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Systematizing heterogeneous expert knowledge, scenarios and goals via a goal-reasoning artificial intelligence agent for democratic urban land use planning

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ABSTRACT

The tasks of democratic urban land use planning, as subjective-objective combined decision-making efforts that require considerable time and energy, have heretofore been accomplished mainly through deep human thought or by voting. In this paper, we introduce a goal-reasoning artificial intelligence (AI) agent that can assist with these tasks by combining traditional scenario planning, multicriteria decision analysis (MCDA) with a novel goal-oriented Monte Carlo tree search (G-MCTS) method. G-MCTS conducts goal-oriented searches to meet the needs of heterogeneous goals and provide the best land use solutions. We evaluated this method on a real-world planning case, and the results show that 1) the goal-reasoning AI agent is good at performing complex goal reasoning tasks with many heterogeneous expert knowledge; 2) different human planning manuscripts could be integrated into a better solution via a goal-reasoning AI agent; and 3) the goal-reasoning AI agent has the potential to make comprehensive decisions during a democratic political agenda. We conclude that the goal-reasoning AI agent, via an improved reinforcement learning (RL) method of G-MCTS, provides vast potential for assisting in subjective-objective combined urban land use planning and many other similar fields by weighing heterogeneous goals, reproducing human inspiration, and acting as a reflexive sociotechnical system.

1. Introduction

Developments in computer science have enabled software's utility in revealing the typical evolutionary mechanisms of complex urban systems (Batty, 2007; Friedmann, 1993; Healey, 2006) with regard to geography, ecology, sociology, political-economics, urban studies and many other areas. These applications provide professional assistance in urban land use planning (e.g., Liang et al., 2018; Stevens, Dragicevic, & Rothley, 2007). In traditional planning approaches, urban development is simulated under different scenarios via cellular automaton models (CA) (e.g., Aguilera, Valenzuela, & Botequilha-Leitão, 2011; Clarke & Hoppen, 1997; Feng & Liu, 2013; Santé, García, Miranda, & Crecente, 2010) or multiagent-based models (MA) (e.g., Bone & Dragi'cevi'c, 2010; Khansari & Hewitt, 2020) with rule-based evolutionary mechanisms to make decisions. However, these approaches suffer from the weakness that the corresponding data, mechanisms, and simulating methods in different scenarios are often too heterogeneous for the calculations to automatically provide a comprehensive conclusion. Accordingly, the most sophisticated analyses and systematic decision-making tasks are accomplished only by trusting the decisions of planning experts and decision makers, who often have discrepant worldviews, desires, judgment standards and social networks, or by voting during urban planning conferences.

Moreover, compared to those of empirical and structuralist approaches, the weaknesses of the current computer-assistant urban planning methods, such as scenario simulation, still hold something of a controversial air in the urban planning domain. Urban planning is a subjective-objective combined domain in which urban spaces are mainly produced under human goals (Christophers, 2011; Harvey, 2012; Lefebvre, 1991) and multidisciplinary expert knowledge is put into practice (Friedmann, 1973). Rittel and Webber argued that urban planning problems are “wicked problems” that should be solved by

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discussion (Rittel & Webber, 1973), and Lewis argued that urban planning problems are "ill-defined" social problems (Lewis, 1984). In fact, most real-world urban land use planning issues seldom follow changeless rules. Over the past fifty years, many planning frameworks have been proposed, such as advocacy planning (Davidoff, 1965) and collaborative planning (Healey, 1997; Roy, 2015), and many other researchers have followed these lines of research and have combined their methodologies with systems theory and complexity science (Hopkins & Knaap, 2018; Innes & Booher, 1999; Lai, 2018). Due to many conflicting issues, such as the increasing diversity of expertise areas and the current trend of democratized planning, the use of participatory or collaborative planning methods for land use planning has proven to be more effective (Aoki, 2018; Jelokhani-Niaraki & Malczewski, 2015). In fact, planning experts and decision makers still prefer to use both empirical methods for acquiring goals, with the help of "big data," and structuralist approaches for political discussion together to address real-world urban planning tasks.

In the case of China, the urbanization process is a form of "hybrid urbanization" that involves a combination of socialist and market economies (McGee, 2009) in which urban space production is gradually being transformed into a land operation strategy that allows local governments to maximize land lease revenue (e.g., Chen & Wang, 2013; Zhao & Chen, 2018). Curiously, in 2019, the Chinese government instituted a major reform known as "Multiple Planning Unification" in which land use planning, urban planning, and many other planning systems would be unified into "National-Land-Space-Planning" (Jiao et al., 2019), which tried to emphasize unique blueprint, science nature and public participation. However, this reform came to be no easy task because many accumulated conflicts in land use exist between local and central governments, between environmental protection and economic development, and among previous planning systems. These conflicts need to be solved as soon as possible by new political agendas, especially given the current information age and a world environment that emphasizes democratic planning. In this situation, a goal-reasoning AI agent could provide assistance by connecting the rational mechanism of thinking with the democratic decision-making process by applying an advanced AI algorithm combined with a human-AI working pattern.

Thus, engaging in deep judgment, weighting issues, and systematizing fragmented expert knowledge and heterogeneous goals are crucial. However, in most contemporary accounts, empirical computer-assisted methods, such as CA, MA and artificial neural network (ANN)-based expert systems (Grekousis, 2019; Liang et al., 2018; Rumelhart, Hinton, & Williams, 1986), and structuralist approaches, such as multicriteria decision analysis (MCDA) (e.g., Bonissone, Subbu, & Lizzi, 2009; Faria et al., 2018), are not well combined. There are at least two frequent situations in which an AI agent seldom plays the key role that merit further study: (1) addressing more than two heterogeneous goals' decision-making tasks during a democratic political agenda and (2) integrating different human planners' manuscripts into a better one in an automated manner via an AI agent. Moreover, academic and media preoccupation with the supervised learning (SL) AI method, which is used to fetch information from the environment through many "eyes," distracts us from a wider appreciation that AI agents are mainly used for making thoughtful decisions by acting as "brains." Accordingly, our research argues for and offers contributions to a new body of knowledge in which heterogeneous expert knowledge, goals, information and scenarios can be considered via a goal-reasoning AI agent, and in which traditional subjective-objective combined judgment tasks regarding urban land use planning can be handled by human-AI interaction in real time (see Fig. 1). Goal-reasoning AI agents are extremely useful not only for land use planning, as we have discussed, but also for potential applications in transportation, public infrastructure investment, ecological protection, and many other subjective-objective combined urban planning domains.

To implement such a work pattern, the work presented here developed a novel approach that combines the traditional scenario-simulation planning method, MCDA and a goal-oriented MCTS (G-MCTS) algorithm (see Fig. 4). This approach first uses scenario-simulation, or other possible methods, to obtain heterogeneous goals of different decision makers as an ideal high-level goal-oriented heuristic; then, it uses the G-MCTS algorithm to fulfill the heuristics as much as possible to reproduce human inspiration. Our G-MCTS methodology was initially inspired by the MCTS approach in the AlphaGo game-playing system architecture (Silver et al., 2016; Silver et al., 2017); however, social decision-making methods, such as MCDA, were also integrated into it. Considering that human goals are usually heterogeneous and that the relevant reasons underlying urban systems are considerably more complex than those encountered in a game, it is novel to apply the G-MCTS, as a representative of reinforcement learning (RL)o subjective-objective combined urban planning issues.

In this research, testing the G-MCTS goal-reasoning AI agent includes three stages. In the first stage, we focus on evaluating the performance of the G-MCTS algorithm, using metrics such as accuracy, resource consumption, comprehensibility, and degree of intelligence. Second, we are interested in researching the question of whether our G-MCTS land-use-planning AI agent can conceive of creative strategies such as those conceived by human planning experts. Third, we try to indicate the practicability of our G-MCTS goal-reasoning methodology in a real urban land use planning process to illustrate the feasibility of developing a deep RL-based goal-reasoning AI agent by learning from feedback.

The remainder of this paper is organized as follows. A literature review summarizing the disadvantages of the current urban land use planning methods and the challenges of developing a goal-reasoning AI agent appears in Section 2. The work pattern of the G-MCTS methodology is explained in Section 3, and we report the test results in Section 4. In Section 5, we compare the G-MCTS goal-reasoning system with other AI systems and explain a few details of the G-MCTS searching tree. Finally, conclusions and suggestions for future work are provided in Section 6.

2. Literature review

2.1. Current decision-making methods in the urban planning domain

Expert knowledge of urban land use and the corresponding evolutionary mechanisms are mainly used to generate rational goals that can be revealed by mathematical approaches or by expert software implementations, such as SPSS (Palardy, Boley, & Gaither, 2018), FRAGSTATS (Cushman, McGarigal, & Neel, 2008), STATA (Chen & Wang, 2013) and Eviews (Zhao & Chen, 2018). Some specialized domains of urban planning offer the possibility of following rules or trends observed over a long period of time, such as estimating urban land-growth boundaries (Liang et al., 2018; Xu, Gao, & Coco, 2019) and ecological services (Dennis & James, 2016). Based on this condition, many computer-aided methods could be used to simulate the objective world or to provide predictions based on existing expert knowledge and historical data with appropriate assumptions such as using the CA models and MA models mentioned above, and via algorithms such as simulated annealing (Feng & Liu, 2013; Kirkpatrick, Gelatt Jr., & Vecchi, 1983; Westphal, Field, & Possingham, 2007), genetic algorithms (Chamberlain & Meitner, 2009; Holland, 1975), random forests (Gounaridis, Chorianopoulos, Symeonakis, & Koukoulas, 2019), and artificial neural networks (ANNs) (Grekousis, 2019; Liang et al., 2018; Rumelhart et al., 1986). These computer-aided methods, including many heuristics, are mainly used for solving nondeterministic polynomial complete (NPC) problems of urban systems (e.g., Bone & Dragi'cevi'c, 2010; Westphal et al., 2007), general goals by past experience, while accuracy rates are crucial in these methods when attempting to determine or achieve objectives. However, the other part of urban planning tasks is reasoning these goals with a Markov decision process (MDP) nature in which judgments are altered by newly

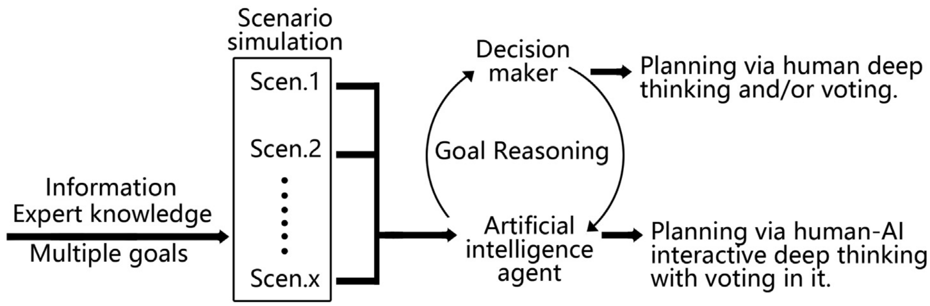

Fig. 1. Systematizing heterogeneous information, expert knowledge, scenarios and goals via a goal-reasoning artificial intelligence agent.

observed site states, newly revealed mechanisms, and available action sets at the present moment. In MDPs, the goals, rules, and interaction effects are uncertain and varying in time. In this instance, how to define the goals and balance them are usually social agendas.

