TOWARDS AN EMPIRICALLY INFORMED AGENT-BASED MODEL FOR COLLECTIVE GROUNDWATER MANAGEMENT

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ABSTRACT

Collective groundwater management is a challenging case of the common-pool (CPR) management problem. Since the 1970s, empirical studies have disproved the notion that the 'tragedy of the commons' is the inevitable fate of any CPR. Complex systems theory, which rejects the rational economic actor-based ontology of neoclassical economics, has been employed widely to explain the emergence of cooperation in CPR research. Agent-based modelling (ABM) is a powerful computational tool to study the emergent dynamics of complex systems; however, combining empirical data with ABM in economics is challenging. In this study, I employ ABM to develop a preliminary model for collective groundwater management in southern India based on empirical behavioural data. I briefly present the results of the model and propose avenues for further model development. The proposed model can find applications in policy research and as an interactive role-playing game for aiding future behavioural studies.

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Pranandita Biswas

1. Introduction

Groundwater depletion presents a major environmental challenge in many developing countries (Meinzen-Dick et al., 2018). Groundwater is an example of a common-pool resource (CPR), i.e., a finite resource that is easily available to multiple users.

CPR management has been contentious throughout history. In the twentieth century, the dominant view among economists was that all CPRs are destined for eventual destruction because every user will attempt to maximize resource extraction while contributing as little as possible to resource maintenance. This reasoning behind this 'tragedy of the commons' is founded in the assumption of the individual as the *Homo economicus*: the rational, selfish, utility-maximizing agent at the core of mainstream economic theory (Hardin, 1968).

Since the 1970s, growing empirical evidence has challenged this reasoning (Ostrom & National Research Council (U.S.), 2002). Instead of exhausting CPRs, users can evolve complex institutions to regulate resource use. To explain the emergence of such inter-agent cooperation, a fundamentally different ontological approach and model of human behaviour is necessary.

One such approach that has become widespread in CPR studies since the 1990s is the complex systems approach. It possesses ontological similarities with earlier institutional economics in envisioning the economy as a dynamic and evolving system, not static and equilibrium-seeking as understood in the neoclassical approach. From a behavioural perspective, the complex systems approach assumes agents to be heterogeneous, not representative, and their behaviour to possess both instinctive and rational elements, not solely the latter (Arthur, 2021).

Agent-based modelling (ABM) is a central tool for studying complex ecological–economic systems in CPR research. ABM employs computational methods for modelling systems bottom-up from micro models of agent behaviour. ABM thus allows analytically intractable problems to be solved and artificial experiments to be conducted in the social sciences (ibid.).

Bridging ABM with empirical research presents unique challenges due to the high complexity and difficulty of collecting data for validation (Janssen & Ostrom, 2006). Inspired by this, I propose an empirically founded agent-based model in the context of groundwater management in regions of southern India that are grappling groundwater depletion due to increased irrigation pressure. As a starting point, I develop a preliminary model based on behavioural data collected through role-playing games by Meinzen-Dick et al. (2018).

The paper is structured as follows. Sections 2 and 3 provide an overview of complex systems economics and CPR research, respectively, focusing on their ontological foundations and historical development. Section 4 outlines the methodology of ABM. Section 5 explains the case study and nature of the data used. Section 6 describes the preliminary model and its assumptions, and Section 7 presents the outcomes of this model. Section 8 proposes avenues for further model development, and Section 9 presents concluding remarks.

2. From market equilibrium to complex systems

At the heart of the mainstream neoclassical analysis of the economy is the *Homo economicus*, the perfectly rational human with complete information about market prices past, present, and future. The *Homo economicus* bases its actions solely on optimizing calculations with the aim of maximizing its 'utility', which is assumed to be some function of commodities that can be bought on the market. Crucially, the decisions of the *Homo economicus* are not influenced by institutions, social structures, or other agents. Further, every individual, whether consumer, investor, or firm, is identical in its goal of maximizing utility (Elsner et al., 2015, Chapter 5).

This analysis follows a mechanistic ontology: the macro-level market outcome is the sum of the individual's actions—guided by the invisible hand of Smith, the neoclassical market naturally moves to equilibrium. Aggregate demand and supply equate, and a Pareto optimal allocation of goods is achieved. Markets, like actors, are rational (ibid.).

These highly artificial assumptions are inadequate to capture the complexity of real-world economic problems outside of highly competitive markets. Prior to the marginalist revolution of the late 19th century, classical political economists perceived the economy as being dynamic and evolving, as opposed to the static, equilibrium-seeking neoclassical market. Many influential economic concepts from the 20th century, such as Veblen's institutional critique and Schumpeter's ideas of creative destruction disrupting the Walrasian 'circular flow' of equilibrium, went beyond the equilibrium formulation (Bush, 1987; Breschi et al., 2000).

