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An Incentive Mechanism Based on a Bayesian Game for Spatial Crowdsourcing

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ABSTRACT Crowds are playing an increasingly important role in the research and application of geoscience by providing spatial data via crowdsourcing. However, low-public participation and poor quality of data submissions have greatly restricted the application of spatial crowdsourcing (SC) and other similar models, thus garnering the attention of scientists in this field. In this paper, we design a precise incentive mechanism based on a Bayesian game for SC that successfully avoids the conditions limited by the Gibbard–Satterthwaite impossibility theorem. Under this mechanism, the outsourcer carries out a Bayesian game with the participants under the circumstance of incomplete information by setting a certain amount of reference information that is not visible to the participants. Participants gain far more utility by telling the truth than that of they gain by lying and thus have a stronger motivation to submit higher-quality data. In implementing this mechanism to automatically compute the actual utility of participants and integrate data results, we propose a geometric primitive matching algorithm based on the Jaccard coefficient. Through both rigorous theoretical analyses and real experiments, the incentive mechanism that we propose is incentive-compatible and can greatly improve data quality.

INDEX TERMS Spatial information, crowdsourcing, incentive mechanism, Bayesian game, Jaccard coefficient.

I. INTRODUCTION

Crowdsourcing, developed in the Web 2.0 environment, is a model by which people contribute their labor and knowledge to a project under the condition of full information sharing. In recent years, spatial crowdsourcing (SC) [1], which inspires crowds to submit spatial information of true ground targets, has become a topic of great interest in the field of geoscience and has been widely used in land use [2], [3], disaster prevention and mitigation [4], [5], resource exploration [6], environmental protection [7], etc. The United States [8] and the European Union [9] have released citizen observation plans and have implemented several large SC projects. The crowd thus plays an increasingly important role in the research and application of geoscience.

However, the crowdsourcing model is not impeccable, as it can be difficult to encourage crowd participation generally. Crowdsourcing is different from outsourcing, and there is no contractual relationship between the crowd and the outsourcer. Whether the public participates is completely voluntary. Without an incentive, a crowdsourcing plan often can only recruit a very small number of people, a phenomenon referred to by scholars as the 90-9-1 rule [10] or the 1% [11] principle. As a result, participation enthusiasm is diminished, and the crowdsourcing plan cannot be completed within the expected time or at all. Without exception, SC is facing the same problem. Take Tomnod [12], an SC platform, for example: On 22 September 2017, Puerto Rico, a territory of the United States, was hit by Hurricane Maria, and a crowdsourcing project was launched to encourage people to participate in the visual interpretation of remote sensing images to identify damaged targets such as collapsed houses, damaged roads, and flooded farmland; one year later, however, less than 75% of the tasks were accomplished, and the timeliness of this plan was greatly reduced. For disaster prevention and mitigation, we have also established a crowdsourcing platform for damaged target recognition, but there have been few enthusiastic participants, and the spatial information they have submitted is not satisfactory. Therefore, an SC plan has two core problems to be solved: how to recruit more people involved and how to enhance the motivation of participants to submit high-quality data.

At present, research in this area mostly focuses on participant motivation and data mining algorithms. Researchers consider that people who participate in crowdsourcing must have some internal or external motivation, such as money [13], [14], curiosity, occupation, interest, self-actualization [15], altruism [16], sincerity, or appeal to knowledge or opinions [17]. The main methods of extracting qualified content from spatial information contributed by the public are the simple voting method, the expectation maximization method [18], the Bayesian data fusion approach [19], and the open-source method [20]. These methods can be used only when the information submitted by the participants achieves a certain accuracy. When these methods are used to judge the quality of the data, the outsourcer will give the initiative to the participants, and the participants will be motivated to tell a lie; for example, when using the simple voting method, participants can submit bad information via collusion to obtain rewards and avoid punishment. Clearly, SC faces a dilemma.

Therefore, a good crowdsourcing plan must implement a reasonable incentive mechanism to promote public enthusiasm to participate in it. Many scientists have noted that it is highly important to implement an incentive mechanism in crowdsourcing [13], [21], [22]. Under a suitable incentive mechanism whereby participants who submit high-quality information are rewarded and those who submit poor-quality information are punished, participants will be more willing to submit correct information. Otherwise, participants will be more willing to submit incorrect information. At this point, determining which participants should receive more rewards or remuneration requires the outsourcer to determine whether the information submitted by someone is of high or low quality.

Unlike other crowdsourcing scenarios, for which it is easy to judge the convergence point of a task or it is clear whether the task has been completed (such as the project of finding a hot-air balloon [23]), SC possesses unique characteristics. First, the task is complex. The participants must submit all of geometric information and attribute information correctly, and the outsourcer must correctly check the spatial primitives one by one. Because of the enormous amount of data, the latter is difficult for the outsourcer. Second, SC is a cooperative task [24] that must be accomplished through public cooperation; otherwise, the advantage of crowdsourcing—that is, a large number of people offer a great amount of strength—will not be brought into play. Therefore, it is necessary to reanalyze the structure of the SC model and design a better incentive mechanism.

Mechanism design is the reverse engineering of game theory [25], [26] to make a set of rules for a game. Here, we demonstrate a new incentive mechanism based on a Bayesian game (IMBG). By establishing hidden reference information, this scheme creates an incomplete information environment. This Bayesian game between the outsourcer and the participants incentivizes the participants to tell the truth rather than to lie because the expected utility of honesty is much higher than that of deceit. Therefore, the mechanism can not only enhance the enthusiasm of the public but also improve data quality. Furthermore, to implement this mechanism, a geometric primitive matching algorithm based on the Jaccard coefficient [27] (GPMJC) is designed to precisely check and aggregate the results submitted by the crowd automatically. To the best of our knowledge, this is the first study to design IMBG and GPMJC algorithms for improving the data quality of SC.

The remainder of this paper is organized as follows: In the second section, we summarize work related to mechanism design. In Section III, we illustrate the IMBG for SC and demonstrate its rationality. In Section IV, we elaborate the GPMJC algorithm, which is used to judge whether participants have submitted high- or low-quality data. In Section V, we obtain a real data set through an SC project and validate the effectiveness of the IMBG based on these data, including the degree of participation and the accuracy of the results. Finally, Section VI concludes this article.