For democratic planning and decision-making, the most widely used decision support tool is the multicriteria decision analysis (MCDA) method (e.g., Bonissone et al., 2009; Faria et al., 2018). Recently, the GIS-MCDA method (e.g., Jelokhani-Niaraki, 2018; Jelokhani-Niaraki & Malczewski, 2015; Musakwa, Tshesane, & Kangethe, 2017) has been used to integrate geographic information systems (GIS) and MCDA into a web platform to reconcile diverse values, objectives, and interests of the populace into acceptable outcomes. In the MCDA process, the voting method is the most popular approach for generating solutions (Malczewski, 2006), and the ordered weighted averaging (OWA) method is also frequently used to generate criteria by means of considering and balancing human judgments (Yager, 1988). The MCDA process is usually based on two assumptions: (i) the objectives or goals are comparable via quantitative methods, either by their value attributes or by the number of human supporters, allowing humans to weigh them differentially, and (ii) these objectives or goals should have no interaction effect (also known as being "non-commensurable" in MCDA), or the interaction effects should not be seriously considered so that people can weigh them easily. In addition to the above two conditions, however, we still need some methods for making complex decisions if people' values are divergent, if goals and mechanisms are heterogeneous, and if interaction effects exist among them.

Fig. 2 shows such an example: a simple decision-making problem that cannot be solved solely by simulation or the MCDM method. In Fig. 2, the problem involves two heterogeneous goals that can be partially satisfied or reasonably abandoned: choosing the best series of actions for a salesman to take while balancing the goals of (i) visiting most cities and (ii) traversing the shortest distances. The MCDA method can be used for weighting the two goals if they are considered irrelevant; however, in fact, they are highly relevant. So, although the two goals are heterogeneous, the processes of weighting them and calculating the interaction effects should not be separated. Even if the weights of the two goals are assumed to be temporarily equal (0.5 and 0.5), the best solution is still unknown unless an algorithm is used to solve the interaction problem. Moreover, the simulation method cannot be used here because of the social and MDP contexts. In the same vein, many urban planning problems, wherein heterogeneous goals affect each other via transformations in land use, traffic arrangement, and environmental governance, among many other factors, still urgently need some effective methods for making complex decisions. Consequently, using a goal-reasoning AI method for urban planning tasks that combines the computing method of the interaction effects using existing expert knowledge and the voting method to implement democratic decision-making together, as we have tried to implement in this study, might be a better choice.

2.2. The challenges to develop a goal-reasoning AI agent and corresponding solutions

AI approaches constitute a developing and continuous exploration domain defined by "thinking or acting similar to humans" (Russell & Norvig, 2012). The development of an AI agent to integrate heterogeneous expert knowledge and to reason about goals for better plans includes many challenges, both in the AI and the urban planning aspects (Aha, 2018; Bengfort & Cox, 2015; Bonissone et al., 2009; Cox, 2018; Roberts, Borrajo, Cox, & Yorke-Smith, 2018; Rodela et al., 2017; Santé et al., 2010). The first challenge is the heterogeneity problem mentioned above. Subtle relationships and biases exist between value-oriented algorithms and goal-oriented human decision making, and pure value-oriented algorithms cannot provide useful information for decision makers in some extreme urban land use planning cases (see Fig. 3). In fact, both decision makers and computers are "boundedly rational" during the decision-making process, and they often seek satisfactory solutions rather than the most accurate solution (Gershman, Horvitz, & Tenenbaum, 2015; Hay, Russell, Tolpin, & Shimony, 2012; Healey, 2006; Simon, 1982). If an AI agent focuses on goal-oriented heuristics (a higher cognition level or human criterion—the number of goals, for example) than on trivial value-oriented heuristics (criteria that focus on specific objective values), it might be possible to solve this problem and provide the connections between heterogeneous expert knowledge and decision makers (see Fig. 3). The first benefit of an AI agent that uses high-level goal-oriented heuristics is that the agent can focus on the fulfillment degree of human goals that are usually available throughout the decision-making process instead of addressing the problem of heterogeneous data and rules. The other benefit is that the results could satisfy the requirements of more people for a democratic urban land use planning agenda and for social collaboration at the political level.

The second challenge of developing a goal-reasoning AI agent for urban land use planning originates from the endless extension of goals with complex interaction effects in the MDP of urban planning issues, which is similar to the formulation of the "wicked problem" that Rittel and Webber have posited (Rittel & Webber, 1973). In the AI domain, an MDP is a sequential decision process that is formalized as a tuple (S, A, T, R) in which the action is decided by the available current state instead of by past states (Georgievski & Aiello, 2015; Sutton & Barto, 2018; Zhuo, Muñoz-Avila, & Yang, 2014). For MDPs, many planning AI systems use reinforcement learning (RL) methods, such as the Monte Carlo tree search (MCTS) (e.g., Coulom, 2006; Hoock et al., 2010; Kocsis & Szepesvári, 2006; Silver et al., 2016), to search for the best series of actions. Obviously, the MCTS method could also be used for goal-reasoning in urban land use planning tasks.

Many other trivial issues exist regarding the use of AI technology for urban land use planning. For example, goal-reasoning AI agents could decompose goals into subgoals to search for optimum solutions and to achieve better effectiveness, such as in the A* search or hierarchical task network (HTN) methods (Bulitko, Björnsson, & Lawrence, 2010; Georgievski & Aiello, 2015; Kose, 2018; Zhuo et al., 2014). In Fig. 2(b),

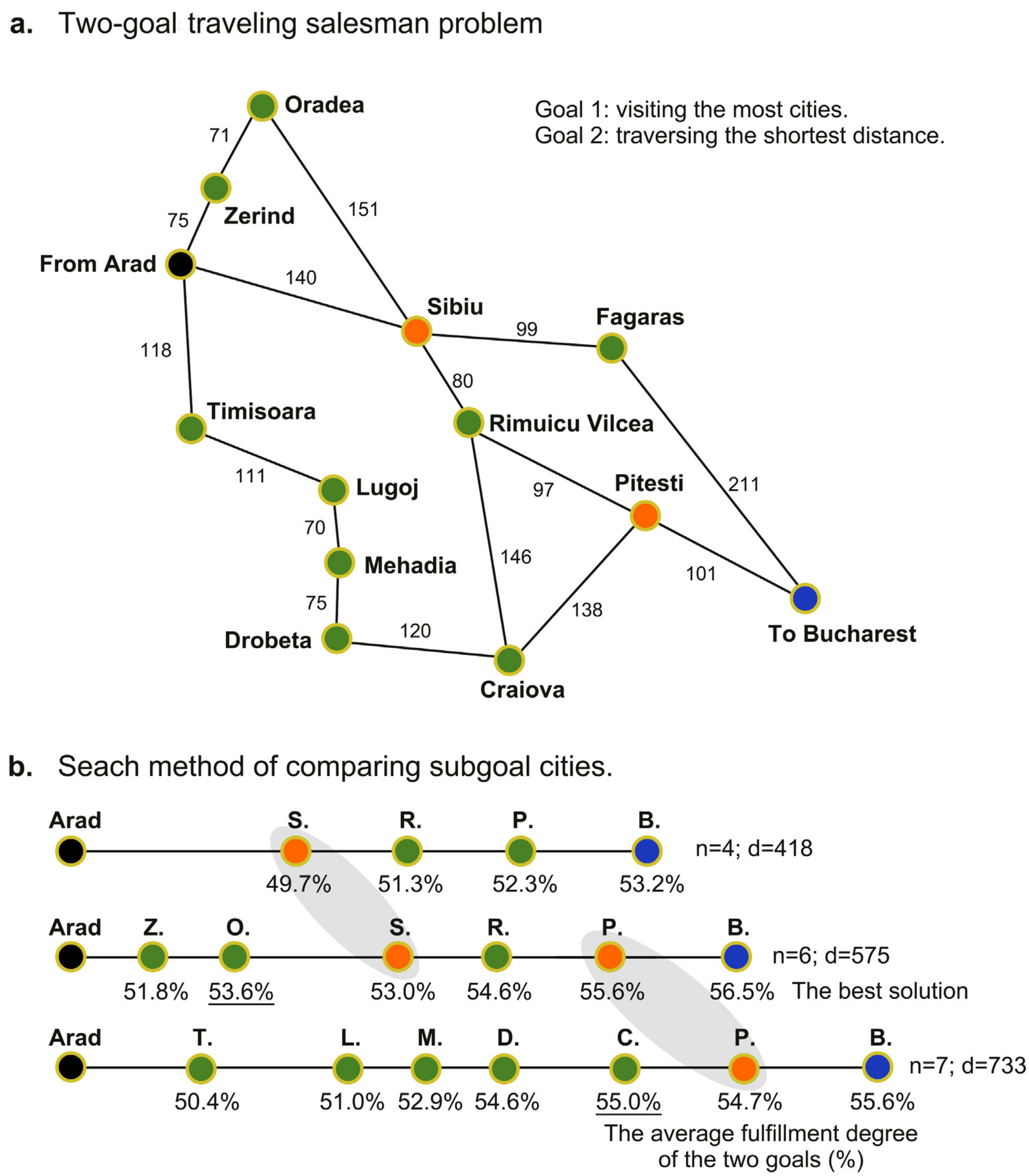

Fig. 2. The multiple-goals traveling salesman problem (mgTSP).
Taking the two goals in the Figure as examples, in (a), we need to determine the series of traveling actions that allow visits to the greatest number of cities while traveling the shortest distance, starting in Arad and ending in Bucharest. These two goals are heterogeneous and have interaction effects. In (b), we provide three possible solutions that start from Arad and, next, visit Sibiu, Zerind, and Timisara, respectively. The number of cities visited is n ($n \in [0,12]$), and d is the traversed distance. If the salesman wants to visit all 12 of the cities, one possible travel distance is 1556, in which case $d \in [0,1556]$. If the two goals are temporarily assigned weights of 0.5 and 0.5—without considering the interaction effect—the second solution, which starts by visiting Zerind ($n = 6$ and $d = 575$), is the best solution, such that the average fulfillment degree of the two goals is calculated by $f_{zerind} = (6 / 12 + (1556–575) / 1556) / 2 = 0.565$. Note that this solution neither represents the shortest route nor does it visit the largest number of cities; moreover, it does not include all the local optimum-value cities, such as Oradea and Craiova, as shown in figure b. If the mgTSP has an infinite number of cities, one available method for determining the best solution is to compare the fulfillment degree of the subgoal cities, such as Sibiu or Pitesti, as subheuristics. Moreover, the weights of 0.5 and 0.5 may conversely be changed by the latest observations. In general, decision-making should include the calculation of the interaction effects and the goal-weighting method systematically.

