ ; $initagents = \emptyset$ ;  $initresult = \emptyset$ ; $Grid \leftarrow \text{Segment } Area_L \text{ into grid cells with width} = P_{grid}$ ,for  $i = 1$  to  $\text{length}(Grid)$      $Square = Grid[i]$ 's spatial coordinates;     $features = \text{Intercept the spatial data in the range of } Square \text{ from } DB_{area}$ ;     $GD \leftarrow (Square, features)$ ;    for  $i=1$  to  $\text{length}(GD)$          $VM_{grid} = \text{Use } GD[i].features \text{ to generate the heights, textures, and locations of typical objects}$ ;         $RunningSpace = (initagents, initresult)$ ;         $VM_{Landscape} \leftarrow VM_{grid}$ ;         $Square = Grid[i].Square$ ;         $Influence = 0$ ;         $CL \leftarrow (Square, Influence, RunningSpace)$ ;         $VM_{Landscape} \leftarrow \text{Perform three-dimensional reconstruction of } L \text{ through } DB_{area}$ ;         $VGE_{landscape} = (VM_{Landscape}, GD, CL)$ ;**End****Algorithm 1** VGE construction (VGE-C).

The VGE-C algorithm can be used to generate a virtual environment  $VGE_{landscape}$  based on geographic data. The “*features*” of each *GD* indicate the Grid’s location and spatial characteristics, specifically including the following:

**Row position:** The number of the northernmost grid in the divided grid.

**Column position:** The number of the easternmost grid in the divided grid.

**Row distance:** The horizontal distance of the grid from the center point of the  $Area_L$ .

**Column distance:** The vertical distance of the grid from the center point of the  $Area_L$ .

**Straight-Line distance:** The straight-line distance from the cultural landscape.

**Ground attributes:** Wide paved road surface 0, ordinary pedestrian road surface 1, vegetated road surface 3, shrub-covered difficult-to-walk surface 4, and inaccessible areas 5.

**Elevation difference:** The difference in elevation from the cultural landscape data.

**Neighbor differences:** Obstruction areas for walking, such as nearby Area boundaries and walls.

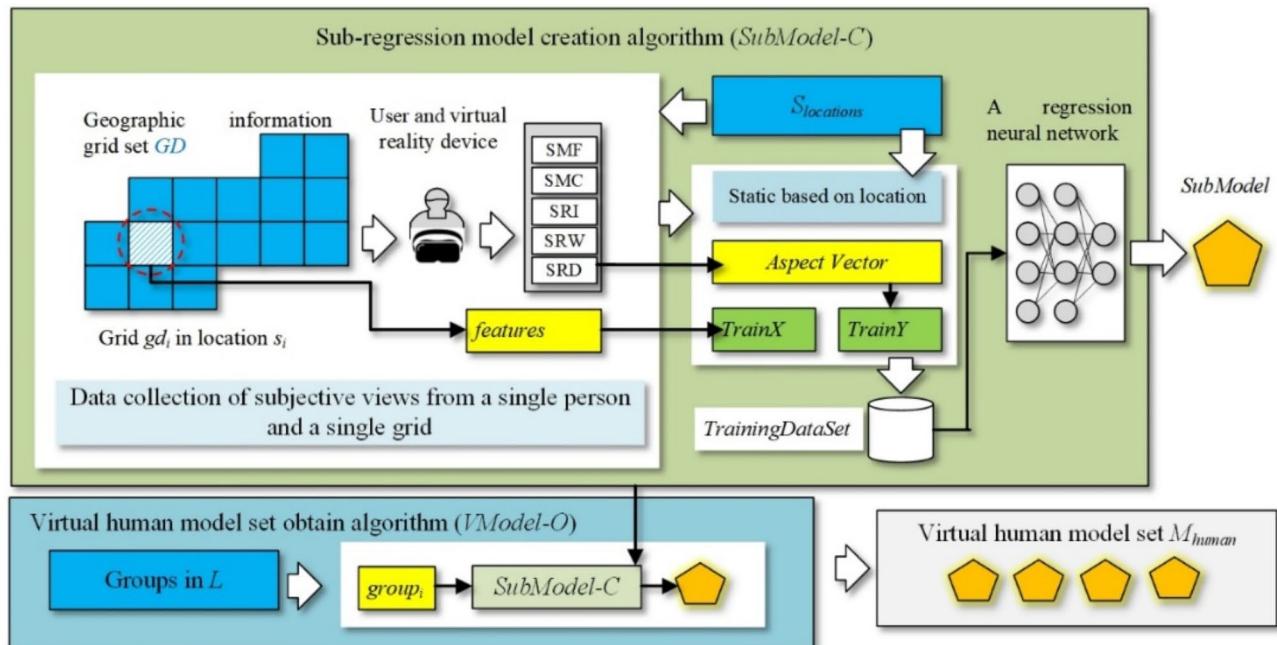
We normalize all attributes by dividing them by their respective maximum values within the overall *GD*, effectively mapping the data to the 0–1 range. This preprocessing step allows the subsequent neural network model to readily handle the given attributes. This environment can support VR display and interaction as well as model construction and inference.

*Creation of the virtual human model set*

Specific individuals’ identification and dissemination of cultural landscapes are affected not only by external objective factors (such as the geographical environment and landscape type) but also by subjective factors such as individual perspectives, the extent to which the individuals are affected by the landscape, and communication aspirations. For these subjective features, it is difficult to obtain training datasets and create corresponding models using traditional machine learning methods. With the SC-VGE method, however, subjective features can be quantitatively collected by leveraging the interaction process between users and a VGE to obtain the corresponding data; the specific process is shown in Fig. 4.

As shown in Fig. 4, in SC-VGE, an individual’s interactive behavior within  $VGE_{landscape}$  is divided into discrete time periods. More specifically, continuous interaction behavior is spatially divided into grid cells with a size of  $P_{grid}$  and temporally divided into time intervals of  $P_{interval}$ . Within a specific grid cell and time interval, an individual’s subjective behavior toward the cultural landscape of interest can be characterized by the following aspects:

- (1) Subjective preference for moving to grid cells that are farther from the landscape (SMF).
- (2) Subjective preference for moving to grid cells that are closer to the landscape (SMC).
- (3) Subjective assessment of the rate of influence within the influence range of the landscape (SRI).
- (4) Subjective assessment of the rate of willingness to engage in interactions with others regarding the landscape (SRW).



**Fig. 4.** Overall process of the proposed method VGE construction process.

(5) Subjective assessment of the rate at which the influence of the landscape decays (SRD).

These five subjective characteristics associated with a single individual and a single grid cell have a random nature. To capture the underlying patterns of this randomness, SC-VGE adopts a strategy in which typical locations  $S_{locations}$  are manually selected in  $GD$  and then a group of people  $gp_i$  uses virtual devices to collect data at these location points multiple times. The output subjective opinions for a location point are processed using the mean method, as follows:

$$aspect(gd_i) = \frac{\sum (SMF, SMC, SRI, SRW, SRD)}{N}, \quad (1)$$

Formula 1 can be used to quantify the subjective opinions of a group at a geographical location. This formula calculates the mean vector of a specific group on 5 aspects. The higher the values of the corresponding dimension of the vector, the higher the possibility of the corresponding subjective behavior. When the value is 1, it means that it is close to 100% likely to occur, and when it is 0, it means that it is basically impossible to occur. The quantitative results for a group at multiple geographical locations can then be used to train a regression model for prediction. The entire process is described by Algorithm 2.