II. RELATED WORK

The public will actively participate in crowdsourcing projects only if they are motivated by material or psychological factors. Paying rewards often involves problems such as privacy leakage and distrust. Determining how to pay rewards reasonably comprises the incentive mechanism. In recent years, proposed crowdsourcing incentive mechanisms have mainly fallen into the following categories. 1) Game-theory-based mechanisms. For example, Yang *et al.* [28] designed an incentive mechanism using a Stackelberg game to maximize the utility of the platform when the platform is the leader while the users are the followers. Li *et al.* [29] proposed two incentive mechanisms to stimulate mobile users to contribute indoor trajectory data for crowdsourcing-based indoor localization with differential privacy to prevent mobile users' privacy leakage based on a two-stage Stackelberg game. Wu *et al.* [30] designed a Stackelberg-game-based mechanism by which the requester fixes a certain total payment to encourage participants to participate in a task. 2) Auction-based mechanisms. For example, to solve the problem that users should be selected as sensors in each time slot, aiming to maximize social welfare and ensure the long-term participation incentive of users, Gao *et al.* [31] proposed a Lyapunov-based VCG auction policy for on-line sensor selection. Additionally, Yang *et al.* [28] proposed an auction-based incentive mechanism that is computationally efficient, individually rational, profitable, and truthful. For a specific task that is budget-constrained and requires one or more skills, Zhang *et al.* [32] proposed a solution based on reverse auction theory, assigning tasks to competent people and preventing false quotations. Zhu *et al.* [33] proposed an incentive mechanism based on reverse auctions and Vickrey auctions to prevent malicious competition behavior and the "free-riding" phenomenon in crowdsourcing services. Zhang *et al.* [34] designed a truthful auction with countermeasures against false-name attacks as an auction-based incentive mechanism for crowdsourcing. Li et al. [35] proposed a randomized combinatorial auction mechanism for the social cost minimization problem. Luo *et al.* [36] designed an incentive mechanism for scenarios involving heterogeneous types of workers (and the beliefs about their respective types) using an asymmetric all-pay contest (or auction) model. 3) Contract-theory-based mechanisms. For example, Zhang *et al.* [37] analyzed the typical contract problems of adverse selection and moral hazard and indicated that contract theory is a useful framework for motivating the third party's participation in emerging wireless networks of multimedia and location-based mobile services. In addition, incentive mechanisms other than the three categories mentioned above have been proposed. For example, Zhang *et al.* [38] designed a crowdsourcing tournament to maximize the principal's utility in crowdsourcing and provide continuous incentives for users by rewarding them based on the rank they achieved.

In this paper, we are more concerned about the quality of the data participants submit. Dai *et al.* [39] proposed an integrated incentive mechanism that utilized reverse auction, gamification, and reputation updating to incentivize crowds to actively participate and provide high-quality sensing data. In addition, incentive mechanisms proposed by researchers to improve data quality are as follows: determining data quality through users' reputation history [40], [41], evaluating data quality through behavioral representations associated with users [42], [40], improving data quality by an expectation maximization algorithm [43], using participant confidence to measure the quality of data generated [44], assessing data quality based on the past experience of mobile users [45], etc.

However, when the result set is finite and contains at least three elements, each participant's preference covers all strict total preference relations on the result set, and the social choice function is full projection, the Gibbard–Satterthwaite impossibility theorem shows that the social choice function is incentive-compatible for the dominant strategy only if it is dictatorial [46], [47]. Therefore, there are loopholes in the application of the abovementioned incentive mechanism to SC. Malicious participants can use these loopholes to maximize their utility. Therefore, the abovementioned incentive mechanisms can hardly be applied to SC systems.

Unlike macrotasking crowdsourcing [48], SC is microtasking crowdsourcing that requires the cooperation of many participants. In this scenario, designing a Bayesian game to motivate participants to submit real information about true ground targets can avoid the conditions defined by the Gibbard–Satterthwaite impossibility theorem. Because the expected utility of honesty is much higher than that of deceit, the approach is incentive-compatible.

The 9-Intersection Model (9IM), a topological model proposed by Egenhofer [49]–[52] and developed by Clementini *et al.* [53], [54] used to perform spatial analysis, has become the standard for describing the spatial relations of two geometries in two dimensions. This model specifies very strictly that two geometries are topologically equal if their interiors intersect and no part of the interior or boundary of one geometry intersects the exterior of the other. Based on this model, when the difference between two polygons using the Boolean operation NOT is zero, two geometric primitives are deemed to coincide with each other [55]–[58]. However, deviations caused by operation, instruments or computer systems are inevitable in practical spatial information projects; therefore, we cannot use these methods to determine whether two geometric primitives coincide with each other when these deviations must be tolerated.

We propose a geometric primitive matching algorithm based on the theory of the Jaccard coefficient, defined as intersection over union over the range of [0, 1], which can express the degree of overlap between two geometric primitives.

For clarity, Table 1 lists the parameters and their meanings, as used in this paper.

TABLE 1. Lookup table for key parameters.

Parameter	Definition
S_p	Results submitted by participant p
o_{pi}	Geographic information primitive in S_p
N_p	Number of primitives in S_p
u_e	Utility one participant gains when o_{pi} is incorrect
u_c	Utility one participant p gains when o_{pi} is correct
U_p	Total utility one participant gains
U_o	Total utility outsourcer gains
T_{pi}	Indicator of whether o_{pi} is correct
T	Number of ground targets in one area
O	Set of ground targets in one area
o_t	One ground target in O
O_{seed}	Ground targets set as seeds
T_{seed}	Number of ground targets in O_{seed}
S_{os}	Strategies set of outsourcer
S_p	Strategies set of one participant
S_p^j, S_p^o	One element of S_p
$f(S_p^j, O_{seed})$	Social choice function
$P(S_p^j, O_{seed})$	Joint probability of S_p^j and O_{seed}
$P(O_{seed} \| S_p^j)$	Probability of O_{seed} under condition S_p^j
$P(O_{seed} \| S_p^j)$	Probability of S_p^j under condition O_{seed}
M_p	Number of elements in S_p
M_c	Correct primitives in S_p^j
M_c^1	Random variable, correct primitives coincide with seed
M_c^0	Random variable, correct primitives miss coinciding with seed
M_e	Erroneous primitives in S_p^j
M_e^1	Random variable, erroneous primitives intersect with seed
M_e^0	Random variable, erroneous primitives miss intersection with seed
$P(M_c^1)$	Probability of M_c^1
$E(M_c^1)$	Expectation of M_c^1
$P(M_c^0)$	Probability of M_c^0
$E(M_c^0)$	Expectation of M_c^0
$D_p(M_c^1)$	Variance of M_c^1, risk

III. INCENTIVE MECHANISM BASED ON BAYESIAN GAME

Suppose that an outsourcer wants to obtain spatial information about certain types of ground objects in one geographic

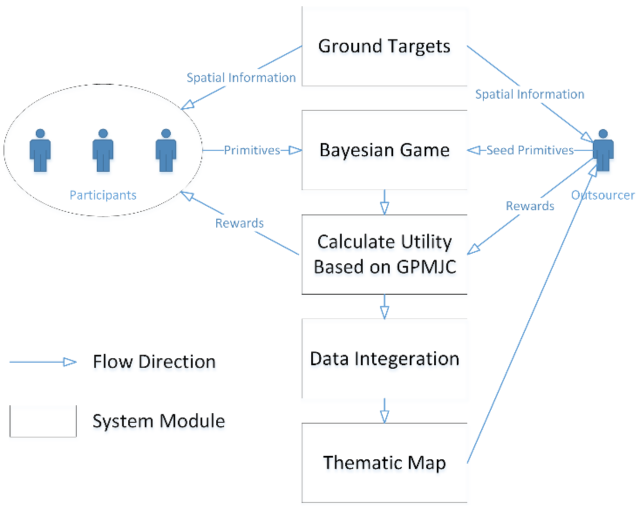

FIGURE 1. **Work flow of IMBG.**

area and encourages public participation with certain types of incentives; we make the strategic choices of the participants and the outsourcer independent under this mechanism. Because the conditional probabilities of each strategy are equal to each other, this scenario is a Bayesian game. The IMBG consists of the following modules, as shown in Fig 1. 1) According to their consideration, each participant extracts the spatial information of a certain number objects as a game strategy. 2) The outsourcer randomly chooses a certain number objects in the region, obtains their correct spatial information as seed primitives, and takes these seed primitives as a game strategy to participate in the game. 3) The outsourcer gives each participant a reward calculated by the GPMJC algorithm. 4) Data integration is carried out according to the correct rate of each participant in the game process. 5) The system generates thematic maps and delivers them to the outsourcer.