we provide a heuristic algorithm that uses subgoal cities to infer the best solution when the goal-reasoning problem has an enormous number of state spaces. Despite this, however, how to address the interaction effects among the subgoals is another challenging issue (Georgievski & Aiello, 2015; Ghallab, Nau, & Traverso, 2004). In most goal-decomposition search mechanisms, the action results lead to optimistic adoptable solutions when the subgoals are negative, such as in the game process (see Fig. 3(a)-C as an example), but pessimistic unadoptable solutions when they have interaction effects and should therefore be replaced by some other merged actions resembling human inspiration (see Fig. 3(b)-C as an example). So, if an AI agent could reach every state space (under the premise of "boundedly rational"), evaluate them, and then make a satisfactory selection instead of using rules to achieve the best solution (as many expert systems have attempted), human inspiration could be reproduced by an AI agent amazingly well (Silver et al., 2016; Silver et al., 2017).

In addition, urban planning AI agents should provide clear causal relationships for legislative purposes, and the results should be explainable instead of interpretable (see the mosaic solutions in Fig. 3D as examples). Although the MCTS combined with a supervised learning (SL) method has achieved state-of-the-art performance for solving uncertain problems with an enormous number of state spaces, the more

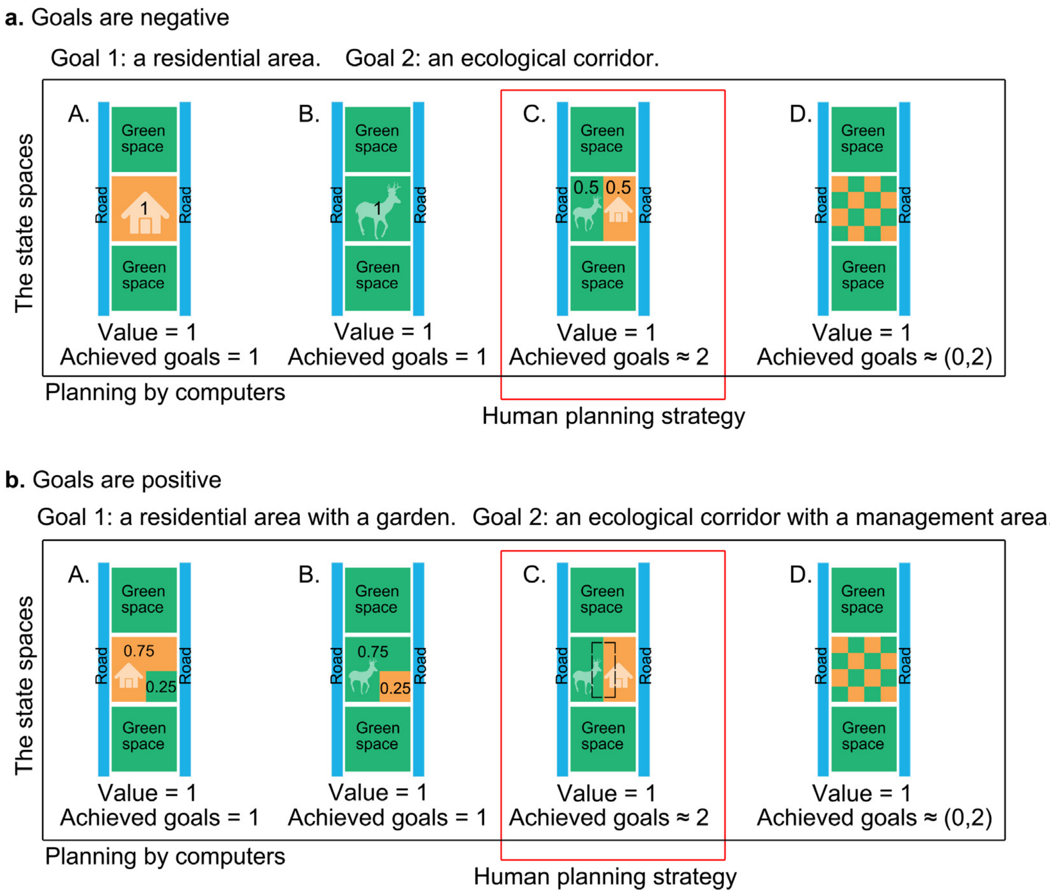

Fig. 3. The subtle biases between value-oriented algorithms and goal-oriented human decision-making in the land use planning domain.
In this land use planning case, the use of central land needs to be planned. In the value-oriented algorithms, the two goals should be normalized to values between 0 and 1 for computation. Unless more rules are provided, the identically optimum value = 1, (meaning that the land is used either for Goal 1 or Goal 2); those calculation offered by computers in state spaces A, B, C and D provide no useful information, so decision makers cannot distinguish which choice is better. The state space D, which is representative of many mosaic solutions, is a reasonable choice for computers but is too complicated for humans to understand. However, state space C (Achieved goals ≈ 2 in panels (a) and (b)) has the potential to be more easily accepted as a goal-oriented planning strategy by human decision makers partly because the marginal benefits usually have a positive relationship with the number of achieved goals instead of values which identically equal 1. In the positive case shown in panel (b), state space C can fulfill more goals via land use cooperation, in a manner known as human inspiration.

Table 1
The heterogeneous goals in the scenario simulations with the corresponding rules.

Goals	Domains	Corresponding objective values	Corresponding rules
G_1	Economics urban planning	Increasing the gross domestic product (ΔGDP)	Multivariate linear equation $\Delta GDP = 1.47 \times \Delta UMS + 3.01 \times \Delta UGS + 6.40 \times \Delta URS + 1.74 \times \Delta UCS$
G_2	Urban ecology	Increasing the ecosystem services (ECO)	Linear equation $ECO = 2 \times UGS$
G_3	Sociology urban planning	Increasing the equity degree of urban green space (EQU)	Image recognition $EQU = (E_x + E_y) / 2$
G_4	Ecology landscape	Increasing the connectivity of green spaces by ecological corridors (COR)	Image recognition $COR = L_{cor} \times S_{cor}$
G_5	Urban planning	Achieving an appropriate proportion of urban commercial space (UCS)	Empirical expert knowledge
G_6	Urban planning	Achieving an appropriate proportion of urban residential space (URS)	Empirical expert knowledge

the AI agent focuses on achieving accurate solutions, the more difficult it is, as a contradiction, for the AI agent to persuade stakeholders at the political level.

3. Method

3.1. Scenario simulation and acquiring the priority images

Goals can be established either by scenario simulation using expert knowledge or by other reasoning and input methods. In our research, we used scenario-simulation functions with simplified rules for simplicity, substituting these complex expert systems based on the assumption that each existing instance of expert knowledge, system and scenario can provide rational goals and because the G-MCTS method, as a metamodel, is mainly used for balancing and reasoning across heterogeneous goals.

Taking a mesoscale (10 km × 10 km) urban land use planning task as an example, the planning feature usually requires weighing and balancing the economic, ecological and social values or solving other tricky problems by determining the land use, in which scientific verification and political negotiation are integrated. We tested the G-MCTS AI agent and evaluated its usability on a real-world case of an industrial zone case in Yantai, China, where the local government was seeking a kind of "sustainable" land use plan. We specifically selected six representative heterogeneous goals in multisubject domains for testing (see Table 1). In goal G_1, the relationships between the area of land use and the increase in GDP can be expressed by a multivariate linear equation in which different types of urban land have different weights for increasing the GDP (Barala, Keenan, Sharma, Stork, & Kasel, 2014; Zhao & Chen, 2018). The weights are real values taken from empirical studies. In G_2, urban green spaces provide ecosystem services in social-ecological urban systems by harboring biodiverse habitats, and improving water conservation, food production, and education, with different types of units being used for measurement (Dennis & James, 2016; Yang, Guan, Xia, Jin, & Li, 2018). Here, we use a simplified linear equation to express the relationship between the urban green space area and the total amount of ecosystem services. In G_3, urban green spaces are affected by family income, race, and social status (Heynen, Perkins, & Roy, 2006; Wolcha, Byrneb, & Newellc, 2014). In our simulation, we identify the proportions of green land cells on the x- and y-axes of the land use image and calculate the degree of spatial equity as the EQU value. Other equity rules, such as the effect of family income, are temporarily excluded. In G_4, ecological corridors are crucial for ecosystem integrity. We use image recognition technology to find potential ecological corridor locations. G_5 and G_6 are goals that are directly relevant to urban land areas and are confirmed via empirical expert knowledge by urban planning experts. The transform mechanisms of G_1–G_4 are rule based, whereas those of G_5–G_6 are subjective judgments. We believe that these goals, as examples, cover a wide range of the relevant domains for mesoscale (10 km × 10 km) urban land use planning tasks. The scenario-simulation function can be operated based on a GIS platform or can be executed independently, as we did, using the GMCTS-for-Urban-Planning software.[3]

The variables marked with the symbol Δ are relative values. The variables containing USs are explained in Fig. 6. E_x and E_y are the proportions of green land cells on the x- and y-axes in the land use image. L_{cor} is the corridor length, and S_{cor} is the area of the green spaces connected by the corridor.

Site images of urban land use are the most indispensable basic data in urban land use planning. These images usually contain more than 10^6 pixels, and more than 5 possible land use state spaces exist in each pixel. Urban land use images can be acquired from government planning documents with 100% accuracy at the legal level or by analyzing satellite images using machine learning, which provides limited accuracy. We recommend the former as the source of data in conjunction with some simple rules for urban land use classification. We used a simple algorithm that selects the most-frequent-pixel usage as the usage of the corresponding land cells to convolve image pixels. These pixels, segmented by roads or into 50 × 50-pixel regions can be convolved into a "land cell" to reduce the total number of state spaces to the level of the game of Go, which is still very difficult for goal-reasoning within a reasonable time. Additionally, the state spaces are reduced again by the land cell packing method in the goal-oriented searching phase (see Section 3.3).