Since the 1990s, complex systems analysis, with its roots in the natural sciences, has been formally applied to economics. Specifically, treating the economy as a 'complex system' implies changing the assumptions about agent behaviour as follows:

i. Agents are heterogenous, not identical 'representative agents'.
ii. Agent behaviour follows simple rules, not sophisticated optimizing calculations.
iii. Agent behaviour is influenced by the behaviour of other agents.
iv. Agents do not have complete information.

These assumptions entail a rejection of the mechanistic ontology of neoclassical economics: the aggregate system outcome cannot be predicted as a simple sum of individual behaviour. Rather, it is an *emergent property* that arises through the *interactions* among agents. On the macro level, these behavioural assumptions imply that the market is not rational and naturally equilibrium seeking but rather dynamic and evolving. This provides opportunities for the self-organization of actors outside of commodity-exchange markets and formal governance structures (Kirman, 2017; Arthur, 2021).

In the next section, I discuss the application of complexity economics to the problem of common-pool resource management.

3. Common-pool resource management and complexity

Common-pool resources (CPRs) are a class of resources characterized by the following features: (i) low ease of exclusion, i.e., ability to restrict use of the resource to specific users, and (ii) high subtractability, i.e., the degree to which the resource used by one used by one user becomes unavailable to another user. For example, a large fishery that is costly to fence and free for all to fish satisfies both these criteria (Ostrom et al., 1994, Chapter 1).

CPRs have historically been of interest from the perspective of resource sustenance. Conventional economic reasoning based on the assumption of the rational, selfish, utility-maximizing *Homo economicus* (Section 2) inevitably leads to the following outcome: as each user aims to extract as much as possible for their own benefit, the finite CPR ultimately gets depleted. This concept was immortalized by Hardin in 1968 through the phrase, 'the tragedy of the commons', which has since become ubiquitous in economics (ibid.).

Within such reasoning, only two options are available to prevent the tragedy of the commons: centralized bureaucratic regulation and privatization. Although Hardin adopted the assumption of the rational *Homo economicus* in his analysis, he differed from neoclassical scholars in favouring government control over private markets. Others such as Demsetz who were influenced by Hardin's ideas advocated for privatization and property rights. Commons management was largely seen as a binary choice between centralization and privatization with no possibility of bottom-up governance (Ostrom, 1990, Chapter 1).

3.1. The tragedy of the commons as a prisoner's dilemma

Hardin's tragedy of the commons is often demonstrated in game theoretic formulation as a case of the prisoner's dilemma. As an illustration, consider a common-pool irrigation reservoir, such as a lake, that is used by several farmers.

In a two-player game, each farmer can play one of two strategies against their opponent: cooperate or defect. Cooperation means adhering to a fixed quota of water that can be pumped from the reservoir, whereas defection means pumping as much water as possible to maximize one's profits. If both players cooperate, they both make an equal profit (call this R, the cooperator's reward). If one cooperates and the other defects, the defector makes a profit (T, the temptation to defect) while the cooperator makes a loss (S, the sucker's payoff). However, if both defect, the resulting depletion of the reservoir will reduce the profits of both players. The resulting payoff is called the penalty for defection, P.

This game outcomes are represented as a payoff matrix, where C and D in the row and column headings represent the strategies of cooperation and defection, respectively (Fig. 1).

	$\boldsymbol{C}$	$\boldsymbol{D}$
$\boldsymbol{C}$	(R, R)	(S, T)
$\boldsymbol{D}$	(T, S)	(P, P)

Fig. 1. Prisoner's dilemma payoff matrix.

The prisoner's dilemma is a specific type of game that is defined by the following condition on the structure of the payoff matrix.

$$T > R > P > S \tag{I}$$

The CPR problem (a type of *social-dilemma problem*) described above follows this structure.

As a player does not know in advance what strategy their opponent will adopt, the *dominant strategy* for an individual player, i.e., the strategy that one is *always better off* choosing, is defection. To see this, imagine that both choose to cooperate (top left in payoff matrix). Then, they each get a payoff of value R. If either player chooses instead to defect, their payoff increases because $T > R$. Now take the case where both defect (bottom right), both receiving payoffs of P. If a player chooses to cooperate instead, their payoff decreases because $P > S$. The mutual defection strategy (D, D) is thus the Nash equilibrium.

Note that the Nash equilibrium is a sub-optimal strategy. The globally optimal strategy where both players receive the highest possible payoff is (C, C). This gives rise to an apparent paradox in economics—individual rationality leads to collectively irrational outcomes. Unlike the case of the free market, rational behaviour of individual agents does not generate Pareto optimal outcomes in situations governed by the prisoner's dilemma structure, such as in CPR and other social-dilemma problems (Ostrom, 1990, Chapter 1; Epstein, 2006; Chapter 9).