A. TRADE BETWEEN OUTSOURCER AND PARTICIPANT

The task of a cyber-citizen participating in SC is to provide spatial information of earth surface targets to the outsourcer. The spatial information of ground objects includes two parts: geometric and attribute information. Geometric information is represented by geometric figures such as points, lines, and polygons formed by spatial positions, and attribute information is represented by descriptive information such as words and numerical values.

In an SC project, there is no contractual relationship between the outsourcer and the participant, but the two are gaming. Through the game, each party adopts a certain strategy to interact with the other to maximize its utility.

We can describe the game model as follows:

Suppose that participant p submits his or her results $S_p = \{o_{pi} | 1 \leq pi \leq N_{pi}\}_{pi=1}^{N_p}$, where o_{pi} represents one of the geographic information primitives and N_p represents the number of primitives in S_p. If o_{pi} is correct, participant p gains utility u_c; now, set $T_{pi} = 1$. If o_{pi} is incorrect, participant p gains utility u_e; now, set $T_{pi} = 0$. The utility obtained by participant p is synthesized into the following expression:

$$U_p = \sum_{pi=1}^{N_p} \left(u_c \times T_{pi} + u_e \times \left(1 - T_{pi}\right)\right) \tag{1}$$

The wrong primitives are without meaning to the outsourcer; that is, the latter part of the formula is negative for the outsourcer such that the outsourcer's utility is as follows:

$$U_o = \sum_{pi=1}^{N_p} (u_c \times T_i - u_e \times (1 - T_i)) \tag{2}$$

The outsourcer and the participants are all rational decision-makers—one of the basic conditions of game theory [59]; therefore, they are consistently able to find the best strategy to maximize their utility. However, the strategy may not necessarily be their true type, and they may also tell a lie. For example, the participants can adjust the number of correct and erroneous primitives according to rules of the game. We hope that both the outsourcer and the participant can achieve their highest expectations, namely, incentive compatibility [25] or Pareto efficiency [60]. Therefore, we must design a reasonable mechanism to induce participants to tell the truth. The core of mechanism design is the social choice function, which is the combination of a series of rules in a game [61]. Thus, when using the abovementioned simple voting method, expectation maximization method, Bayesian data fusion approach, or open-source method as the social choice function, participants can find a dictatorial dominant strategy to deceive the outsourcer. If the condition of the game is relaxed to be Bayesian-incentive-compatible, the restriction of the Gibbard–Satterthwaite impossibility theorem can be avoided. When the game reaches equilibrium, the result submitted by the participants is exactly the reaction of their true type.

B. INCENTIVE MECHANISM DESIGN

For SC, the Bayesian incentive mechanism contains two elements: indirect revelation mechanisms and Bayesian incentive compatibility.

Suppose the outsourcer wants to obtain the spatial information of T ground objects in an area; that is, $O = \{o_t | 1 \leq t \leq T\}$. Thus, we can design the incentive mechanism as follows:

1. The two parties of the game are the outsourcer os and one participant p.

2. Outsourcer os selects a certain number $T_{seed}(T_{seed} < T)$ of ground objects in O and obtains absolutely accurate spatial information about them to create seeds set O_{seed}. O_{seed} constitutes one of his or her possible strategies. All possible seeds sets form his or her strategies set; that is, $S_{os} = \{O_{seed} | O_{seed} \subset O\}$, where O_{seed}, which has $\sum_{T_{seed}=0}^{T} \binom{T_{seed}}{T}$ possibilities, is one subset of O. Generally, O_{seed} accounts for a small proportion of O as a reference set [62], [63]. Outsourcer os randomly arranges the seeds that are invisible to the participants and thus creates an incomplete

information environment, which is the basis of the Bayesian game.

3. The candidate strategies set of participant p is all the possible results that he or she can submit; that is, $S_p = \left\{S_p^j \mid S_p^j = \left\{o_i \mid 1 \le i \le N_p\right\}, 1 \le j \le M_p\right\}$, where N_p and M_p are natural numbers. Although there are infinite possibilities for the results submitted by participant p, the strategies set S_p is finite and countable when N_p and M_p are given. Additionally, an unalterable fact is that the number of correct elements in S_p^j will not exceed T. How many elements in S_p^j are correct or incorrect depends on the personal skill level and subjective strategy choice of participant p. Every participant p can choose his or her strategy S_p^j from the set S_p to maximize utility.

4. If one primitive in S_p^j coincides with one seed in O_{seed}, then participant p gains utility u_c. If one primitive in S_p^j intersects with one seed in O_{seed} but the two are not congruent, then participant p gains utility u_e. Each seed can be hit by the participant only once. The maximum number of seeds that participant p hits is T_{seed}. Therefore, the social choice function can be defined as

$$f\left(S_p^j, O_{seed}\right) = \mathrm{C}\left(S_p^j, O_{seed}\right) \cup \mathrm{C}_{-}\left(S_p^j, O_{seed}\right) \tag{3}$$

where function $\mathrm{C}(\cdot)$ returns the primitives that coincide with corresponding seeds and function $\mathrm{C}_{-}(\cdot)$ returns the primitives that intersect with some seeds but that are not congruent.

The utility that participant p gains from the outsourcer is

$$U_p = u_c \times |C\left(S_p^j, O_{seed}\right)| - u_e \times |C_{-}\left(S_p^j, O_{seed}\right)|. \tag{4}$$

As shown in Fig. 2, there are 15 ground targets in one geographic area. The outsourcer selects 5 randomly and obtains their absolutely accurate spatial information. One participant submits spatial information pertaining to 9 targets. Comparing the spatial information of the two sides, 2 primitives are correct and 1 is incorrect. Thus, the utility gained by this participant is $2u_c - u_e$.

C. INCENTIVE COMPATIBILITY

One reasonable incentive mechanism is incentive compatibility. We analyze and clarify the incentive compatibility of the mechanism in three respects: the basic principle, the maximization of utility and the risk participants take.

1. Outsourcer os and participant p are independent when choosing strategies in the abovementioned game; therefore, the joint probability of choosing their strategies separately is

$$P\left(S_p^j, O_{seed}\right) = 1 \Big/ (M_p \times \binom{T_{seed}}{T}) \tag{5}$$

The belief function of outsourcer os can be solved by Bayes formula as follows:

$$\begin{aligned} P\left(S_p^j \mid O_{seed}\right) &= P\left(S_p^j, O_{seed}\right) \Big/ \sum\nolimits_{S_p^o \in S_p} p\left(S_p^o, O_{seed}\right) \\ &= 1/M_p \end{aligned} \tag{6}$$

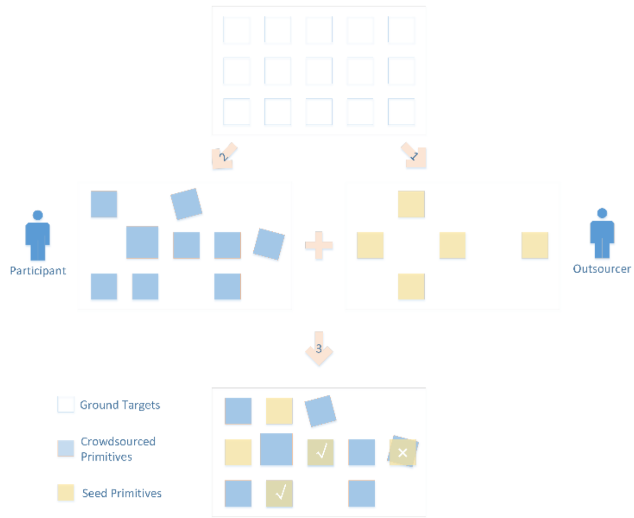

FIGURE 2. Illustration of Bayesian game-based incentive mechanism.