Another indispensable task in scenario simulations is to acquire the land cell priority images via a priority network (p_c). We show these priorities as images presented in RGB colors standardized between 0 and 255 for monitoring. Distinguishing priority land to obtain the action sequences of urban land use planning is a traditional method with a long history (McHarg, 1995; Steinitz, 2002). These priority images (see Fig. 5) are not used for value computations but to select the position of land cells in the subsequent G-MCTS (see Section 3.3). Each priority image can be generated by sequencing the land cells' ability to fulfill the corresponding goal by corresponding rules during the simulations. For example, in Fig. 5(a), the original urban industrial lands have the highest priority for achieving GDP. In panel (c), the lands in the lower left of the image have the highest priorities for achieving green space equity. We note that small-scale changes in priority do not influence the selection of nodes because the selection process continues until the subheuristics are achieved following the corresponding priority orders. However, mistakes will occur if the priorities have large-scale errors, because the definitive satisfaction of human goals follows these priority orders in the G-MCTS.

[3] The software can be downloaded at "https://github.com/GMCTS/GMCTS-for-Urban-Planning"

3.2. Acquiring goal-oriented heuristics and the weights of goals

Experts and decision makers can evaluate their goals on the basis of rules with the aid of professional scenario-simulating functions just as expert systems do. Different scenario simulations may affect each other via land cell transformation. However, in our method, the interaction effects are solved in the searching phase if needed; therefore, the experts and decision makers are asked only to confirm their reasonable goals and corresponding objective values in each scenario while properly considering the interaction effects. In addition, a planning manuscript could be taken as a comprehensive goal ranked from 0 to 100 (see Section 3.4). The program transforms the goals (as shown in Table 1) into an array of goal-oriented heuristics (H):

$$H[\alpha] = \{G_1, G_2, G_3,\ldots, G_\alpha\}, \tag{1}$$

where α is the number of goals. The heuristics (H) represent the ideal situation in which every decision maker's requirement can be satisfied. Accordingly, the heuristics (H) provide an ideal reference for searching. In addition, H is flexible in the MDP of real-world goal-reasoning tasks because new goals can be added to the heuristics at any time.

Besides, the weights of the heterogeneous goals, used during the evaluation phase of the G-MCTS method, obtained either through subjective judgments by experts or through voting with a political agenda, as occurs in many MCDA processes. The G-MCTS method should move beyond objective criteria because there are not any objective criteria (either single or multiple) on which all stakeholders will agree. If many people are interested in the same goal, it could be weighted according to the number of supporters to improve the democratic decision-making process. We acknowledge that the weight-setting task is the most difficult part of real land use planning work, and the weights are usually determined by human political rights. In our experimental test, we use 1/α as a fixed weight for the α goals.

3.3. Using the G-MCTS to determine the best step actions

The G-MCTS methodology is developed to achieve the best sequence of land use step actions that can be acquired by satisfying the overall goal-oriented heuristics (H), that are explainable, and that can be used to guide real-world urban renewal practices. Accordingly, the selection, expansion, evaluation, and backup phases in the classical MCTS algorithm are improved by a series of new methods developed specifically for this purpose. The core differences in our G-MCTS compared with other MCTS architectures are the methods for decomposing many heterogeneous goals into subheuristics to support goal-oriented searching and combining goal-oriented searching with land-cell rollout searching in the MCTS. In addition, the nodes in G-MCTS are defined by multiple subgoals rather than the values in specialized expert fields. The heuristics (H) are decomposed into n equivalent subheuristics (h) for the subsequent G-MCTS search process, as follows:

$$h[\alpha] = \frac{H[\alpha]}{n}, \; n \in [1, C], \tag{2}$$

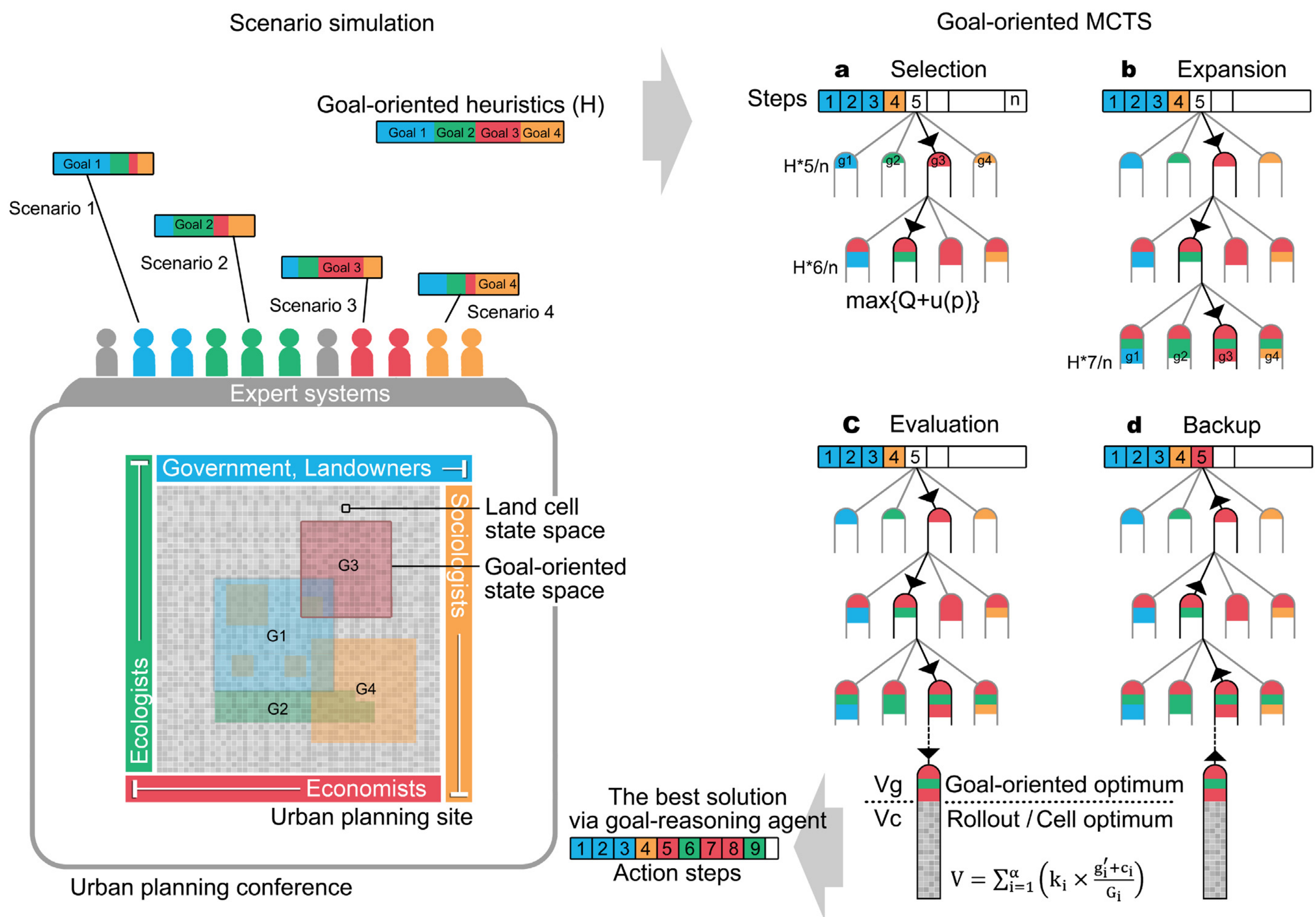

Fig. 4. Schematic of the G-MCTS methodology for urban land use planning.
The schematic shows the methodology combining multiple-scenario simulation planning, high-level goal-oriented heuristic, MCDA, and the G-MCTS. In urban planning conferences, experts and decision makers must achieve a compromise among their heterogeneous and conflicting goals. This methodology first simulates the scenarios of urban land use changes based on the rules of expert knowledge to obtain the ideal goal-oriented heuristics (H) for the subsequent G-MCTS search. The search begins by decomposing the goals into n subheuristics for selection and expansion, and it ends by the MCDA method. The evaluated value V is the percentage of the total goal fulfillment. As the search proceeds, Vg gradually substitutes Vc step by step in the G-MCTS. Finally, the G-MCTS provides the best sequence of step actions in the global optimum that allows the decision makers to fulfill their goals.

where C is the number of land cells in the planning site. Each subheuristic (h) occupies a layer in the search tree, and each subgoal in h ($g_{\alpha d}$) occupies a node as an optional action (see Fig. 4). As a result, n layers and n × α nodes exist in the top of the search tree. Each subheuristic (h) will be satisfied by a set of holistic state space changes to many land cells (we call these sets "land cell packs"); therefore, the subsequent G-MCTS process involves performing searches that focus on optimal goals instead of optimal values. During the search process, the subheuristics (h) are satisfied layer by layer by the best choice of nodes for each layer until the nth layer is reached and the total heuristics (H) is approximated.

(1) Selection. The algorithm sequentially selects the most promising node from root nodes to leaf nodes during the selection phase. The standard upper confidence bound apply to tree algorithm (UCT algorithm) (Hay et al., 2012; Kocsis & Szepesvári, 2006; Segler, Preuss, & Waller, 2018; Silver et al., 2016)

$$a_t^* = \underset{a_t \in \mathscr{A}(s_t)}{\operatorname{argmax}}\left(\frac{Q(s_t \mid a_t)}{N(s_t \mid a_t)} + c \times \frac{\sqrt{\log N(s_t \mid a_{t-1})}}{1 + N(s_t \mid a_t)}\right), \tag{3}$$

is used to balance the selection of high-value and unexplored nodes. A leaf node is directly evaluated by a rollout when the node is visited for the first time; otherwise, it is expanded by processing via the next expansion policy before evaluation.

(2) Expansion. The expansion policy ensures that a leaf node constantly grows by α nodes to achieve the corresponding subheuristics in the new layer (d). The subheuristic

$$g_{\alpha d} = G_\alpha \times \frac{d}{n} \tag{4}$$

is achieved by selecting a node that is actually satisfied by the actions of an entire urban land cell pack. Thus,

$$Q(s_g \mid a_g) = \sum_{i=m}^{n} q_i(s_{cell} \mid a_{cell}), \tag{5}$$

where Q is the value of a node (a land cell pack) and q_i represents the values of the corresponding land cells. Accordingly, the total number of state spaces can be reduced substantially through this packing method. The priority images of different goals are used here for cell selection.

(3) Evaluation and rollout. When a series of subheuristic nodes are selected, a goal-oriented evaluation is performed simultaneously. The evaluation result is an array that represents goal achievements. Taking node g_1 as an example, the goal-oriented value is an array such that

Table 2
The accuracy and time consumption of n-step G-MCTS.