**Input:**  $VGE_{landscape}$ ,  $S_{locations}$ ,  $gp_i$

**Output:**  $SubModel$

**Begin**

$TrainingDataSet = \emptyset$ ;

$VI =$  A group of users  $gp_i$  interact in  $VGE_{landscape}$ . The users are guided to move to selected locations in  $S_{locations}$  for testing, and their choices for (SMF, SMC, SRI, SRW, SRD) are collected.

for  $i=1$  to  $\text{length}(S_{locations})$

$gdi =$  Obtain grid cell location  $S_{locations}(i)$  from  $VGE_{landscape}.GD$ ;

$aspect =$  Statistically analyze the five subjective characteristics in  $VI$  using formula 1;

$trainx = gdi.features$ ;

$trainy = aspect$ ;

$TrainingDataSet \leftarrow (trainx, trainy)$ ;

$SubModel =$  Build a neural network for regression analysis;

Train  $SubModel$  using  $TrainingDataSet$ , where  $trainx$  corresponds to the model input and  $trainy$  corresponds to the model output;

**End**

**Algorithm 2** Regression submodel creation (*SubModel-C*).

The *SubModel* created by *SubModel-C* is a simple three-layered network consisting following layers:

**Input layer:** Serves as the initial processing stage, employing a linear activation function. It receives input data with a dimension of 8 and transforms it into an output dimension of 16, containing 24 neurons within this layer.

**Intermediate layer:** which introduces non-linearity through the use of the ReLU activation function. This layer takes the 16 outputs from the input layer as its input and processes them to produce an output dimension of 10, containing 10 neurons within this layer.

**Output layer:** Utilizing a linear activation function, It receives the 10 outputs from the intermediate layer and produces the final output with a dimension of 5, containing 5 neurons within this layer. The output of the neural network is a 5-dimensional vector corresponding to formula 1.

we can obtain a neural network model *SubModel* that can take the geographic feature data of a grid cell as input and output the probability of a specific group making a certain subjective decision. This model needs to predict the tendency of the virtual human towards the next action. Since the investigation and data collection based on virtual reality require the actual use of relevant devices, the relevant dataset cannot be too large. At this time, if the introduced neural network structure is too large (too many layers and powerful structures while large enough to remember the specificity of all data), it is more likely to cause overfitting. In our method, we deliberately use a relatively simple neural network model to avoid overfitting when the dataset is small. This model captures the overall trends in the training data rather than focusing on specific features. We can effectively represent the response of this area for the majority of people, thus improving the generalization ability.

People who are active around cultural landscapes may belong to a variety of groups, such as young students and middle-aged people. In SC-VGE, *Group* = { $gp_1, gp_2, \dots, gp_n$ } is used to describe all population groups in a region, where  $gp_i = (pct, gfeature)$ , with *pct* being the percentage of  $gp_i$  in the total population and *gfeature* being the group's description. As shown in Fig. 3, in the SC-VGE method, data are collected for each group in *Group*, and the *SubModel-C* algorithm is run to form virtual human model set  $M_{human} = \{m_1, m_2, \dots, m_n\}$ . This process is described in Algorithm 3.

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**Input:**  $VGE_{landscape}, S_{locations}, Group$

**Output:**  $M_{human}$

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**Begin**

$M_{human} = \emptyset;$

for  $i=1$  to  $\text{length}(Group)$

$submodel = SubModel-C(VGE_{landscape}, S_{locations}, Group[i])$

$M_{human} \leftarrow submodel;$

**End**

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**Algorithm 3** Virtual human model set obtain (*VModel-O*).

The *VModel-O* algorithm can convert the subjective processes of all population groups around a cultural landscape into a model set  $M_{human}$ . This bridges the gap between geographic information and subjective cognition, laying the foundation for subsequent inference tasks.

During the process of data collection, we need people from a specific group to participate. Our study represents the first exploration in the field of the interrelationships between human subjective perceptions and regional/spatial dimensions. Collecting subjective human perceptions inevitably involves addressing factors like emotions and physical conditions. During participant recruitment, we prioritized individuals in stable mental and physical states to minimize such variables. It is impossible to entirely eliminate environmental influences on human perceptions during experimentation, as “sensation” is inherently intertwined with contextual surroundings. Cultural landscapes and environments form an inseparable whole (e.g., the same sculpture elicits different effects in commercial districts versus parks). This rationale underlies our development of a “virtual geographic environment” rather than relying on simplistic metrics like distance or time to assess influence. Furthermore, The above parameters are obtained through statistics, which further prevents the method itself from collecting users' personally identifiable privacy data, making the method more secure in application.

*Creation of multiple agents interacting with the cultural landscape*

In the process of inferring the influence range of cultural landscapes, agents can be used to represent individuals participating in the landscape cognition process, and multiple agents can be used to represent groups participating in the landscape cognition process. Accordingly, the entire reasoning process is realized through the activities of all agents. In SC-VGE, a set of agents  $AG = \{ag_1, ag_2, \dots, ag_n\}$  is established using the groups *Group* and the model set  $M_{human}$ . This process is described in Algorithm 4.

**Input:**  $Group$ ,  $M_{human}$ ,  $P_{number}$   
**Output:**  $AG$

**Begin**

$AG = \emptyset$ ;  $InitLocation = \text{default location}$ ;  $InitInfluence = \text{default influence}$ ;

**for**  $i = 0$  to  $\text{length}(Group)$

$Number = Group[i].pct \times P_{number}$

$InnerModel = M_{human}[]$ ;

$InnerLocation = InitLocation$ ;

$InnerInfluence = InitInfluence$ ;

$AG \leftarrow \text{Repeat the creation of } P_{number} \text{ tuples with content } (InnerModel, InnerLocation,$

$InnerInfluence)$ ;

**End**

**Algorithm 4** Agent creation (Agents-C)

In this formula,  $P_{number}$  represents the total number of agents to be created; the minimum value of this quantity is the number of elements in the  $Group$ , and the maximum value is the capacity that the computational environment can accommodate (typically far exceeding the requirements of SC-VGE simulations). Using the Agents-C algorithm,  $P_{number}$  agents can be generated. The proportion of individuals in each group is allocated in accordance with the description of  $Group$ . Each agent is described as  $ag_i = (InnerModel, InnerLocation, InnerInfluence)$ , where  $InnerModel$  is a model from  $M_{human}$  that can predict the next behavior of  $ag_i$ ,  $InnerLocation$  corresponds to a grid cell location in the  $GD$  of  $VGE_{landscape}$ , and  $InnerInfluence$  corresponds to an initialized value of influence that decreases over time and distance.

For an agent  $ag_x$ , when it is in a location  $gd_p$ , it can take the geographic attributes of  $gd_i$  as input and use its  $InnerModel$  to infer a predicted vector.

$$Act_x = ag_x.InnerModel(gd_i.features) = (SMD, SMC, SRI, SRW, SRD), \quad (2)$$

this formula, through the prediction of the  $InnerModel$ , can obtain a vector of the probability of an agent's future behavior  $Act_x$ . This vector contains the five subjective behaviors mentioned above and can drive the agent's subsequent action selection. Based on the results of formula (2),  $ag_x$  can perform the following actions:

**Action 1** Move to a neighboring grid cell: Based on the distance to  $L$ , the neighboring grid cells of  $gd_i$  can be divided into two groups: the set of neighboring grid cells farther than  $gd_i$  from  $L$ , denoted by *Farther*, and the set of grid cells closer than  $gd_i$  to  $L$ , denoted by *Closer*.  $ag_x$  draws a float random number  $rnd$  between 0 and 2 to select its movement strategy, as shown in formula (3):

$$Strategy(ag_x) = \begin{cases} \begin{array}{l} \text{Moving to a grid in the } Farther \text{ set} \\ \text{Moving to a grid in the } Closer \text{ set} \\ \text{Not moving} \end{array} & \begin{array}{l} rnd < Act_x.SMF \\ Act_x.SMF \leq rnd < (Act_x.SMF + Act_x.SMC) \\ rnd \geq (Act_x.SMF + Act_x.SMC) \end{array} \end{cases}, \quad (3)$$

Formula (3) utilizes a random number that determines the three possible movement directions of the agent in the grid. If the random number is in the range  $[0, Act_x.SMF]$ , it means that the agent will move away from the culture landscape. If the random number is in the range  $[Act_x.SMF, Act_x.SMF + Act_x.SMC]$ , it means that the agent will move towards the landscape. If the random number is in the range  $(Act_x.SMF + Act_x.SMC, 2]$ , the agent will remain stationary.