Similarly, the belief function of participant p can be solved by

$$P\left(O_{seed} \mid S_p^j\right) = P\left(O_{seed}\right) = 1 \Big/ \binom{T_{seed}}{T} \tag{7}$$

Thus, the mechanism satisfies the basic conditions of the Bayesian game, that is, belief consistency.

2. The incorrect primitives in the result submitted by participant p based on his or her strategy cannot coincide with the seeds because the seed primitives are correct. Therefore, these incorrect primitives can be deleted when calculating their positive expected utility. If M_c primitives in S_p^j are correct, among them, M_c^1 primitives coincide with the seeds and M_c^0 miss; hence, $M_c^0 = M_c - M_c^1$. Therefore, the number of real primitives not submitted by participant p is $T - M_c$.

When $M_c + T_{seed} \le T$, the number of primitives that coincide with the seeds M_c^1 obeys a hypergeometric distribution; that is, $M_c^1 \sim H(T, M_c, T_{seed})$. therefore, the probability

$$P\left(M_c^1\right) = \frac{\binom{M_c - M_c^1}{T - T_{seed}} \times \binom{M_c^1}{T_{seed}}}{\binom{M_c}{T}}, \tag{8}$$

where $M_c^1 = 0, 1, 2, 3, \ldots, min(M_c^1, T_{seed})$ and its expectation is

$$\begin{aligned} E\left(M_c^1\right) &= \sum\nolimits_{M_c^1=0}^{min(M_c^1, T_{seed})} \frac{\binom{M_c - M_c^1}{T - T_{seed}} \times \binom{M_c^1}{T_{seed}}}{\binom{M_c}{T}} \times M_c^1 \\ &= M_c \times T_{seed} / T \end{aligned} \tag{9}$$

Therefore, the expected utility U_p of participant p is a function of M_c, as follows:

$$U_p\left(M_c\right) = u_c \times M_c \times T_{seed} / T \tag{10}$$

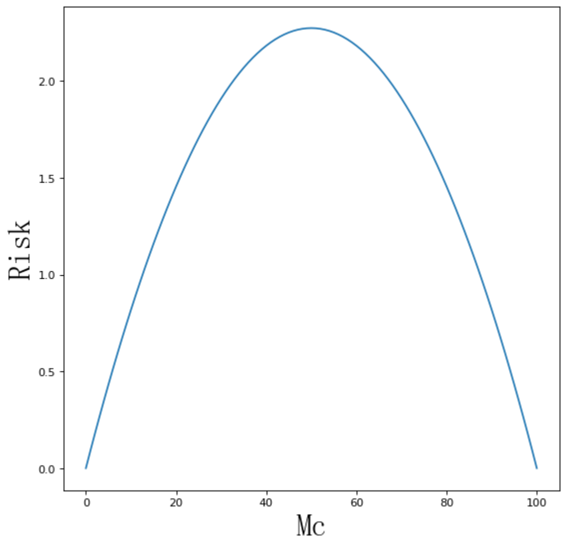

FIGURE 3. Risk of one participant.

When $M_c + T_{seed} > T$, there are at least $M_c + T_{seed} - T$ primitives coinciding with the seeds, and $M_c + T_{seed} - T$ is not easily expressed by hypergeometric distribution. However, the number of seeds M_c^0 that are not hit by the result submitted by participant p obeys a hypergeometric distribution; that is, $M_c^0 \sim H(T, T - M_c, T_{seed})$. Therefore, the probability

$$P\left(M_c^0\right) = \frac{\begin{pmatrix} T - M_c - M_c^0 \\ T - T_{seed} \end{pmatrix} \times \begin{pmatrix} M_c^0 \\ T_{seed} \end{pmatrix}}{\begin{pmatrix} T - M_c \\ T \end{pmatrix}}, \tag{11}$$

where $M_c^0 = 0, 1, 2, 3, \ldots, min(M_c^0, T_{seed})$ and its expectation

$$E\left(M_c^0\right) = \sum_{M_c^0=0}^{min(M_c^0, T_{seed})} \frac{\begin{pmatrix} T - M_c - M_c^0 \\ T - T_{seed} \end{pmatrix} \times \begin{pmatrix} M_c^0 \\ T_{seed} \end{pmatrix}}{\begin{pmatrix} T - M_c \\ T \end{pmatrix}} \times M_c^0$$
$$= T - M_c \times T_{seed} / T \tag{12}$$

The expected utility not attained by participant p is

$$U_p(T - M_c) = u_c \times (T - M_c) \times T_{seed} / T \tag{13}$$

Therefore, the expected utility that participant p obtains is the total utility $u_c \times T_{seed}$ minus the utility $U_p(T - M_c)$ he or she did not receive:

$$\begin{aligned} U_p(M_c) &= u_c \times T_{seed} - U_p(T - M_c) \\ &= u_c \times M_c \times T_{seed} / T \end{aligned} \tag{14}$$

Regardless of whether $M_c + T_{seed} \leq T$ or $M_c + T_{seed} > T$, the expected utility is always a function of M_c.

Similarly, if there are M_e erroneous primitives in the result submitted by participant p and M_e^1 primitives hit the seed, then the negative expected utility obtained by the participant is

$$U_p(M_e) = u_e \times M_e \times T_{seed} / T \tag{15}$$

Clearly, $U_p(M_e)$ is independent of M_e^1.

Thus, the total utility participant p gains is

$$\begin{aligned} U_p &= U_p(M_c) - U_p(M_e) \\ &= (u_c \times M_c - u_e \times M_e) \times T_{seed} / T \end{aligned} \tag{16}$$

U_p is clearly a monotonic, linearly increasing function of $M_c - M_e$, where $0 \leq M_c \leq T, M_e \geq 0$. U_p reaches its maximum only when $M_c = T$ and $M_e = 0$; that is, the only Nash equilibrium in the game is that participant p submits the T primitives of earth surface targets correctly.

3. We use the variance to calculate the risk of participants and consider the two situations $M_c + T_{seed} \leq T$ and $M_c + T_{seed} > T$ comprehensively. The support of the stochastic variable M_c^1, which obeys a hypergeometric distribution, is $\{\max(0, M_c + T_{seed} - T), \min(M_c, T_{seed})\}$. The variance can be calculated by

$$D_p\left(M_c^1\right) = M_c \times \frac{T_{seed}}{T} \times \frac{T - T_{seed}}{T} \times \frac{T - M_c}{T - 1} \tag{17}$$

The derivation function of $D_p\left(M_c^1\right)$ about M_c is

$$\frac{\partial D_p\left(M_c^1\right)}{\partial M_c^1} = \frac{T_{seed}}{T} \times \frac{T - T_{seed}}{T} \times \frac{1}{T - 1} \times (T - 2M_c) \tag{18}$$

Setting $\frac{\partial D_p(M_c^1)}{\partial M_c^1} = 0$, $M_c = T/2$.