Search rounds of a subtree (r)	Time consumption (hour)	Total steps (n)													
		1	2	3	4	5	6	8	12	16	24	32	48	64	96
10	Less than 0.1	**0.921**	**0.921**	**0.926**	0.929	**0.959**	0.927	0.958	0.932	0.963	0.963	0.957	0.966	0.959	0.966
100	0.1-1	**0.921**	**0.921**	**0.926**	**0.937**	0.959	0.957	0.969	0.985	**0.988**	0.962	0.957	0.971	0.959	0.969
1000	0.1-1	--	--	--	**0.937**	0.953	0.963	**0.976**	0.983	**0.988**	**0.982**	0.989	**0.991**	**0.990**	**0.994**
10000	1-10	--	--	--	--	0.953	**0.975**	**0.976**	**0.984**	**0.988**	0.970	**0.990**	0.966	0.983	0.965
100000	More than 10	--	--	--	--	--	**0.975**	**0.976**	**0.984**	**0.988**	/	/	/	/	/

$$V_g = \{g_1, g_2', g_3', \ldots, g_\alpha'\}, \tag{6}$$

where $g_1$is equal to $g_{\alpha d}$ and $g_\alpha{}'$ is the value for achieving the corresponding G_α; this value is newly calculated if the goals have interaction effects.

G-MCTS also has a cell-oriented rollout phase, which is essential for pulling the final evaluation into the same benchmark for backup purposes and for comparisons among nodes by evaluating the remaining land cells that were not selected during the goal-oriented selection (see Section 5.2). In fact, the rollout phase consists of local optimal cell-by-cell searching in priority order, which is fast but unable to achieve the global optimum. The total cell-oriented local optimal evaluation value is the array

$$V_c = \{c_1, c_2, c_3, \ldots\ldots, c_\alpha\}, \tag{7}$$

where c_α is the total value of the remaining land cells to achieve the corresponding G_α. The total evaluation value (V), which represents the degree to which the heuristic H can be satisfied for the backup, can be calculated via the multivariate linear equation

$$V = \sum_{i=1}^{\alpha} \left(k_i \times \frac{g_i' + c_i}{G_i} \right), \tag{8}$$

where k_i represents the weights of goals acquired by voting. Eq. (8) can be considered as a simplified form of the MCDA method.

(4) Backup. The total evaluation values (V) and visit counts (N) of all the traversed nodes are updated during the backup phase for the next round.

The entire G-MCTS uses n subtrees extracted from the parent tree for the n-step search. The results of each subtree are added to the parent tree after each step's search is complete. In each subtree, the above four phases are run r times, the subtree architecture becomes deeper, and when a subtree search is completed, the algorithm chooses the node with the highest V in the first expanded layer as the final action in this step. The next step's subtree then uses this node as the root node for expansion (see Appendix A). Finally, the program provides the best sequence of step actions to fulfill as many of the goals as possible, which in reality consists of many packed land cell actions.

3.4. The human-AI agent interaction prior to the DRL method (optional)

Achieving human-AI agent interaction is crucial in two respects. 1) It allows the consideration of accumulated human knowledge and planning experiences. Specifically, a human planning manuscript or report is usually a comprehensive document that contains a number of obscure goals with significant meanings. Thus, it could be an effective way to acquire personal opinions and integrate the plans of multiple people into a better plan. 2) It could provide feedback, allowing deep reinforcement learning (DRL) methods to achieve better performances. That is, human planning manuscripts or reports can provide many types of feedback, such as new goals, weights, and priorities for evaluating the former goal-reasoning algorithm and adjusting the existing parameters using a combination of the deep artificial neural network (ANN) and DRL to improve the evaluation after the G-MCTS process. In the machinery field, this type of test could be applied repeatedly in a closed environment. However, in urban land use planning domains, too few feedbacks exist to augment the performance of the DRL, and the feedbacks are usually either unknown or originate from several people's opinions. Although the DRL method could be configured and used when feedback is abundant, the key problem is how to make the goal-reasoning AI consider information from human judgments. In our research, the human planning manuscript can be considered as a 5th goal, and the goals can be ranked from 0 to 100 with their corresponding priority order for the next goal-reasoning task (Section 4.4).

4. Test results

4.1. Accuracy, resource consumption, and comprehensibility

The weighted accuracy (the average fulfillment percentages) of G_{1-4} increased from 92.14% in the 1-step G-MCTS to 97.61% in the 8-step G-MCTS and 98.98% in the 32-step G-MCTS (see Table 2 and Fig. 6), revealing that the accuracy of G-MCTS increases remarkably when the implementation decomposes goals into n-step goal-oriented searching. The accuracy of G-MCTS increases substantially by gradually increasing the proportion of goal-oriented searches when solving the principal macroscopic contradictions and by reducing the proportion of rollout searching based on local land-cell optima. In fact, pursuing the global optimum is the key for human decision makers to reach their reasoning goals. The curves of the goal-oriented values (V_g) and the land cell optimum values (V_c) reveal an X-shaped crossing (see Fig. 8(a)), and the fulfillment degree based only on land cell value optimum searching as the rollout method is 79.22% (Fig. 6(f)). This result also shows that the local land cell optimum method, as a type of traditional overlapping analysis (McHarg, 1995; Steinitz, 2002), may not be the best way to approach goal reasoning.

In addition, the goal-decomposition method is essential for G-MCTS to include in-depth goal reasoning; goal decomposition is a widely used method for decision makers in goal reasoning, but it is usually difficult for them to accomplish. In G-MCTS, n is a positive integer, and $n \in [1, C]$. When $n = 1$, the search degrades to a process that compares these goals in their entirety and selects the best goal among G_1–G_4 as the result—this process can easily be accomplished through deep human thought. However, when n is larger than 1, the total fulfillment degree of all four goals may be better, but the reasoning process also becomes more difficult. When $n = C$, a 10^6-layer search tree will never complete because a home computer can reach a depth of only approximately 10–20 layers in one day. A more serious problem occurs when n becomes too large; the result is a mosaic image that contains no clues that humans can understand. In Table 2, heuristics (H) are decomposed into 1–96 steps for comparison. The method for setting step (n) and round (r) must balance accuracy, search speed, and

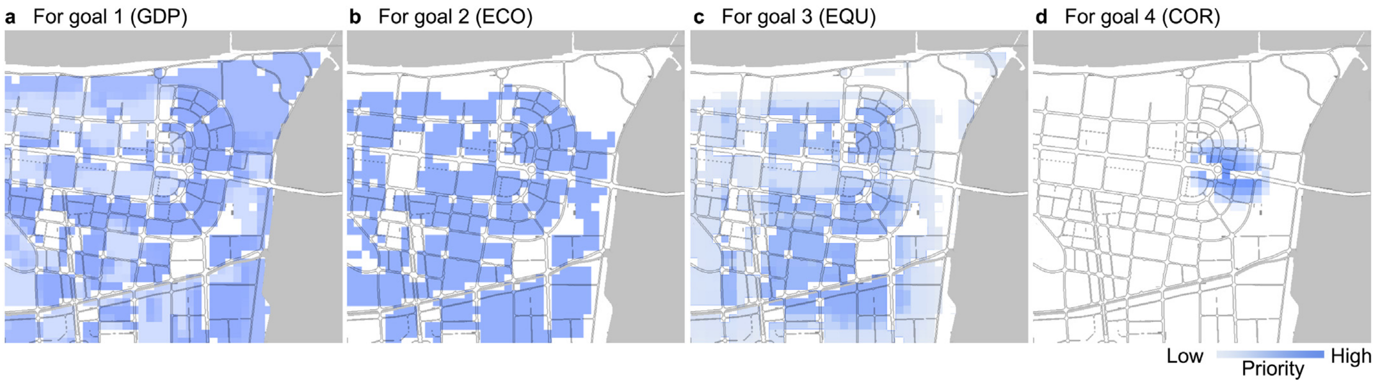

Fig. 5. The priority images during the scenario simulation.

comprehensibility. Deliberately pursuing increased accuracy by means of increasing the number of steps has no significant positive effect in satisfying the goals, and it results in mosaic solutions when the step (n) is excessively large.

4.2. The intelligence behind providing strategies

Beyond the ability to provide the best step actions for fulfilling goals, G-MCTS AI also has the ability to arrange the land cell packs into reasonable positions to match the strategies. In Fig. 6(f), Goal 1 (G_1) appears to be neglected when using only the land cell value optimum algorithm, and the solution manifests little consideration. Clearly, the yellow-colored residential lands will never appear regardless of how the sequences of the cell-level actions are changed, just as when using the overlapping analysis method (McHarg, 1995; Steinitz, 2002). However, in Fig. 6(g) and (h), the results of the 8-step and 32-step G-MCTS satisfy the requirements of G_1 by using planning strategies that arrange urban residential lands into a secondary priority position to achieve the global optimum instead of simply neglecting it.

The clear action steps (shown in the “steps” legend) can be used to acquire the causality relationships between the initial goals and the planning result. The selected goals in each step are shown in Fig. 8(b) and (c), indicating that a specific goal must be fulfilled before other goals to satisfy more decision makers. However, this goal need not be entirely fulfilled, and the other goals become increasingly important as the steps progress. The results in Fig. 8(c) show the four waves (G_4-G_2-G_1-G_3) of the four goals as an approximate sequence through which humans can settle their disputes and put their goals into real-world urban renewal practice.

Based on, and in addition to, the four goals in Fig. 6, we include two more goals: the 5th goals are achieving 12%, 18%, and 24% urban commercial space (UCS) in the entire site for consideration (see Fig. 7), and the 6th goal is achieving a constant 30% urban residential space (URS). Three strategies, namely, A, B and C, are observed when the 6th goal is added, indicating that the UCS and URS could be arranged into different positions for the global optimum in the MDP processes. The corridor (in the middle top of the images) can be surrounded by either commercial streets in A1 or by residential blocks in B2, and the newly added commercial spaces have two optional positions in either C1 or C2. The most important characteristic of these strategies is that they are packed actions of land cells instead of mosaic actions. Therefore, urban planners and decision makers could be inspired by these strategies.

Clearly, the goal-oriented heuristics (H) cannot be 100% satisfied, especially the game cases for urban land use arrangements, and the search result in game cases obtained by the cell-value optimum should be much lower than the global optimum; The rollout result in the five goals' reasoning (UCS = 24% in Fig. 7b by 8-steps G-MCTS) is less than 40%, while the rollout result is 79.44% in the four goals' reasoning. However, the fulfillment degrees in the five goals' reasoning are approximately 94% which are close to 97% in the four goals' reasoning. These results indicate that the key for developing strategies via the G-MCTS goal-reasoning AI approach is transforming the game problems using local land cells to cooperation problems on critical issues as a holistic viewing pattern.