**Action 2** Record the influence of the landscape in the current grid cell: When  $ag_x$  is at location  $gd_p$ , it can record the influence of the cultural landscape in the  $CL$  of  $VGE_{landscape}$ :

$$cl_i.influence = \begin{cases} ag_x.influence + \alpha \times Act_x.SRI & Act_x.SRI > 0 \\ ag_x.influence + \alpha \times 0.1 & Act_x.SRI = 0 \end{cases}, \quad (4)$$

After this influence is recorded, it also affects  $ag_x$  itself:

$$ag_x.InnerInfluence = ag_x.InnerInfluence + \alpha \times Act_x.SRI, \quad (5)$$

where  $\alpha$  is a number in the range  $(0, 1]$  that represents the percentage of the influence that is reflected in actions. Formula (4) and (5) demonstrate the dual influence of cultural landscape influence on agents and grids. On the one hand, agents can influence grids; on the other hand, the subjective assessment values of grids also have a reinforcing effect on agents, forming a continuous relationship between the local spatial grids and the agents.

**Action 3** Interact with other agents in the same grid cell: In a multiagent system, there may be many agents at location  $gd_i$ .  $ag_x$  draws a float random number  $rnd2$  between 0 and 1; if  $rnd2 < Act_x.SRW$ , then another agent  $ag_y$  will be randomly selected with equal probability, and  $ag_y$ 's  $InnerInfluence$  is affected by  $ag_x$  as follows:

$$ag_y.InnerInfluence = ag_y.InnerInfluence + \alpha \times ag_x.InnerInfluence, \quad (6)$$

Formula (6) demonstrates the relationship between two agents at the same location. Its key contribution lies in revealing how group size and interaction willingness influence the scope of cultural landscape. More individuals with a higher propensity to engage in interactions create a result where cultural landscapes can have a broader and more impactful influence.

**Action 4** Record a decay in the degree of influence of the landscape: As time goes on,  $ag_x$ 's *InnerInfluence* will gradually decrease, corresponding to the following formula:

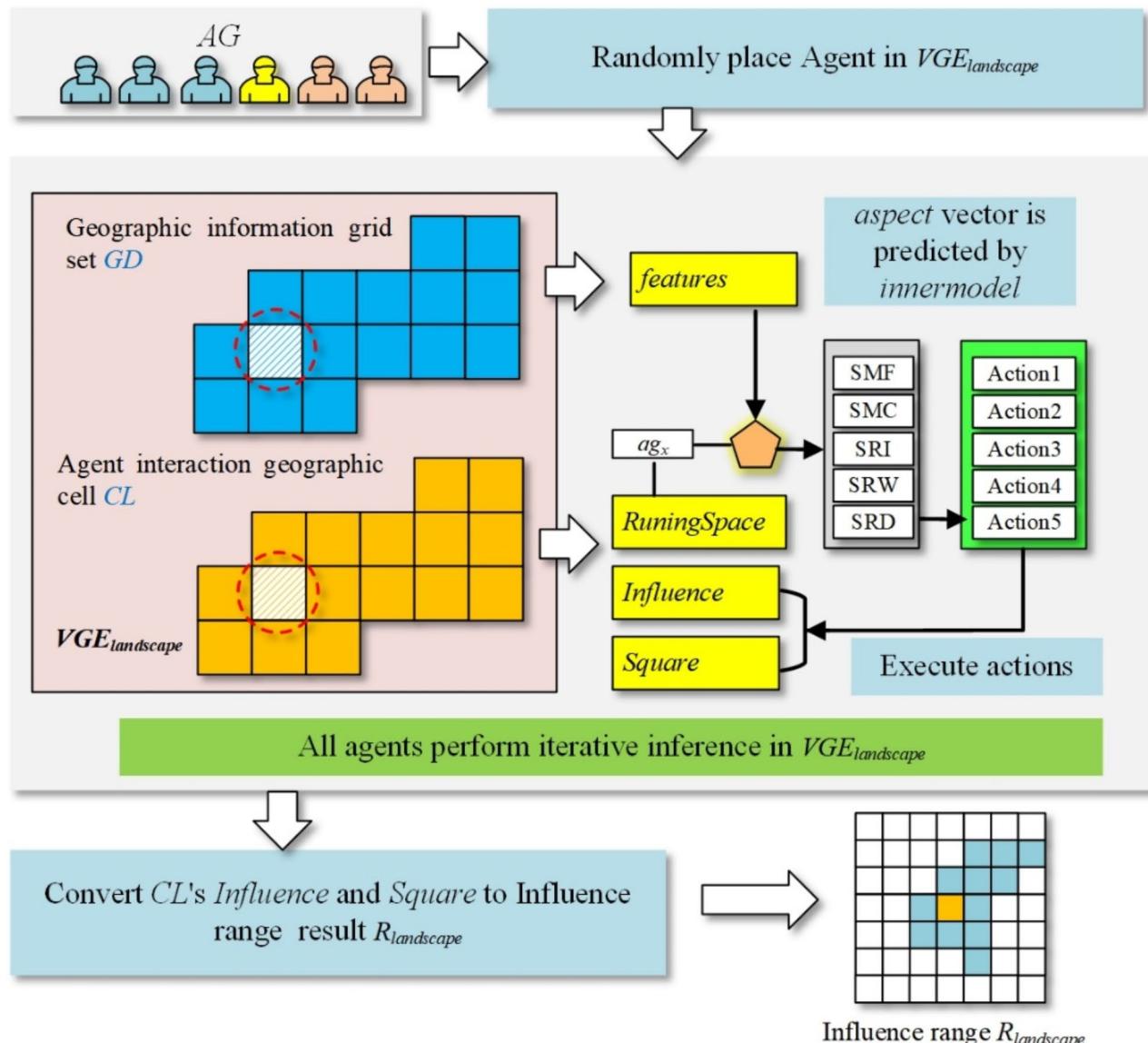
$$ag_x.\text{InnerInfluence} = ag_x.\text{InnerInfluence} - \beta \times Act_x.\text{SRD}, \quad (7)$$

where  $\beta$  is a factor in the range (0, 1] that determines how quickly decay occurs. This formula captures the dynamic decrease in landscape influence over time. As the SC-VGE algorithm iterates, the landscape's influence on the agent's behavior progressively weakens. Absent any fresh external influence, the agent's *InnerInfluence* decrease steadily, eventually reaching zero and triggering Action 5.

**Action 5** Change to an inactive state: When  $ag_x$ 's *InnerInfluence* drops to 0, this indicates that  $ag_x$  is no longer within the influence range of the cultural landscape. At this time,  $ag_x$  changes to an inactive state; in the subsequent time period,  $ag_x$  will not perform any actions.

#### Inference of the cultural landscape's influence

After AG is obtained, each  $ag_i$  can participate in the process of inferring the influence range of the cultural landscape by performing actions in  $VGE_{landscape}$ . This process is shown in Fig. 5.