At this point, $D_p\left(M_c^1\right)$ reaches the maximum value. When $M_c = T$ or 0, $D_p\left(M_c^1\right)$ reaches a minimum value of 0. As shown in Fig. 3, we set $T = 100$ and $T_{seed} = 10$; the risk a participant p takes increases with the number of correct results he or she submits, reaching a maximum of 2.27 at $M_c = 50$ and then decreasing to 0 at $M_c = 100$. This finding suggests that participants take the lowest risk in two situations: not participating in crowdsourcing tasks or submitting completely correct results.

The analysis above indicates that participants must submit more accurate results if they want to gain more utility and decrease their risk; furthermore, receiving more high-quality data yields the highest outsourcer utility. Therefore, the incentive mechanism we propose is incentive-compatible. If the utility paid by the outsourcer constitutes a sufficiently large incentive, the participants have sufficient motivation to complete the crowdsourcing task with high-quality data.

IV. GEOMETRIC PRIMITIVES MATCHING AND DATA AGGREGATION ALGORITHM

One key to implementing the abovementioned incentive mechanism is to decide which primitive completely coincides with one seed. Manual processing of these data is unrealistic. Thus, we need machine automation.

A. GEOMETRIC PRIMITIVES MATCHING ALGORITHM BASED ON JACCARD COEFFICIENT

The Jaccard similarity coefficient, which is defined as the size of the intersection divided by the size of the union of two sample sets, is an excellent algorithm for measuring the

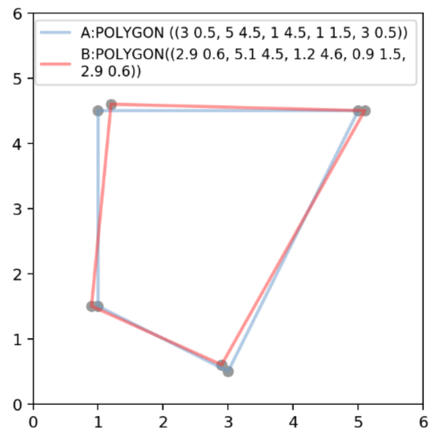

FIGURE 4. J(A,B) = 0.934, where A = POLYGON ((2.9 0.6, 5.1 4.5, 1.2 4.6, 0.9 1.5, 2.9 0.6)) and B = POLYGON((2.9 0.6, 5.1 4.5, 1.2 4.6, 0.9 1.5, 2.9 0.6)).

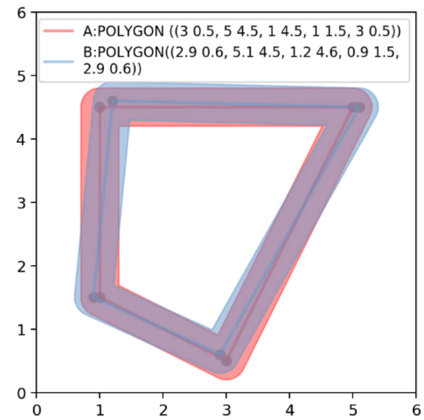

FIGURE 5. J(Buffer(A),Buffer(B)) = 0.239, where A = POLYGON((3 0.5, 5 4.5, 1 4.5, 1 1.5, 3 0.5)), B = POLYGON((2.9 0.6, 5.1 4.5, 1.2 4.6, 0.9 1.5, 2.9 0.6)), and θ = 0.3.

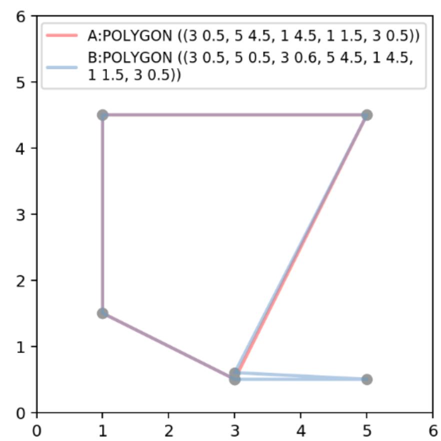

FIGURE 6. J(A,B) = 0.982, where A = POLYGON ((3 0.5, 5 4.5, 1 4.5, 1 1.5, 3 0.5)) and B = POLYGON ((3 0.5, 5 0.5, 3 0.6, 5 4.5, 1 4.5, 1 1.5, 3 0.5)).

similarity of two sets of discrete samples. With the increase in intersection, the degree of similarity of the two sets increases. Based on the same principle, the overlap degree of two polygons increases with the increase in their intersection area. We redefine the Jaccard coefficient expression to calculate the degree of overlap of two geometries as follows:

$$J(A, B) = \frac{area(A \cap B)}{area(A \cup B)} \tag{19}$$

where function $area(\cdot)$ represents the area of the corresponding variable. The expression represents the value of the overlapping area of the two polygons A and B divided by their merged area. Whether a polygonal primitive submitted by someone and a seed polygonal primitive are congruent can be directly judged by the Jaccard coefficient. If the Jaccard coefficient is close to 1, the polygonal primitives are judged as congruent; otherwise, they are not.

However, when the area of each of the two primitives is very large, even if the boundary of the two primitives deviates greatly, the Jaccard coefficient is still very close to 1. As shown in Fig. 4, the Jaccard coefficient of polygons A and B is 0.934. However, if we establish a buffer zone with a threshold θ for A and B based on the boundary, the Jaccard coefficient of their buffer polygons will clearly be less than 1. For example, $J(A, B)$ is only 0.239 when $\theta = 0.3$, far less than 1, as shown in Fig. 5. If polygon A has flying points, the Jaccard coefficient of A and B is 0.982, very close to 1, as shown in Fig. 6. Additionally, if we create buffers for A and B based on the boundary, the Jaccard coefficient of their buffer polygons is 0.237, far less than 1, when $\theta = 0.3$, as shown in Fig. 7. Therefore, calculating the Jaccard coefficient based on the buffer zone of the boundary of the two geometric primitives alone can precisely indicate whether the two coincide with each other. The buffer polygon of A and B in (19) should be calculated as follows:

$$Buffer(X) = buffer(X, \theta) - buffer(X, -\theta) \tag{20}$$

where function buffer$(\cdot)$ represents the outward buffer of a polygon X with a positive or, inward, negative value. Thus, the Jaccard coefficient expression used to compare two geometrical primitives is

$$J(A, B) = \frac{area(Buffer(A) \cap Buffer(B))}{area(Buffer(A) \cup Buffer(B))} \tag{21}$$

$J(A, B)$ is dimensionless with a range of [0, 1]. The results of numerical simulation show that the buffer radius θ is positively correlated with $J(A, B)$. The smaller the value of θ is, the smaller $J(A, B)$ becomes. The buffer radius θ of two polygons should be set according to the actual accuracy requirements of real projects. The higher the accuracy requirements are, the smaller the buffer radius and the greater $J(A, B)$ become.

For projects that need to detect point and line targets, we can still establish a buffer for each of the primitives to use this algorithm to judge the degree of overlap of point and line primitives.