4.3. Comparison between the G-MCTS AI agent and human planners

Before the three human planners started their planning efforts, we explained how these four goals were calculated by expert knowledge and simulated by the scenario-simulation processes. They were asked to try their best to satisfy these four goals while being allowed to use their own planning skills and accumulated knowledge as guidance. The G-MCTS AI agent completed the planning in approximately 10 min, so we gave them 30 min to finish their work in manuscript form. After the planners finished their planning efforts, they were asked to describe how they responded to the expert goals in their manuscripts and how they evaluated the results that were produced by the G-MCTS AI. The three human planning manuscripts are shown in panels i, j, and k in Fig. 6. The interview and evaluation results are summarized as follows:

- The human planners tried to find multiple strategies to fulfill goals in their planning reports, as did the G-MCTS AI. For example, the manuscript in Fig. 6(i) contains the same strategies for planning a green space surrounded by residential spaces. The human planners paid more attention to the special Goal 1 than to other analogous goals and gave more weight to this goal as a human preference in their planning manuscripts. However, the G-MCTS gave the four goals equal weights of 0.25 during the test. As a result, the degree of goal fulfillment by the human planners was lower than that achieved by the G-MCTS AI agent.
- The human planners usually discounted the goals that contradicted their own planning knowledge and planning experiences, such as developing in a green way (see the manuscript in Fig. 6(k) for an example). We asked, “If you do not believe these original experts' goal setting, how do you integrate the three different manuscripts that you produced, since you definitely trust your own work?” The planners fell silent; they then wanted to see how the G-MCTS AI systematized their own manuscripts and used the results that the AI provided as references, although they did not plan in exactly the same manner as was presented in the AI results.
- The human planners reported that the inspirations for their planning manuscripts stemmed partially from expert and historical knowledge, but they felt that the G-MCTS AI could help them incorporate this knowledge with new information in a rational manner and provide another type of inspiration. They believed that if human planners do not know the interaction effect of goals in complicated real-world situations, the only thing they can do is optimize the existing recommendations, which would enable the G-MCTS to

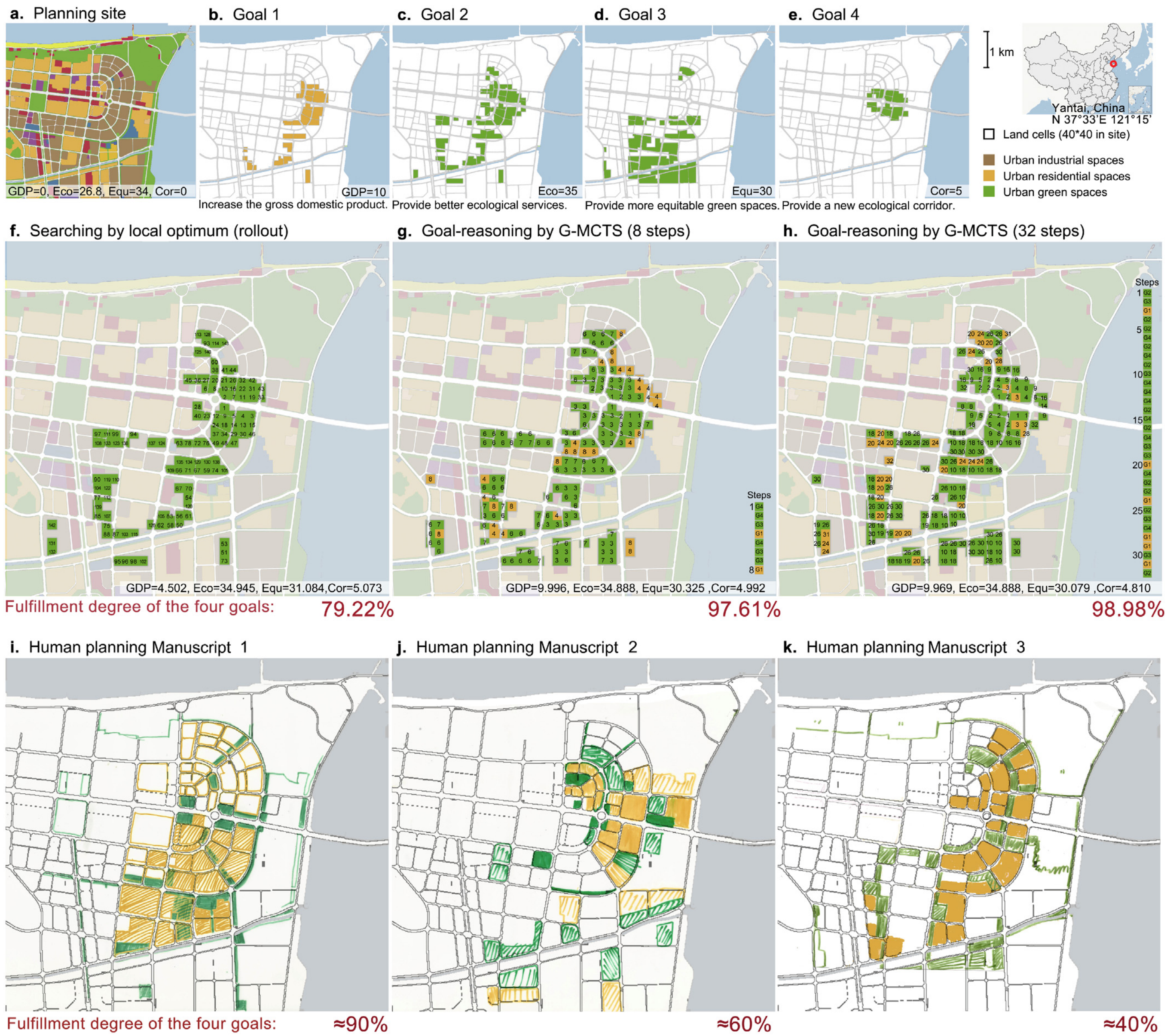

Fig. 6. The four goals' reasoning results of urban land use planning via the G-MCTS agent.
In this urban land use planning case, panel (a) shows the initial situation of the planning site. The four heterogeneous goals from economics, ecology, sociology, and landscape domains with corresponding objective values needing to be fulfilled are shown in panels (b), (c), (d) and (e). Clearly, Goal 1 conflicts with the other three goals, while Goals 2, 3 and 4 are partially consistent. In panel (f), searching by only the land cell value optimum algorithm considers urban residential spaces to always be less important than urban green spaces in every land cell. However, in panels (g) and (h), the planning is ingenious, and the fulfillment degree is much higher, with clear action steps (as shown in the "steps" legend) for achieving these four goals. The results in panels (i), (j), and (k) are the human planning results for fulfilling the four goals using their own accumulated knowledge as guidance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

provide valuable assistance.

4.4. Human-AI agent interaction using the human manuscript

Obviously, the three human planning manuscripts in our tests fall considerably short of a DRL agent's requirements. However, in our research, we achieved the purpose of using human planning manuscript to support goal reasoning during human-AI agent interactions (see Fig. 9), which focused on the four heterogeneous goals and use the human planning manuscript as a fifth goal. It is clearly seen in Fig. 9(i), (j), and (k) that the G-MCTS goal-reasoning method can both perform effective reasoning for multiple heterogeneous goals and flexibly assimilate human planners' intentions for better solutions. Each test takes approximately 10 min to achieve the relatively best solution with an approximately 80% degree of fulfillment.

These tests indicate that different human decision makers could compare notes in real time and avoid unnecessary arguments during democratic urban land use planning tasks when using the G-MCTS goal-reasoning method. These tests also demonstrate that the G-MCTS goal-reasoning method can be utilized as a computer-aided system for goal reasoning for a single planner. The output arbitrarily resembles that of Photoshop software.

These strategies are produced when adding the 6th goal to the G_1–G_5 goals, which involves many comparisons. Moreover, these strategies result in packed actions of land use transformation instead of mosaic actions, making it easier for urban planners and decision makers

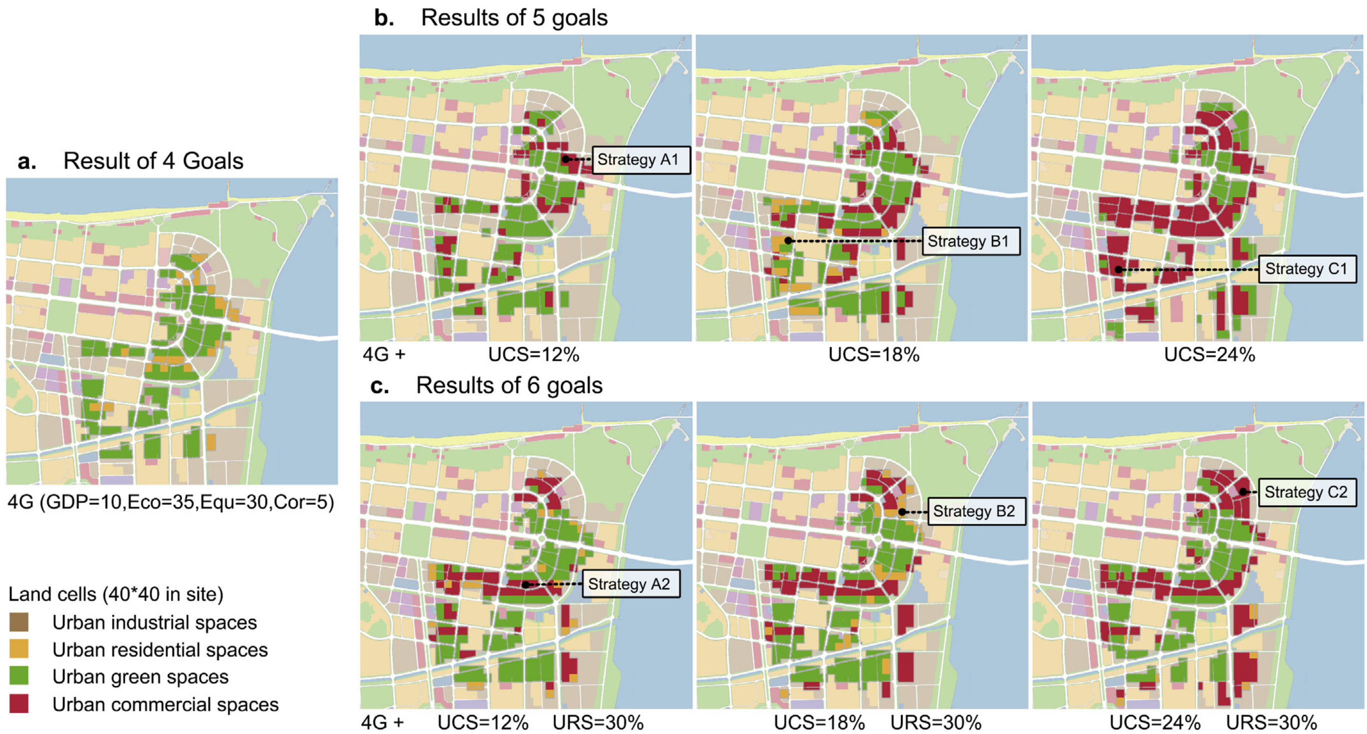

Fig. 7. The intelligence in strategies provided via the G-MCTS agent.

to be inspired by these strategies.