**Fig. 5.** Influence process of the proposed method.

As shown in Fig. 5, all elements in  $AG$  are placed in  $VGE_{landscape}$ , with their initial  $InnerInfluence$  values specified. Then,  $VGE_{landscape}$  is iteratively updated, with each iteration representing a time interval  $P_{interval}$  in the virtual geographical space. During iteration, each  $ag_i$  performs actions 1 to 5 as listed in the previous subsection, which modify the influence attributes of  $CL$  in  $VGE_{landscape}$ . The corresponding process is shown in Algorithm 5.

---

**Input:**  $VGE_{landscape}$ ,  $AG$ ,  $P_{threshold}$   
**Output:**  $R_{landscape}$

---

**Begin**

$ct=1$ ;  $R_{landscape} = \emptyset$ ;

while ( $counter < \text{length}(AG)$ )

$rnd = \text{Generate a random integer from 1 to length}(VGE_{landscape}.GD)$ ;

$vt = AG[ct].InnerModel(VGE_{landscape}.GD[rnd].features)$ ;

if  $vt.SRI > vt.SRD$  then

$VGE_{landscape}.CL[rnd].RunningSpace \leftarrow AG[ct]$ ;

$AG[ct].InnerLocation = VGE_{landscape}.GD[rnd]$ ;

$ct = ct + 1$ ;

$elapsedtime = 0$ ;

while (All agents in  $AG$  are inactive or  $elapsedtime$  has exceeded the maximum value)

All active agents in  $AG$  perform actions 1 to 5;

$elapsedtime = elapsedtime + P_{interval}$ ;

for  $i = 1$  to  $\text{length}(VGE_{landscape}.CL)$

if  $VGE_{landscape}.CL[i] > P_{threshold}$  then

$R_{landscape} \leftarrow VGE_{landscape}.CL[i].Square$ ;

**End**

---

**Algorithm 5** Range inference (*Range-I*).

The *Range-I* algorithm first places all agents at random locations within grid cells where the landscape  $L$  has a direct influence, which are the grid cells where  $SRI > SRD$  for  $ag_i$ . Then, all agents perform actions as described in Sect. 2.4. When all agents have become inactive (no longer propagate the influence of the landscape) or the maximum elapsed simulation time has been reached, the iterative process of influence propagation in *Range-I* is terminated. While active, each agent records the influence of the landscape in  $VGE_{landscape}.CL$ . If any  $cl_i.Influence$  exceeds the threshold  $P_{threshold}$ , this means that the landscape's influence is acting on  $cl_i$ , and, thus, the corresponding region is within the influence range of the landscape; therefore, the corresponding  $cl_i.Square$  is added to the result  $R_{landscape}$ . The final output of the entire SC-VGE method is  $R_{landscape}$ , representing the influence range of landscape  $L$ .

## Experiments

### Method implementation

We implemented all procedures for the SC-VGE method in Python 3.8, including reading and processing remote sensing or UAV images and generating  $VM_{Landscape}$  model content. We built a VR interaction environment using C++ and Unreal Engine, which was used to run virtual models on a computer and report the collected interaction data to a server via a network service. We used FastAPI in Python to collect the interaction data on the server side. We constructed the neural networks for the virtual human model set  $M_{human}$  using PyTorch and implemented the inference process based on the geographic information grid in ArcGIS.

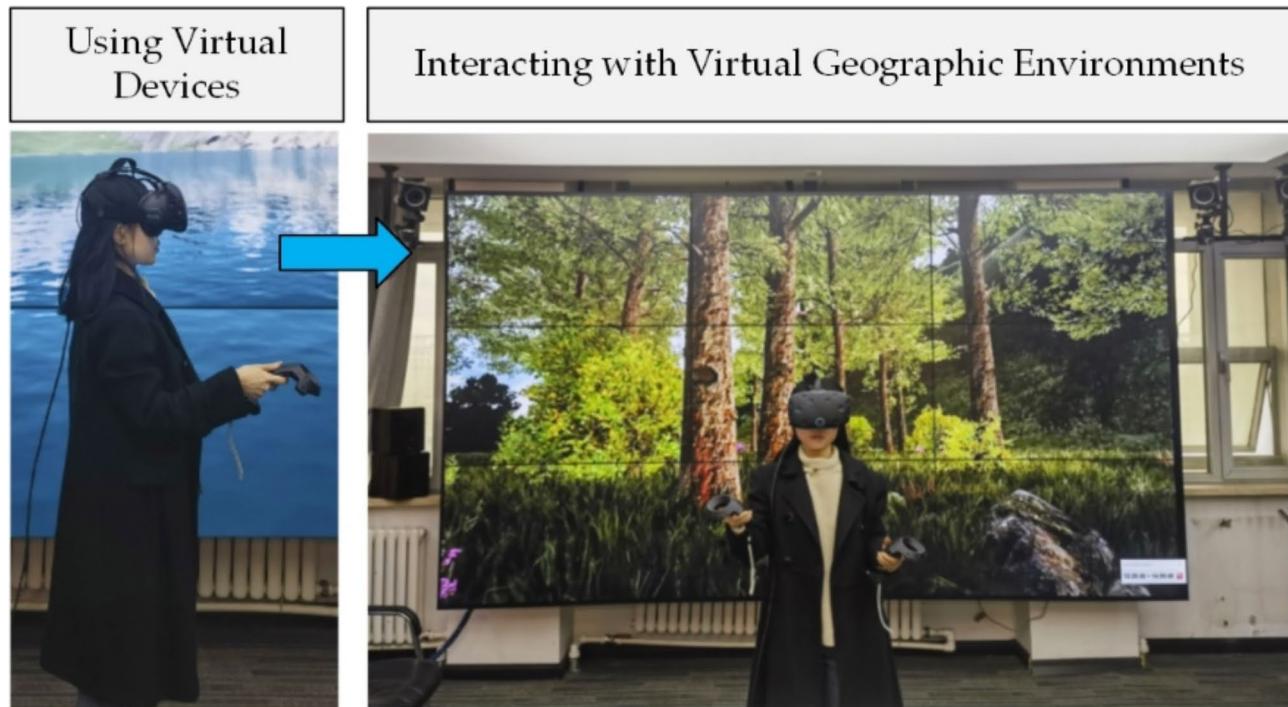
For  $VM_{Landscape}$ , we used default grid cells with a width of  $P_{grid} = 5$  m and time intervals of  $P_{interval} = 5$  min. A grid with  $P_{grid} = 5$  m can better represent the decision-making process in a small area, without having an excessive number of grids within the area, which could lead to difficulties in collecting data and obtaining samples. And a  $P_{interval} = 5$  min is a reasonable enough time for users in the virtual reality environment to make decisions and move within the scope of this grid.  $VM_{Landscape}$  provides the ability to interact with and display three-dimensional real-world scenes, as shown in Fig. 6.

As shown in the figure,  $VM_{Landscape}$  contains real scenes of cultural landscapes. System users explore and interact in this environment, and users' subjective opinion data are collected through interaction devices; eventually, the system can form the virtual human model set  $M_{human}$ .

### Algorithm methods for comparison

To verify the effectiveness of the methods proposed in this paper, we consider five methods, as listed in Table 1, to compare their results in estimating the influence ranges of cultural landscapes.

In conventional geographic range calculations, the four traditional methods in the table have been widely applied and have achieved much success. However, regarding measurement of a subjective range of cultural influence, it is difficult to find a measurable object to serve as the basis for statistical and regression analyses. Therefore, it is necessary to introduce certain means to reflect the inner thoughts of human beings, such as questionnaire surveys. SC-VGE employs VR to collect information, which is more intuitive than questionnaire surveys.