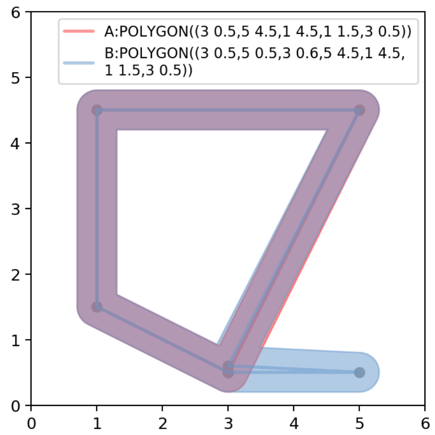

FIGURE 7. J(Buffer(A),Buffer(B)) = 0.237, where A = POLYGON ((3 0.5, 5 4.5, 1 4.5, 1 1.5, 3 0.5)), B = POLYGON((3 0.5, 5 0.5, 3 0.6, 5 4.5, 1 4.5, 1 1.5, 3 0.5)), and $\theta = 0.3$.

Algorithm 1 Data Aggregation

Input: The results of each participant p, $S_p = \{o_i \mid 1 \le i \le N_p\}$

Output: Primitive set with highest accuracy

1: For the result of each participant p, $S_p = \{o_i \mid 1 \le i \le N_p\}$, calculate the number of primitives that coincide with the seeds using (21), calculate his or her accuracy A_p using (22) or (23), and assign A_p to each primitive o_i in S_p;
2: Loop through all results S that are the union of all S_p, search primitives whose geometry intersects with each other and whose attribute data are the same as each other, and then place the primitives into *Otemp*;
3: Search the primitives with the highest A_p in *Otemp*, and insert them into O;
4: Delete the primitives in *Otemp* from S;
5: If S is not empty, return to step 2;
6: Return O.

B. DATA AGGREGATION ALGORITHM

When all participants submit their results, that is, when they each individually complete the game with the outsourcer, we must filter the results submitted by each participant and extract the highest-quality primitives for the outsourcer. If the results submitted by participant p have M_c^1 primitives correct and M_e^1 incorrect, then the accuracy of participant p can be estimated by

$$A_p = \frac{M_c^1 - M_e^1}{M_c^1 + M_e^1} \tag{22}$$

where the range of A_p is $[-1, 1]$ when $M_c^1 - M_e^1 > 0$, $AP_p > 0$. Accuracy A_p is a measure of the credibility of the results submitted by participant p, which is directly proportional to the actual utility of the participants and inversely proportional to the number of primitives that intersect with the seeds. When the accuracy of participants is relatively high, this formula allows for suitable evaluation of the quality of data submitted by participants. When the quality of the submission is relatively low, the following expression can be used:

$$A_p = \frac{M_c^1 - M_e^1}{N_p} \tag{23}$$

At this point, the accuracy is inversely proportional to the total number of elements drawn by a participant; thus, a participant is prevented from submitting a large number of inferior data to gain higher utility.

When the information pertaining to a ground target is submitted by multiple participants, the primitive of this target that belongs to the participant whose accuracy is the highest will be selected according to Algorithm 1.

V. EXPERIMENTS

To verify the effectiveness of the incentive mechanism based on the Bayesian game, we chose part of the Qinghai-Tibet Plateau in China as the test area. We developed and deployed a WebGIS-based SC platform using *Geoserver* and *OpenLayers*, which are open-source platforms for participants to perform interpretation work. Lakes in this area are less affected by human activities than in other areas and have obvious interpretable characteristics on Landsat 8 images, the ground resolution of which is 30 meters. The study region contains 1678 lakes and 87 lake islands. With natural lakes as the targets, we carried out an accurate interpretation of the entire study area and selected 109 primitives, approximately 5% of all primitives, as seeds. We used money to incentivize the public to participate in this SC. The award rules served as the incentive mechanism we designed. We promised the public 109 targets set as seeds randomly and assigned 10 CNY to each seed; that is, $u_c = 10\ CNY$, $u_e = 10\ CNY$. The maximum benefit of one participant was 1,090 CNY. Because the ground resolution of Landsat 8 images is low, there is an uncertain transitional zone of approximately 60 meters between water and land in the images. We set the buffer radius 60 m, which equals the width of 2 pixels in the Landsat 8 images. If the Jaccard coefficient of a primitive drawn by one participant and one seed primitive is greater than 0.333, a validated threshold in this experiment, the primitive is judged to be correct, and the participant can gain the money associated with this seed. Then, we announced the task to the public on multiple social media platforms. Three days later, we received 4921 primitives submitted by 38 participants. Fig. 8 shows the 4796 primitives submitted by the top 20 participants who submitted the most. The number of primitives belonging to each participant is listed in Table 2. The number of results submitted by other participants was too small; therefore, we did not analyze their submissions.

The distribution of the number of elements submitted by participants is close to the linear distribution under the incentive mechanism, indicating that the result has broken through the 90-9-1 or 1% rule.

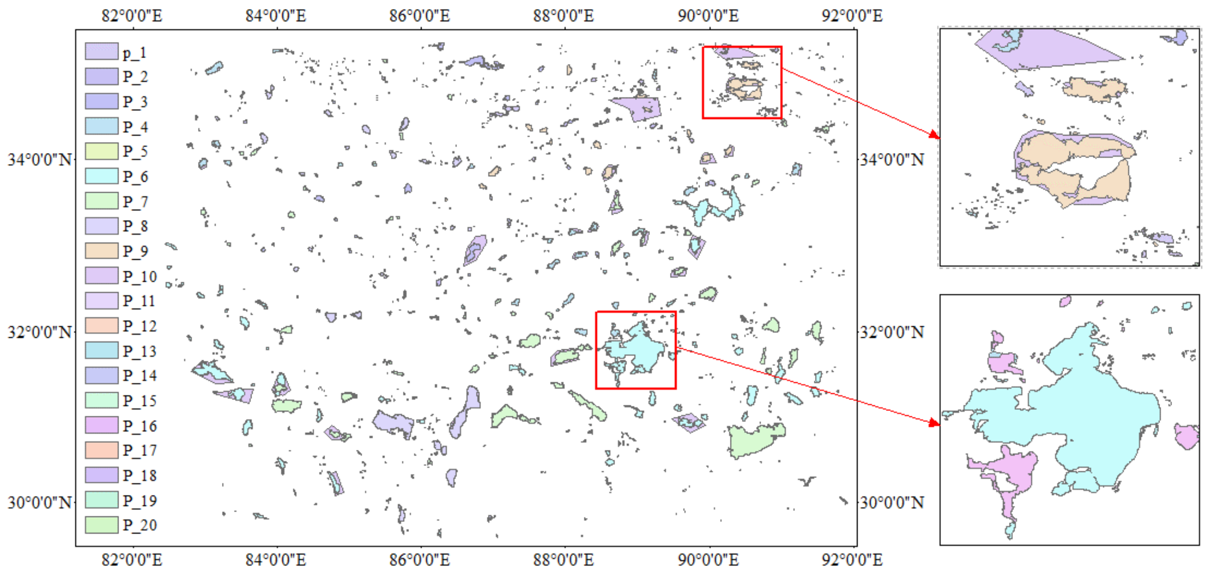

FIGURE 8. Map of data results of the top 20 participants who submitted the most primitives.