The results in Table 2 correspond to the four-goal test in Fig. 5. The fulfillment degrees in bold represent the best results in each column. The results shaded in yellow reveal that when the number of search rounds is large enough for the first step subtree to reach the deepest nth layer, those results are always the best solutions in each column. However, the results in blue indicate that when the number of search rounds is not sufficient to reach the deepest nth layer limited by computing resources, the results are usually suboptimal solutions. In this test, as shown in red, $n = 8–16$ (twice the number of goals) and $r = 1000$ (the first step's subtree can reach more than half of the n layers) are the appropriate settings that balance accuracy, search speed, and comprehensibility.

5. Discussion

5.1. Using a goal-reasoning AI approach for urban land use planning

Our goal-reasoning AI method, as a metamodel, is not yet perfect, similar to many other improving AI applications. Our test results also cannot prove that the goal-reasoning AI method could be substituted for existing political agendas or could perform better than senior human planners—especially when addressing complex urban and social problems (Batty, 2007; Friedmann, 1993; Healey, 2006), because these types of tasks often include many ill-defined problems (Lewis, 1984)—although it can accumulate the existing processing methods for the large amounts of information involved and attempt to assist human beings to make better value judgments among the plethora of heterogeneous expert knowledge bases and goals regarding land use. However, when the a priori knowledge is considered to be complete during the MDP decision-making processes, the G-MCTS AI agent could perform better than did humans at fulfilling goals.

Urban planning AI agents should provide clear causal relationships that can be subsequently used for legislative purposes; that is, their results should be explainable instead of interpretable. Our G-MCTS AI agent, which has been executed on many expert systems and scenario simulations (e.g., Grekousis, 2019; Liang et al., 2018), tries to balance the accuracy and comprehensibility of political intentions when reasoning about goals. MCDA method (e.g., Bonissone et al., 2009; Faria et al., 2018) is added in the evaluation phase as the most feasible approach at present. The novel G-MCTS method that combines the calculation of interaction effects and MCDA incurs a more complicated AI agent in the process of acquiring the causal relationships, but it is an inevitable consequence of providing a better solution than that achieved by the MCDA method when the goals are correlative. Perhaps goal-reasoning AI will affect land use planning agendas as a type of technology capital rather than as a decision support tool in the near future.

5.2. The search tree of G-MCTS

Each run of the search process by G-MCTS has only one parent tree. However, we do not run all four phases of MCTS on this parent tree because if the search is not performed step-by-step using subtrees, it can never reach the bottom layer. To solve this problem, the parent tree initially has one root node that represents the initial state space of the planning site and α nodes for α subgoals. The program copies the parent tree as the subtree for the first step search and adds the results back to the parent tree. The second step search uses the subtree that starts from the best node in the second layer of the first step's search for expansion. As a result, regardless of how many layers are considered, the best action of a step can always be selected via its corresponding subtree. Approximately 10^2–10^4 search rounds in each subtree are sufficient for the entire G-MCTS, which saves significant computational resources (see Table 2). Human goals in urban land use planning are usually limited; therefore, we have not yet tested the G-MCTS under large problem sizes.

The performance of MCTS is, to a large degree, determined by the quality of the rollout policy, although rollout-based value evaluation is frequently inaccurate (Silver et al., 2016). In our G-MCTS, the policy of the land cell optimum rollout can easily select the best state space of a land cell for fulfilling the goals. In addition, the policy of the land cell optimum rollout is used as an important method for balancing the backup values. For example, if 200 land cells exist, one node with 100

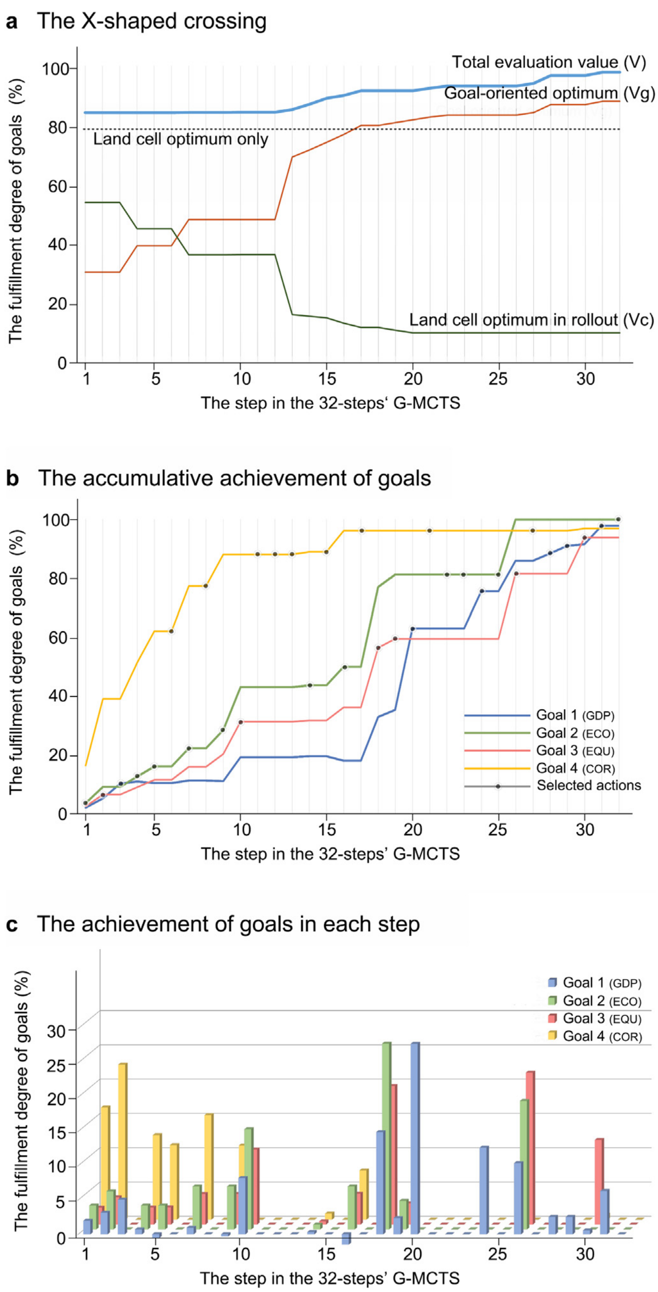

Fig. 8. The performance of G-MCTS for goal reasoning.
In panel (a), G-MCTS gradually increases the proportion of global-optimum goal-oriented searching and reduces the proportion of local-optimum rollout searching. The goal-oriented optimum evaluation values Vg and the rollout evaluation values Vc exhibit an X-shaped crossing at the 7th step.
In panel (b), the four goals are gradually satisfied from 0% to 100% as the steps proceed. Goal 4 is satisfied first, while G2, G1 and G3 are satisfied by the later step actions as a planning strategy. The step actions consist of the goals illustrated as the black marks in each step.
Panel (c) shows the goal achievement at each step. Because of the interaction effects, the selected goal may satisfy other goals, such as steps 1 and 2. Some steps, such as step 20, have no interaction effects, and some steps, such as steps 11 and 21, have no value because the former steps' actions also satisfy these steps' subheuristics (h) until the layer in which the subheuristic's value increases becomes large enough for a new action.

land cells and another node with 10 land cells may make the same contribution to fulfilling G_1. However, the node with 100 land cells usually makes greater contributions to fulfilling other goals than does the node with 10 land cells. Accordingly, the evaluation of the two nodes for all goals may be biased. However, the total values of the remaining cells in different rollouts are more dependent on the number of land cells than on the previous goal-oriented nodes' values. Therefore, the rollouts pull the final evaluation into the same benchmark for comparison if they are added after the goal-oriented selections for evaluations.

We include additional values on the property sheets of the nodes beyond the total action values (V) and visit counts (N). For example, each node needs to update the land cell positions (P_c) and corresponding actions (A_c) so that the next layer's nodes can be generated based on the previous nodes and avoid repeatedly selecting the land cells as a longitudinal series of nodes. Each node can also update the goal-oriented fulfillment degree (V_g in Eq. (6)) and the rollout fulfillment degree (V_c in Eq. (7)) to accelerate the search instead of engaging in repeated computations.

5.3. Comparison between the G-MCTS and other algorithms

Our goal-reasoning AI approach is highly compatible and flexible and can efficiently integrate disparate expert knowledge in the MDP of urban land use planning. Adding or deleting goals does not influence the main search architecture (G-MCTS) used for goal reasoning, and the rules for existing goals in different domains can be coded as independent subroutine. Theoretically, as a reinforcement learning method, our G-MCTS allows for infinite heterogeneous goals at the cost of only a linear increase in programming time; in that sense, G-MCTS is a general method for systematizing heterogeneous expert knowledge, information, and scenario simulations and for goal reasoning.

In the AI domain, supervised learning (SL) is more suited for searching using rule-based knowledge when the rules are assumed to be unchanging over a period of time and situated in a particular place. However, reinforcement learning (RL) is more suitable for an AI agent that can provide more help than SL in the politically agenda-driven situation of urban land use planning. In our G-MCTS methodology, we take the scenario simulations as many rule-based efforts that could be well calculated by supervised learning, as many expert systems have done, and then add the reinforcement learning method to systematize them for the best solutions, during which planning strategies are simultaneously produced. A comparison between G-MCTS and other algorithms is shown in Table 3. We are still endeavoring to determine whether any human planning strategy or goal weightings exist that have perfect data that the AI agent could use for training via deep-SL or deep-RL methods (Arulkumaran et al., 2017).

6. Conclusion and future work

Until now, integrating rule-based expert systems has faced problems of data heterogeneity, varying judgment standards, and many other features; consequently, goal-reasoning tasks are still mainly accomplished by human planners and decision makers. To overcome these challenges, our work attempts to explore a new working pattern in which humans and AI agents interact to find the most comprehensive planning decisions for complex real-world urban land use planning issues. The core approach is combining the scenario-simulation method and MCDA with the G-MCTS method to build a bridge between subjective and objective approaches. We believe that G-MCTS provides a general method that can partially substitute for the sophisticated mental work of decision makers in many subjective-objective combined planning domains, including urban land use, transportation, investment, and ecological protection planning, and can be directly applied to automatically acquire the best scenario among many heterogeneous goals and planning options during a planning conference.