**Fig. 6.** Virtual device interaction and three-dimensional real scenes.

Method name	Method implementation
Spatial Straight-Line Distance Method (S-Line)	In this method, the distance ranges over which a specific group of people believe they are affected by a cultural landscape are collected through a questionnaire survey. The average of these distance ranges is calculated as the influence range value
Spatial Accessible Distance Method (S-Accessible)	In this method, the maximum distance that a specific group of people needs to walk to be continuously affected by a cultural landscape is collected through a questionnaire survey. Based on the A* algorithm, the corresponding path to the cultural landscape is found on the map. The area within the resulting distance range is defined as the influence range of the cultural landscape
Cellular Automata Method (CA)	This method uses CA to expand the influence range starting from the cultural landscape itself. The probability of expansion is obtained through a questionnaire survey
Multiagent Method (MA)	This method simulates a specific population using multiple agents. The actions of the multiple agents are consistent with those considered in the method proposed in this paper. The probabilities and values applied among the multiple agents are obtained through a questionnaire survey
SC-VGE	This method, proposed in this paper, differs from the above methods in a key way: it involves collecting the subjective opinions of the population using a VR environment rather than a questionnaire survey

**Table 1.** Methods for comparison.

Since our research involves a new field of measuring the spatial range of subjective views of specific objects, there is currently no method to measure the accuracy of the influence range of cultural landscapes for certain method, so we have constructed a new verification method:

For a landscape  $L$ , engage a group (or multiple groups) of people to move around the real landscape. Each person continuously records whether their subjective feeling is “inside the influence range” or “outside the influence range” using their mobile phone while moving. After collecting a large amount of data, the recording points are aggregated to geographic information grid cells  $GD$  based on spatial coordinates. Based on a numerical filter, if a grid has more than a threshold, the default value we currently use is 2, this implemented to mitigate the impact of random factors, with a minimum participation threshold of two individuals to ensure validity; the relatively low threshold was strategically chosen to maintain methodological sensitivity while reducing susceptibility to stochastic influences. People recording their own feelings, then this grid can be used as a test sample, and the feelings of the majority of people are taken as the label of the sample. From all the test samples obtained by filtering, a sample set  $Test$  is formed by random selecting an equal number of positive and negative samples based on a certain numerical value. For the output of a method, the consistency between the sample

labels in the test set and its output serves as the basis for accuracy evaluation. At this point, the accuracy of the method is:

$$\text{Overall Accuracy} = \frac{|\text{Samples consistent with the method's output}|}{|\text{Test}|}, \quad (8)$$

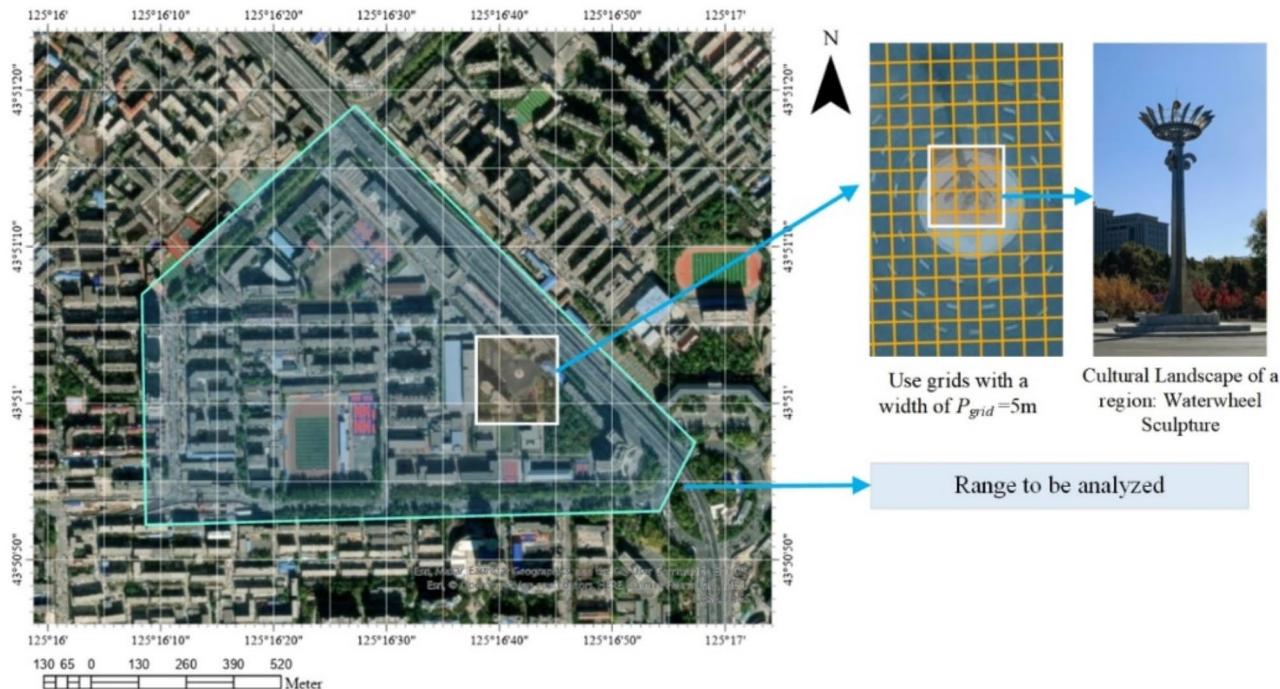
Formula (8) reflects the accuracy of an algorithm in estimating the influence range of a landscape; the higher the value, the closer it is to. Among the aforementioned five methods, S-Line, S-Accessible, and CA are deterministic initialization approaches that yield consistent results under consistent initialization conditions. In contrast, MA and SC-VGE incorporate stochastic elements during agent decision-making processes. For these two methods, we conducted 10 experimental trials and calculated the mean and standard deviation of their over-accuracy in relevant outcomes. The experimental result figures present the best-performing approaches from the corresponding methods in comparative analyses.