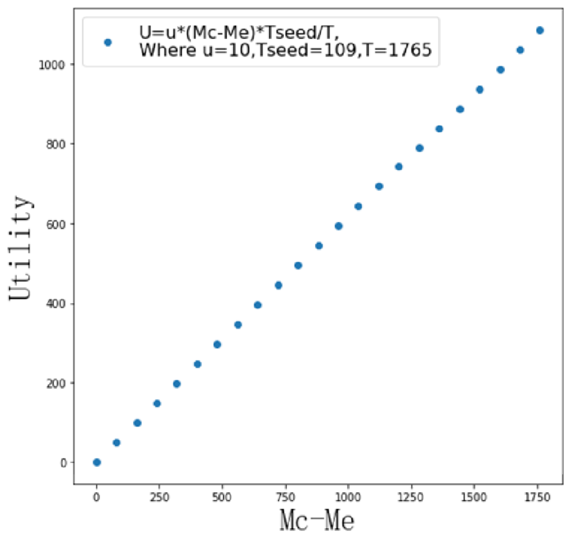

FIGURE 9. Expected utility function.

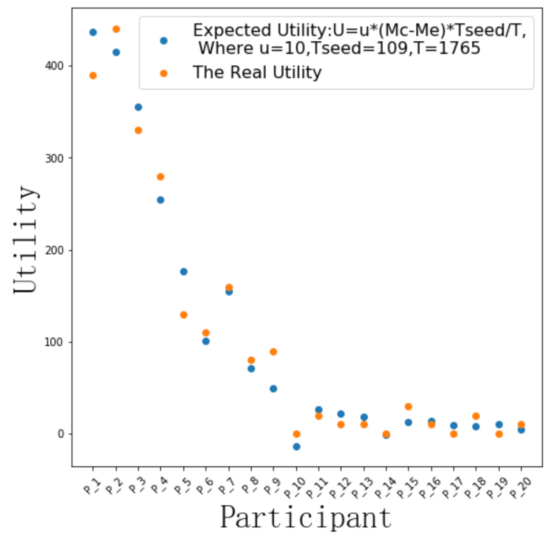

FIGURE 10. Actual utility of each participant.

A. UTILITY ANALYSIS

We compared the result data submitted by each participant and the primitives precisely interpreted by the GPMJC algorithm, the results of which are explained in detail in Section IV. Then, the number of correct primitives M_c, the number of misinterpreted primitives M_e, the number of correct primitives coinciding with the seed M_c^1, and the number of misinterpreted primitives intersecting with the seeds but that were incorrect M_e^1 were obtained. For example, participant P_1 submitted 973 primitives, among which 47 primitives intersected with the seeds, including 43 correct and 4 incorrect primitives. The details of the 20 participants who submitted the most primitives are shown in Table 2.

The strategy adopted by the outsourcer was that the seed primitives were invisible to every participant in the Bayesian game. For every participant, the expected utility was a monotonic, linearly increasing function of $M_c - M_e$ (Fig. 9) according to (22), and the actual utility was a monotonic, linearly increasing function of $M_c^1 - M_e^1$. The expected utilities EU and actual utilities AU were not related to the number of seed primitives set by the outsourcer. M_c^1 and M_e^1 all obeyed a hypergeometric distribution and correlated positively with the number of correct primitives M_c and the number of incorrect primitives M_e separately. The seed primitives were set randomly such that the actual utility of each participant had a slight degree of fluctuation compared with the expected utility; however, the actual utility and

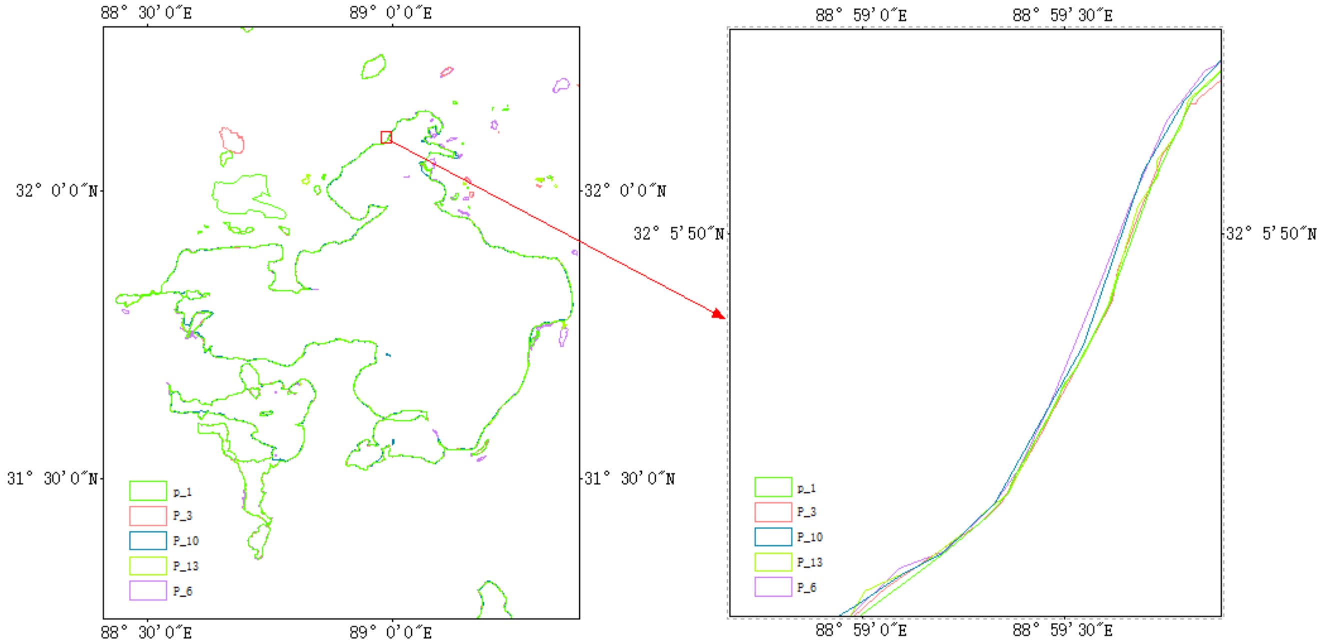

FIGURE 11. One target interpreted by multiple participants: map of primitive piles submitted by P_1, P_3, P_10, P_13, and P_6 and magnification of part of the boundary.