The novel G-MCTS algorithm can effectively apply reasoning to goals and achieve the best solution according to the standard of fulfilling as many goals as possible while computing the interaction effects during the search process and functioning as an improved MCDA

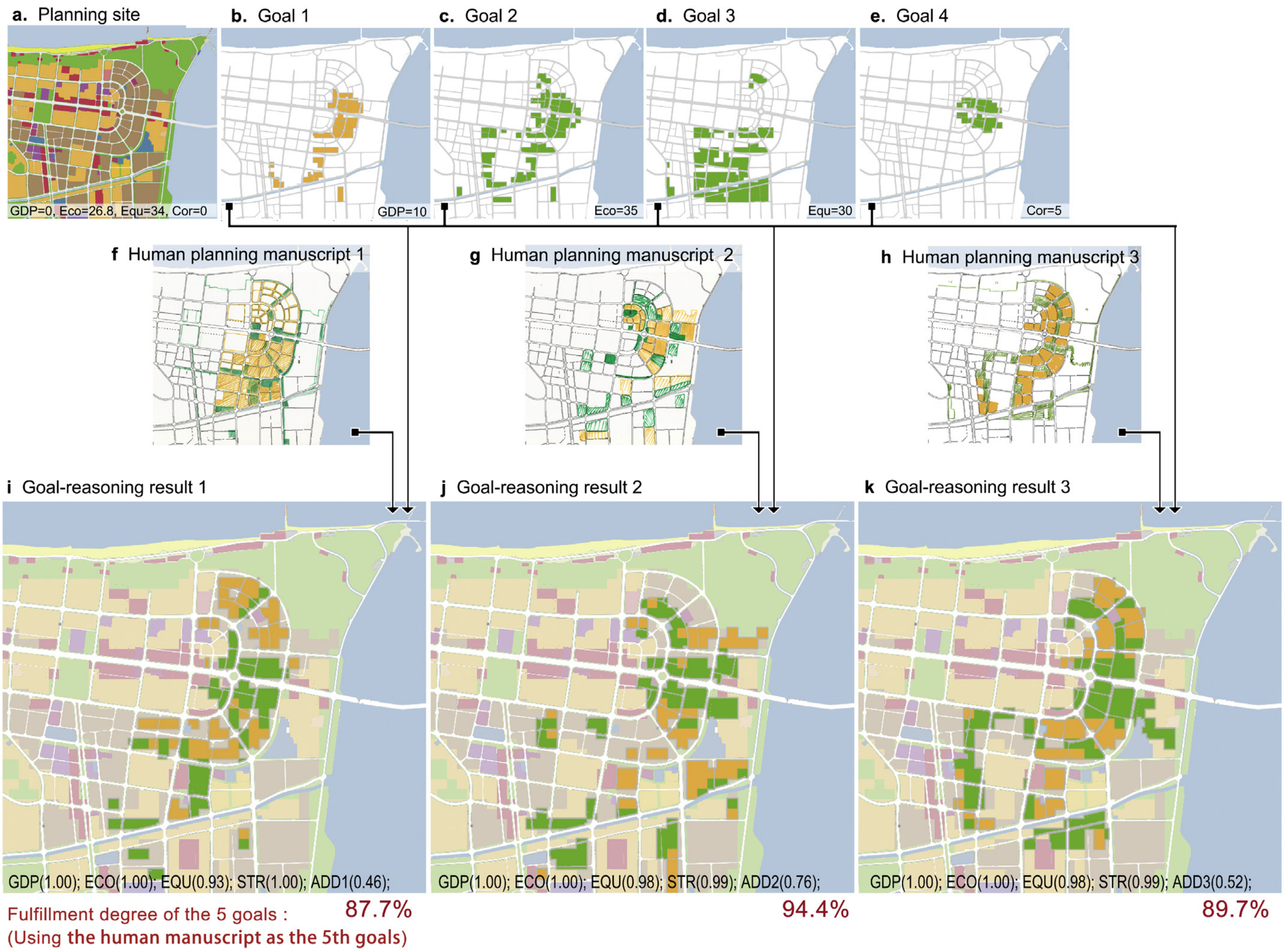

Fig. 9. Reasoning goals via human-AI agent interaction.
In these goal-reasoning tests, the step is 16, the round is 1000, and the five goals' weights are weighted equivalently (0.2). Each test requires approximately 10 min to achieve the relatively best solution. ADD1(0.46) in panel (i) means that the human planning manuscript 1 in panels (f) is satisfied at 46% when achieving the global optimum of 87.7%.

Table 3
Comparison between G-MCTS and other algorithms.

The characteristics of other algorithms		The characteristics of G-MCTS
Overlay analysis	A local optimal searching method	A global optimum searching method
Cellular automaton models (CA) and agent-based models (MA)	Searching among a limited number of state spaces	Searching among an enormous number of state spaces
	Process knowledge and is more objective	Process human judgments and is objective-subjective combined
	The best solution is still unknown	The search results are the best solution
Multicriteria decision analysis (MCDA)	Perform goal reasoning without considering the interaction effects	Perform goal reasoning while considering the interaction effects
	More convenient	More accurate
		The MCDA method could be used for evaluation
Supervised learning and deep supervised learning (ANN and deep ANN, for example)	More accurate based on specific rules	More intelligent based on the current situation
	The learning samples are key	The subjective judgments and feedback are key
	The causal relationship cannot be understood	The causal relationship can be at least partially understood
Reinforcement learning (MCTS, for example)	Achieve state-of-the-art performance in many game environments	Achieves good performance in an open system, such as urban land use planning
	Feedback is abundant in many game environments	Feedback is difficult to obtain in an open system
		Use the heuristic method of decomposing goals
		Can be used to perform heterogeneous goal reasoning
Deep reinforcement learning (ANN + MCTS, for example)	Achieves state-of-the-art performances in many game environments	The performance of a deep G-MCTS that combines ANN and G-MCTS is still unknown in an open system

decision support tool. In fact, the G-MCTS goal-reasoning AI agent transforms game problems involving local land cells cooperatively while regarding issues in a holistic viewing pattern, which is the key for developing strategies via goal-reasoning AI agents. Accordingly, it can balance global and local optima in the same manner that human planners do when planning their manuscripts; thus, it can automatically provide strategies that fulfill multiple goals rather than require deliberate policy programming. We tested our goal-reasoning AI agent on a real-world planning case and evaluated it by comparing the AI-assisted planning results with human planning manuscripts. The results show that the goal-reasoning AI agent is better at performing complex goal reasoning than are human planners but weaker at applying accumulated experience.

The lacunae in accumulated experience could currently be handled by both the deep SL and RL AI methods (Silver et al., 2016; Silver et al., 2017); however, how to make decisions regarding heterogeneous goals while following a democratic political agenda still merits further study. Additionally, reasoning human manuscripts offer a potential method for obtaining feedback in constructing a deep goal-reasoning AI agent. Our future work will focus on incorporating this experimental AI agent into a large-scale application. To accomplish this task, we need to provide many new functions for the GMCTS-for-Urban-Planning software and test it on many other planning cases that move beyond simple comparisons between AI agents and human planners. Our research also requires a full comparison with other state-of-the-art artificial intelligence models if possible—especially models that focus on social problems dominated by political agendas.

It is noteworthy that, on the one hand, new AI technologies could produce a more effective political ecosystem; on the other hand, the development of AI technologies requires appropriate policy supports by governments. Therefore, to better understand such a complex relationship between politics and AI technology, we should pay more attention to the view point of reflexivity or the concept of “socio-technical systems” provided by Geels (Geels, Sovacool, Schwanen, & Sorrell, 2017), wherein social functions can be shared by linking technologies, infrastructures, organizations, markets, laws, regulations, and users' practices together. As a result, many niche innovations based on novel AI technologies could be the fundamental forces that can change our social organization and the physical form of cities. Nevertheless, these complex relationships do not prevent us from putting forward appropriate urban or planning policy recommendations. First, the use of goal-reasoning AI in the urban planning domain should be encouraged and incorporated into public policies to establish preventive approaches. Second, governments should pay more attention to critically assessing the contradictory demands currently faced in various fields, which seems particularly important in the era of AI. Third, through our grounded, case-based research, every sector of society needs to be tolerant of applying novel AI technologies, rather than criticize them indiscriminately.

CRediT authorship contribution statement

Weizhen Chen: Methodology, Validation, Writing - review & editing. **Liang Zhao:** Conceptualization, Methodology, Software, Data curation, Writing - review & editing. **Qi Kang:** Methodology, Software, Data curation. **Fan Di:** Software.

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Appendix A

The latest version of the software and the user's manual are provided at a download link: https://github.com/GMCTS/GMCTS-for-Urban-Planning.

```
void GMCTS::OnClickedButtonRun()//main function of G-MCTS.
{
GMTCL_Purpers_Get();//get the goals as heuristics, and the weights.
GMTCL_Sequence_Get();//get the priorities.
GMTCL_Fast_Sequence_Get();//get the cell-oriented searching' results for evaluation.
GMTCL tree;//main tree.
GMTCL *pCur_tree_Branch = &tree;//new subtree.
for (i = 0; i < site; i++)// steps
{
for (k = 0; k < goal_time; k++)//times in each step.
{
while (pCur->isLeaf()==false) //selection phase.
{
pCur = pCur->vpChildren_i[action];
}
if((pCur->isLeaf()==true)&&(pCur->nVisits_i==1))//expansion phase by subheuristics.
{
pCur->expand(&Vg);//expansion by the priorities of land cells, evaluate the packed goal-oriented values.
action_step.push_back(action);//record goal-oriented step action.
}
GMTCL_Purpers_Main_Fastmove(rest_action, &Vc);//get the rollout value under this circumstances.
V = GMTCL_Value_Estamat(Vg,Vc);// V = ∑_{i=1}^{α} (k_i × (g'_i + c_i)/G_i), the MCDA of G-MCTS.
if (V >= value_max)
value_max = V//backup phase.
}//for k
BestAction.push_back(action_step(value_max));//get the best step action after a step's searching.
*pCur_tree_Branch = tree_Branch;//subtree result added back to main tree.
}//for i
GMTCL_Show(BestAction); //show the best results.
```

$$V = \sum_{i=1}^{\alpha}\left(k_i \times \frac{g_i' + c_i}{G_i}\right)$$

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