### Experiments in an urban study area

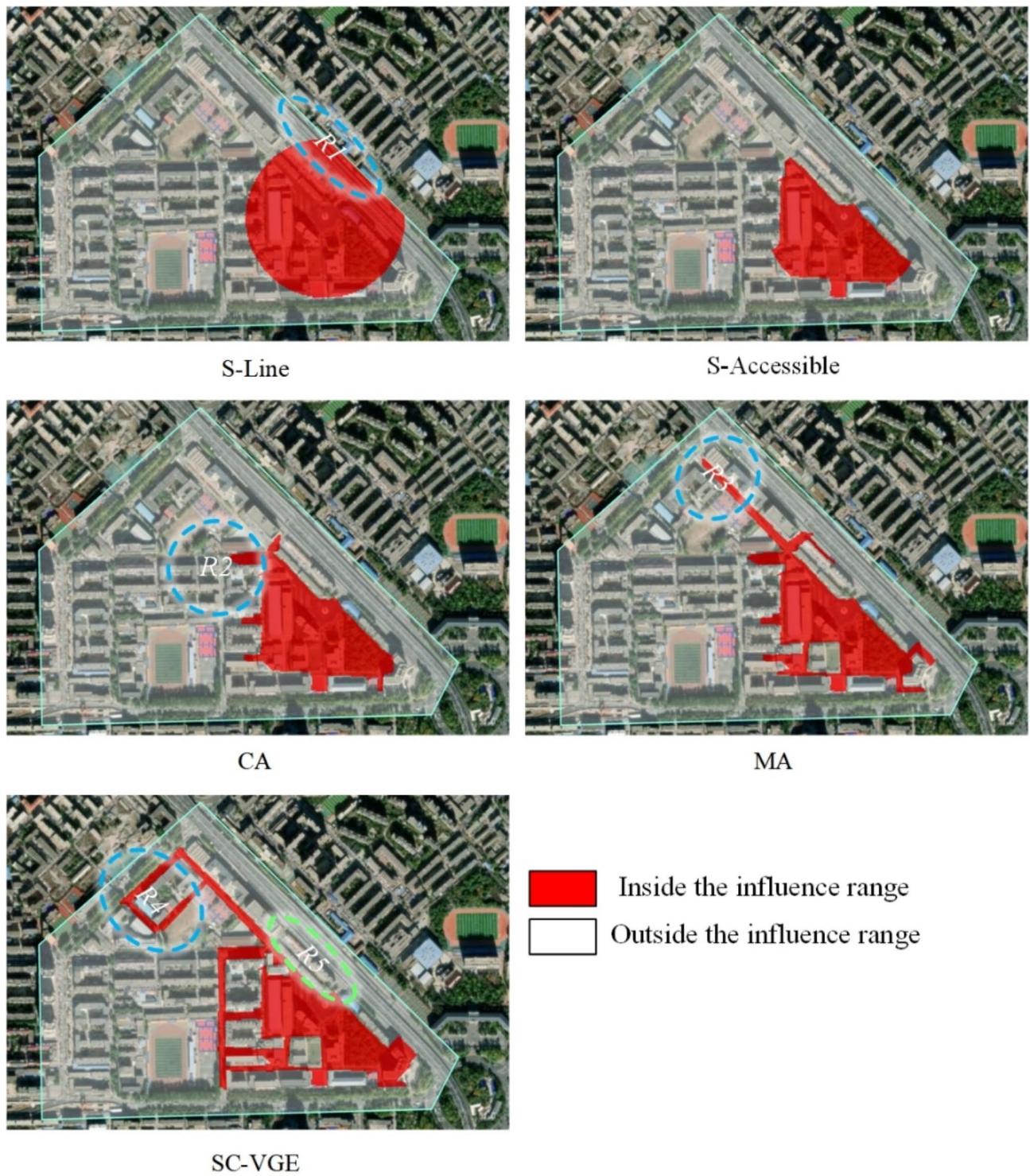
We chose Changchun Institute of Technology (CCIT) as the study area to investigate the influence range of a cultural landscape object in a city. CCIT is located in the urban area of Changchun, Jilin Province, China. The CCIT campus contains a typical cultural landscape object: a waterwheel sculpture. This sculpture represents the notable contributions that CCIT has made to the region in its 70-year history. It has great significance for the school. The study area and the location of the sculpture are shown in Fig. 7.

As shown in Fig. 7, we wish to calculate the influence range of the waterwheel sculpture for the entire college in this area. Our experimental group comprised 50 university students, 50 faculty and staff members, and 50 off-campus visitors. This composition effectively represents the primary population active within the university. All participants utilized VR equipment to interact with  $VM_{\text{Landscape}}$ , gathering the data necessary for SC-VGE. At the same time, these 150 individuals collected test points in the real-world, resulting in a total of 600 test points. We do not record the privacy information of these individuals when collecting data, and none of the methods used in the experiment require privacy content for calculation. All methods could successfully produce an estimated influence range, and the results of the five methods are shown in Fig. 8.

As shown in the experimental results of Fig. 8, there are five typical regions  $R1-R5$ . These regions exhibit highly distinctive features that clearly demonstrate the differences in the outcomes produced by various processing methods. Regarding regions  $R1$  through  $R5$ , we deployed 20 investigators, evenly distributed along the roadways within each region. Each investigator conducted surveys with 10 individuals passing by, subsequently analyzing and classifying the collected data. These regions exhibit the following characteristics: (1)  $R1$  and  $R5$ : Campus walls block students from directly leaving the school. Inside the campus, participants can directly feel the influence due to the proximity to the cultural landscape; while on the main roads outside the campus ( $R5$ ) and in areas completely blocked by building overpasses ( $R1$ ), most passersby are unrelated to the school and are not



**Fig. 7.** CCIT study area and corresponding cultural landscape object. In this figure, all maps and the remote sensing imagery used as the map background were generated using ArcGIS Pro software version 3.1.1 (<https://www.arcgis.com/index.html>).



**Fig. 8.** Results of the five methods for urban study area. In this figure, all maps and the remote sensing imagery used as the map background were generated using ArcGIS Pro software version 3.1.1 (<https://www.arcgis.com/index.html>).

interested in the cultural landscape, so they do not feel influenced. (2) Although the  $R_3$  region is farther away, the cultural landscape can be directly viewed, or people can quickly move to the location of the cultural landscape, so participants within the campus are still strongly influenced. (3)  $R_2$  and  $R_4$  cannot directly see the cultural landscape, but they are adjacent to strongly influenced areas; the influence of the cultural landscape still exists for a certain period, so the influence remains within their easily accessible activity range.

As shown in Fig. 8, the S-Line method directly defines a certain distance around the cultural landscape object as the influence range. This method is the easiest to implement, but as shown by the blue dotted circle  $R1$ , this method will include many areas from which the landscape object is clearly not visible (blocked by buildings) and that are practically far away (not directly connected, necessitating a detour) in the influence range. The S-Accessible method performs better than the S-Line method in this regard, as it filters out some areas that are not actually connected or from which one needs to detour a long distance to reach the landscape object. Nevertheless, the S-Line and S-Accessible methods both reflect only spatiality, not temporality. The CA method, as shown by the region labeled  $R2$ , reflects the extension and continuation of the influence of the cultural landscape object over a period of time. The MA method, because it uses agents that can move, can find that the influence range of the cultural landscape object extends farther in areas where people can move more quickly (such as the main roads on the campus), as shown by  $R3$ .

Compared to the other four methods, the SC-VGE method is more likely to reflect the subjective influence of cultural landscapes and their changes over time. For the MA method, the area within the blue dotted circle is reached by “moving” to that location, and the estimated influence in this area corresponds to the indirect influence of the cultural landscape object. In contrast, the SC-VGE method can find that this area is within the line of sight of the waterwheel sculpture, meaning that the influence in this area is directly produced by the cultural landscape object. Therefore, as shown by  $R4$ , this influence will continue to act for some period of time. Thus, the SC-VGE method more realistically shows the continuous change in the influence of the landscape object on the experimental group. In addition, the SC-VGE method also corrects some errors of the MA method. For example, the green-circled area  $R5$  in the figure is an area that the experimental group rarely enters. Therefore, the SC-VGE method does not include this area in the results.

As shown in Table 2, the SC-VGE method achieved the highest identification accuracy in this research area. This indicates that the SC-VGE method can effectively capture the subjective concept of the cultural landscape influence range and generate more reasonable results.

Regarding the waterwheel sculpture landscape, the SC-VGE method output the influence range of the landscape. From the results, the influence range of the landscape is not very large, because there are many tall buildings and large structures in Changchun City, which make the waterwheel sculpture not very impressive and prominent. In the area closer to the landscape, its influence penetrates into the buildings (the landscape can be seen through the windows of the corresponding buildings). For the area further away, its influence mainly acts on the main road of the school (the landscape can be seen on the main road). Therefore, the direct visual range is the most direct influence range of the landscape. The influence gradually disappears when it is not visible. It can be seen that the roads directly connected to the main road are also within the influence range. The influence disappears in areas far from the main road or areas that are not easily accessible to the landscape. This result shows the typical characteristics of the landscape influence in the campus, and lays the foundation for setting the campus cultural atmosphere and making decisions on the construction of related buildings.