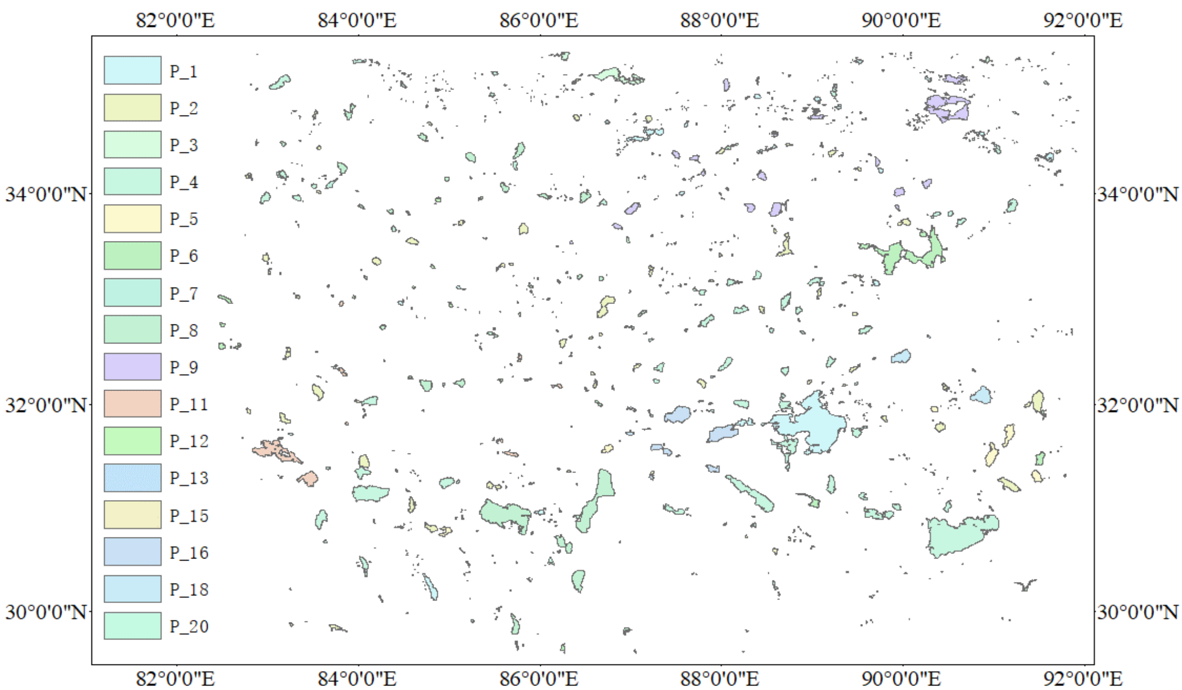

FIGURE 12. Lake distribution map.

$M_c - M_e$ showed a high degree of positive correlation (Fig. 10). In summary, each participant could achieve greater utility only if he or she submitted more correct results and as few incorrect results as possible to increase $M_c - M_e$. Taking participant P_1 as an example, 973 primitives were submitted—840 correct, 133 incorrect; therefore, the expected utility was 436.62, calculated by $10 \times (840 - 133) \times 109/1765$, and the actual utility was 390, calculated by $10 \times (43 - 4)$. Correspondingly, 81 primitives were submitted by participant

TABLE 2. Results for each participant.

Participant	N_p	M_c	M_e	M_c^1	M_e^1	EU (CNY)	AU (CNY)
P_1	973	840	133	43	4	436.62	390
P_2	906	789	117	46	2	415.00	440
P_3	778	677	101	39	6	355.72	330
P_4	507	460	47	29	1	255.05	280
P_5	353	320	33	14	1	177.24	130
P_6	315	239	76	14	3	100.66	110
P_7	312	281	31	18	2	154.39	160
P_8	140	128	12	8	0	71.64	80
P_9	126	103	23	9	0	49.41	90
P_10	81	30	51	2	6	-12.97	0
P_11	45	44	1	2	0	26.56	20
P_12	43	39	4	1	0	21.61	10
P_13	42	36	6	2	1	18.53	10
P_14	40	3	4	0	0	-0.62	0
P_15	37	29	8	3	0	12.97	30
P_16	22	22	0	1	0	13.59	10
P_17	21	18	3	1	1	9.26	0
P_18	19	16	3	2	0	8.028	20
P_19	18	18	0	0	0	11.12	0
P_20	18	13	5	1	0	4.94	10

Total N_p:4796; Total EU:2128.74; Total AU:2120.

P_10—30 correct, 51 incorrect; therefore, the expected utility was −12.97, calculated by $10 \times (30 - 51) \times 109/1765$, and the actual utility was 0, calculated by $10 \times (2 - 6)$ as 0 when the value is less than 0.

All the expected and actual utilities of the top 20 participants are shown in Table 2. Without the Bayesian game-based incentive mechanism, we can only consider all 4796 primitives correct, and the expected costs is 2961.8 CNY, calculated by $4796 \times 109/1765 \times 10$. However, when the filter rules in this mechanism were used, bad primitives were wiped out. Finally, the total expected utility was 2128.74 CNY, and the cost we paid was 2120 CNY.

B. DATA AGGREGATION

We calculated the accuracy using (22) for every participant, as shown in Table 3. For example, among primitives submitted by participant P_1, the number that fully coincided with seed primitives M_c^1, i.e., the number of correct primitives, was 43; furthermore, those that incompletely coincided with seed primitives M_e^1, i.e., the number of incorrect primitives, was 4. Thus, the accuracy A_p of participant P_1 was 82.97%, according to (22). The higher the accuracy is, the greater the likelihood that the primitives of one participant will be correct become. If multiple participants submitted primitives of one ground target, the outsourcer should select the one submitted by the participant with the highest accuracy A_p.

When a lake or islet is interpreted by multiple participants, the primitive of this target that belongs to the participant whose accuracy is the highest will be selected according to Algorithm 1. Take the largest primitive in Fig. 8 as an example. Five participants (P_1, P_3, P_5, P_10, and P_13) interpreted the lake target (Fig. 11). Among those participants, P_1 had the highest accuracy. Therefore, the primitive submitted by P_1 was selected, and the others were discarded.

TABLE 3. The accuracy of each participant and the numbers of primitives accepted and rejected.

Participant	AP	Accepted	Rejected
P_1	82.97%	227	746
P_2	91.67%	433	473
P_3	73.33%	83	695
P_4	93.33%	390	117
P_5	86.67%	62	291
P_6	64.70%	60	255
P_7	80.00%	22	290
P_8	100%	137	3
P_9	100%	126	0
P_10	−50.00%	0	81
P_11	100%	33	12
P_12	100%	28	15
P_13	33.33%	2	42
P_14	0	0	40
P_15	100%	31	6
P_16	100%	21	1
P_17	0	0	21
P_18	100%	19	0
P_19	0	0	18
P_20	100%	15	3

The numbers of primitives selected and abandoned by every participant are shown in Table 3. For example, 227 primitives of participant P_1 were adopted, and 746 were abandoned. Ultimately, 1661 primitives submitted by 16 participants were preserved, including 1602 lakes and 59 islands. If a lake primitive contained islands, we used the island primitive to clip the lake primitive and then obtained the real lake primitive without small patches of land. After subtracting island primitives from lake primitives, we obtained the actual lake distribution map (Fig. 12). The total accuracy of this SC project was 95.3%.

VI. CONCLUSION

For SC projects, an incentive mechanism must be implemented to recruit a large number of participants to complete tasks in a reasonable time. Many studies on crowdsourcing projects have been carried out, and several incentive mechanisms have been proposed. However, through the Gibbard–Satterthwaite impossibility theorem, we find that there are some loopholes in the application of these incentive mechanisms in SC projects involving micro tasks. With these incentive mechanisms, because people have the motivation to lie, the quality of data is not guaranteed. In this study, we designed a Bayesian game-based incentive mechanism with spatial data as the core. In the Bayesian game, because of the hidden reference information, the participants were deprived of the possibility of implementing a dictatorial strategy through collusion or other means. The expected utility that participants gain through honesty is much higher than that gained through deceit. The only Nash equilibrium existing in the mechanism theoretically is that participants submit accurate spatial information. In addition, in implementing this mechanism, we proposed the GPMJC algorithm based on the Jaccard coefficient, which can automatically compare geometric primitives, calculate the utility of participants, evaluate the quality of data results, and integrate data. Finally, the experiment proved that the IMBG is incentive-compatible and can significantly improve the data quality of SC projects. It should be noted that the value of the utility set in the experiment is determined by our assessment of the current average wage level in China. Clearly, as the bonus increases, more participants will participate in this SC project. However, when the bonus is too high, a certain degree of resource waste will arise. A method for finding the best balance, auction or public bidding may be a good solution. Our future work will involve the development of such a method.

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Authors' photographs and biographies not available at the time of publication.