### Experiments in a large park on the outskirts of the City

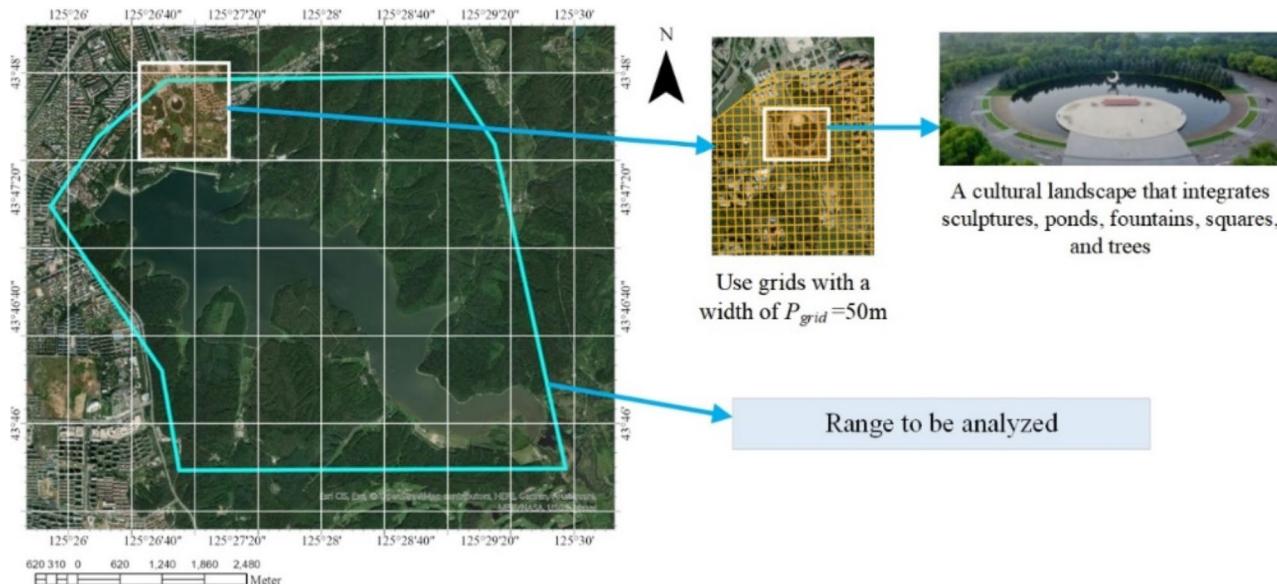
We also conducted experiments in Jingyuetan Park, which is located on the outskirts of Changchun. The differences between this research area and the urban research area are as follows: (1) This area is larger, with more inaccessible regions, such as mountains and water bodies. (2) The cultural landscape of interest is a holistic landscape composed of sculptures, ponds, fountains, squares, and trees instead of a single object. This holistic landscape consequently has a more obvious influence on people interacting with it. The relevant research area and its scope are shown in Fig. 9.

As shown in Fig. 9, the cultural landscape is located in the northeast corner of the research area, which includes a large water body and plaza. A surrounding road runs around the water body, which is used by visitors for sightseeing and fitness. To represent the characteristics of the visitor population within this research area, our experimental group included: 50 young visitors, 50 middle-aged visitors, 50 children, and 50 elderly visitors. These groups cover the majority of park visitors, with some very young or very old visitors, who have difficulty using the equipment, excluded from testing. All groups utilized VR equipment to interact with  $VM_{Landscape}$  to collect the data required for SC-VGE. These 200 individuals collected test points in the real-world, resulting in a total of 800 test points. We do not record the privacy information of these individuals when collecting data, and none of the methods used in the experiment require privacy content for calculation.

To facilitate analysis of a large area, we set  $P_{grid} = 50$  m and  $P_{interval} = 15$  min; since Jingyuetan Park is extremely large in area, using  $P_{grid} = 5$  m in Study Area 1 would result in millions of grids in this area, which would make it difficult to collect data. Therefore, we set  $P_{grid} = 50$  m. This scale can clearly present the analysis results of the entire park. And setting  $P_{interval} = 15$  min provides a reasonably sufficient time for users in the virtual reality

Method	Overall accuracy (%) Mean $\pm$ Std	Notes
S-Line	62.5	Non-random, conduct 1 experiment
S-Accessible	74.7	Non-random, conduct 1 experiment
CA	76.2	Non-random, conduct 1 experiment
MA	80.3 $\pm$ 4.7	Random, conduct 10 experiments
SC-VGE	89.7 $\pm$ 1.3	Random, conduct 10 experiments

**Table 2.** Accuracy of the five methods for the urban landscape research area.



**Fig. 9.** Jingyuetan Park study area and corresponding cultural landscape. In this figure, all maps and the remote sensing imagery used as the map background were generated using ArcGIS Pro software version 3.1.1 (<https://www.arcgis.com/index.html>).

environment to make decisions regarding each grid at this scale. The results of the five methods are shown in Fig. 10 for comparison.

As shown in the experimental results of Fig. 10, there are five typical regions *R6-R10*. The characters of these areas are closely related to the spatial geographical characteristics of the study area (such as the presence of roads) and the purpose of people's visits to these areas. Regarding regions *R6* through *R10*, we deployed 20 investigators, evenly distributed along the roadways within each region. Each investigator conducted surveys with 10 individuals passing by, subsequently analyzing and classifying the collected data. These regions exhibit the following characteristics: (1) The *R6*, apart from the roads, has tall trees in other areas, which are inaccessible to ordinary tourists; (2) Although *R7* and *R8* are slightly far from the cultural landscape, people going to these locations can usually reach them by taking vehicles within the park, so people entering from the park can reach these areas in a short time, and the cultural landscape can still exert its effect; (3) *R9* and *R10* are two very special areas. *R9* is relatively remote and is usually accessed by surrounding villagers by climbing over fences, so they have no contact with the cultural landscape and no goal of appreciate the park. *R10* has no Lack of adequate recreation and landscape, and people who go there usually aim for hiking and exercise; they do not enter from the gate containing the cultural landscape, so they usually do not feel the influence of the cultural landscape.

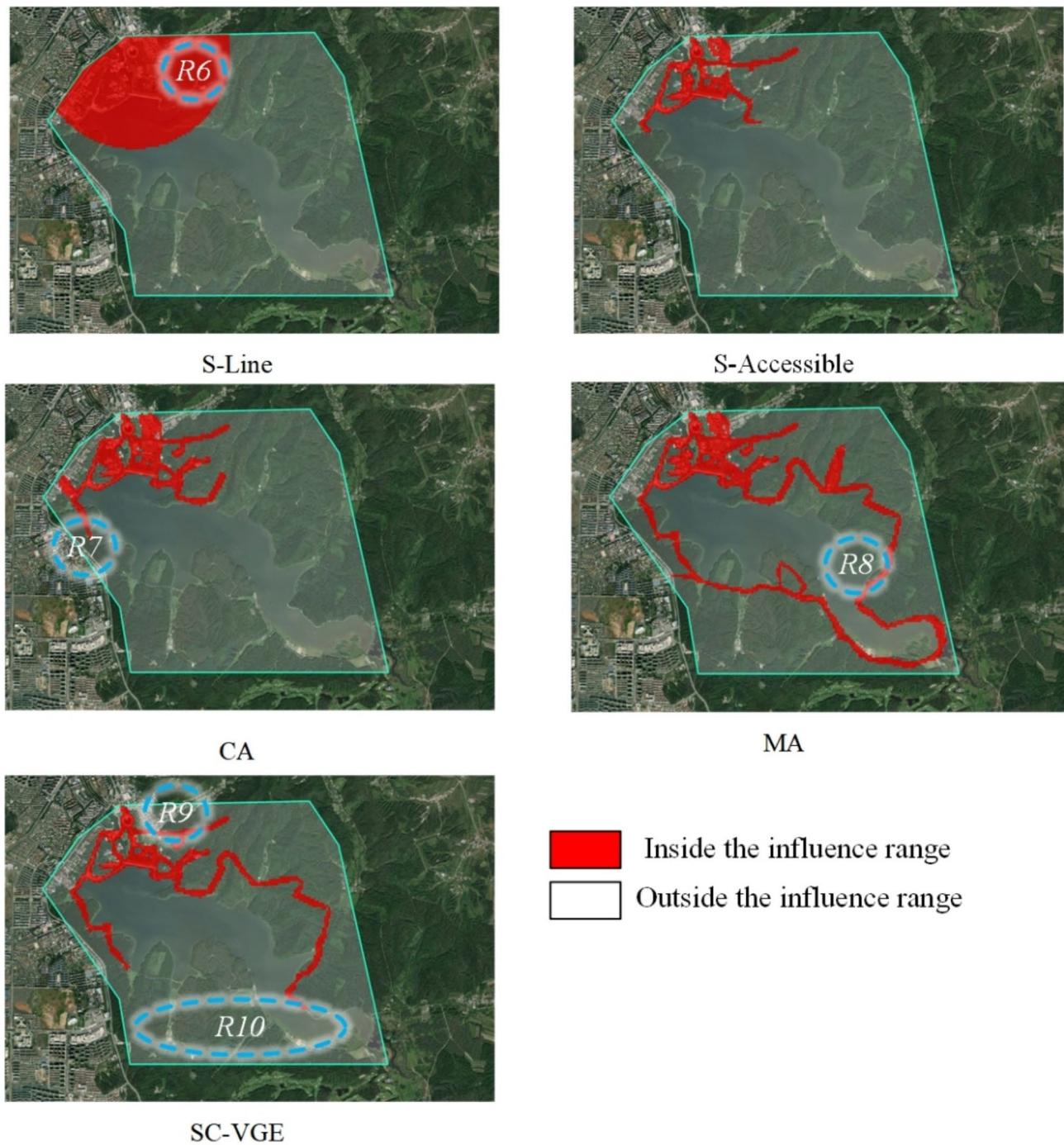
As shown in Fig. 10, the S-Line method includes many inaccessible areas (such as the mountain marked as *R6*) in the estimated influence range. The S-Line and S-Accessible methods still lack temporal characteristics, so their estimated influence ranges are relatively small. The CA method extends the estimated influence range to a certain extent, as shown by *R7*. The MA method introduces mobility of the agents. Since public transportation and electric vehicles can be used in the park, the mobility of the agents is relatively high. Consequently, the predicted influence area covers the main and branch roads throughout the entire park. The key difference between the SC-VGA method and the MA method is that the SC-VGA method can exclude areas where visitors are unlikely to be interested in the cultural landscape. This is because the SC-VGA method considers the subjective purposes of visitors. For example, the regions labeled *R9* and *R10* are excluded from the influence range by the SC-VGA method because they are residential areas or contain other points of interest that are not related to the cultural landscape.

As shown in Table 3, the overall accuracy of S-Line and S-Accessible is relatively low, while that of CA is slightly higher. Overall, SC-VGE has the highest accuracy. Based on the results in Fig. 10; Table 3, the SC-VGA method is superior to other methods for predicting the influence of cultural landscapes.

The SC-VGE analysis of Jingyuetan Park reveals characteristics typical of parks rich in natural features. Dominated by a water body, an internal park loop road, and densely forested mountains, the park's lack of artificial structures allows the this culture landscape to take center stage, leaving a lasting impression on visitors. The influence range primarily follows the contours of the park itself and stretches along its connecting roads. However, this influence weakens with increasing distance, fading entirely near the park's opposite end. This data on the landscape's influence range provides invaluable insights for ensuring consistency between park sculptures and buildings, ultimately contributing to the creation of a cohesive cultural theme for the park.

## Discussion

The development of scenic areas plays a crucial role in the cultural tourism industry of a city, with one of its key elements being "cultural landscapes." The selection of architectural structures and sculptures that can



**Fig. 10.** Cultural influence range of Jingyuetan Park as estimated using the five methods. In this figure, all maps and the remote sensing imagery used as the map background were generated using ArcGIS Pro software version 3.1.1 (<https://www.arcgis.com/index.html>).

Method	Overall accuracy (%)	Notes
S-Line	57.5	Non-random, conduct 1 experiment
S-Accessible	63.5	Non-random, conduct 1 experiment
CA	68.0	Non-random, conduct 1 experiment
MA	$77.3 \pm 3.4$	Random, conduct 10 experiments
SC-VGE	$87.8 \pm 1.5$	Random, conduct 10 experiments

**Table 3.** Accuracy of the five methods for Jingyuetan park.

achieve regional impact effects has traditionally relied on the decisions of individual experts. To the best of our knowledge, our method is the first approach capable of quantifying people's subjective perceptions of "cultural landscapes" into region-wide metrics. In practical applications for scenic area development, our method holds significant value in aiding decision-making processes.

The SC-VGE method innovatively establishes a strategy that integrates virtual reality-simulated geographic environments, subjective perception collection, and region-wide simulation and decision-making. This approach creates a simulation process that more accurately reflects collective authentic experiences. Additionally, since virtual environments suffice for implementation, there is no need for large-scale on-site surveys, drastically reducing both time and economic costs associated with data collection, making it highly promising for practical applications.

However, the SC-VGE method also has limitations: our approach necessitates exploration and interaction within a 3D virtualized environment, and that large-scale urban centers and complex geographic terrains demand the creation of corresponding three-dimensional virtual representations—a task beyond the temporal and financial capacities of ordinary teams. Consequently, the current SC-VGE framework cannot yet support simulations and predictions at city-level or larger scales. In future research, we aim to develop a multi-source data integration mechanism (e.g., leveraging open-source and community-shared resources) to facilitate the construction of 3D virtual environments, thereby enabling our method to adapt to a broader range of application scenarios.

## Conclusion

Cultural landscapes have an influence on people in the surrounding area, and this influence has a certain range. However, this influence is subjective and cannot be found solely by considering corresponding objects in the physical world, making it difficult to obtain good analysis results using traditional methods. This paper proposes the SC-VGA method, which has the following key characteristics:

- (1) A virtual geographic environment (VGE) is introduced to simulate the cultural landscape of interest and its surrounding environment at realistic temporal and spatial scales. This allows users to subjectively perceive the environment based on their knowledge and experience.
- (2) A strategy is established for the collection of various subjective cognitive aspects of cultural influence. These subjective features are then converted into neural network models, which allow subjective cognition to be quantitatively converted into multiagent interactions with the VGE.

By leveraging these two key features, SC-VGA achieves a capability that no traditional method has: modeling the subjective perceptions and opinions of individuals interacting in a geographic environment. In experiments, SC-VGA shows the ability to analyze the influence ranges of cultural landscapes and landscape objects more accurately than traditional methods. SC-VGA demonstrates an important application value of VGE technology: it can be used to collaboratively collect the perceptions and cognition of users regarding their environment and the surrounding landscape in order to further assist in geographic and temporal analysis and decision-making.

## Data availability

The data supporting the conclusions of the article will be made available by the authors upon request. Contacted email: panxin@neigae.ac.cn if needed.

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## Author contributions

Xiangfei She: Conceptualization, methodology, writing—original draft, supervision Xin Pan: methodology, visualization Jian Zhao: data curation.

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