The prisoner's dilemma is one of many formalizations of the *free-rider problem*: users of CPRs are incentivized to free-ride on the efforts of others and not to contribute to the joint effort of preventing resource degradation. This is because the costs of degradation are equally borne by all. However, if every user chooses to free-ride, then the collective benefit is diminished as the resource ultimately gets destroyed (Ostrom, 1990, Chapter 1).

3.2. The institutional challenge to the tragedy of the commons

Early challenges to the ides of the inevitability of the tragedy of the commons arose in the 1970s and 80s from empirical case studies. While some commons met the fate predicted by Hardin, others did not. From the centuries-long indigenous engineering of ecologically sustainable irrigation canal networks in Bali (Lansing, 1987) to the self-organization of lobster fisheries in Maine (Wilson et al., 2007), social scientists have documented the emergence of complex institutions to keep CPR usage within sustainable limits in communities worldwide (Ostrom & National Research Council (U.S.), 2002).

Further, policies based on privatization or centralized control, in addition to their frequently undemocratic and authoritarian implementation, have led to disastrous consequences in many cases. For example, corruption among foresters in nationalized forests has increased unsustainable resource exploitation in many countries (Ostrom, 1990: Chapter 1).

One crucial drawback of models based on the assumption of rational *Homo economicus* actors making decisions independent of each other is that they do not account for the role of *institutions* in influencing behaviour. In institutional and evolutionary economics, institutions are broadly defined as both formal structures, such as government bodies and laws, and informal norms, rules, and values that constrain and enable behaviour (Bush, 1987).

The prisoner's dilemma in Section 3.1 is a *noncooperative game*, i.e., it does not allow the possibility of users reaching binding agreements outside of the explicit rules of the game. This is not a universally accurate representation of reality as humans can develop complex institutions, such as incentive structures and rules for penalties, through negotiations. These institutions can be enforced through mutual agreement and self-organization even outside 'formal' governance structures or laws (Ostrom, 1990, Chapter 1).

The case studies discussed here show the limitations and internal contradictions of *Homo economicus*-based formulations in studying common-property resources. They provide counterexamples to challenge existing theories and reveal the need for new models that account for the heterogeneity of and mutual interactions among agents (Janssen & Ostrom, 2006). Conventional game theoretic models, such as the prisoner's dilemma presented in Section 3.1, failed to capture these complexities because they relied on analytical, equation-based formalizations that did not allow for relaxing the rigid assumptions of rational agent behaviour.

This recognition of the need to incorporate complexity into models as well as the availability of increased computational power led agent-based modelling (ABM) to become a standard tool in the social sciences from the early 1990s. ABM artificially simulates a large number of heterogenous agents who interact and make decisions over many iterations. Modelling such complex interactions is not possible with analytical models, i.e., through mathematical equations, but requires computational methods (ibid.; Janssen, 2005).

CPR problems are particularly suited for ABM formulations due to the large number of heterogenous actors, empirically observed importance of institutional arrangements, and repeated iterations of the game among players. ABM, based on complex systems theory, is a powerful tool to study the bottom-up emergence of community-based governance structures that may refute the predictions of static analytical models, such as neoclassical ones. In the next section, I briefly discuss the methodology and logic of ABM.

4. Agent-based modelling

Agent-based modelling (ABM) uses computer programming to artificially simulate complex systems bottom-up. Rules encoding assumptions about individual agent behaviour and inter-agent interactions are specified, and the emergence of macro-level patterns and phenomena from these can be observed. In the social sciences, ABM provides the opportunity for performing experiments that are infeasible or unethical in real life. The researcher may tweak parameters and rules of behaviour and perform simulations over long periods of time, such as many years or decades, to observe how societies may evolve under different conditions. Further, ABM can incorporate spatiality in an intuitive and visual manner (Janssen, 2005).

4.1. Methodology

Agent-based models consist of two elements:

i. *Cellular automata*

The cellular automata consist of a regular lattice of *cells* that are characterized by a *state*, which can be binary (0 or 1) or continuous. The most commonly used lattices of cells are one or two-dimensional. In every time step, a cell changes state in accordance with some transition rules, which depend on the states of the neighbouring cells (ibid.).

For example, each cell can represent a patch of farmland in a two-dimensional lattice, with the state of a cell indicating whether the crops in it have been infected by a virus. Thus, the transition rules for a cell depend on whether its neighbouring cells are infected.

ii. *Agents*

The agents in a model are the relevant actors, such as consumers, firms, or resource users. In the example of the lattice of farm patches, the agents may be owners of the patches.

As discussed in Section 2, in many problems of relevance to ecological economics, agents cannot be realistically modelled as perfectly rational actors with complete information. Instead, agent behaviour displays both rational and reactive or instinctive characteristics. Importantly, agents are influenced by the actions of other agents.

In the preceding example, an agent may choose to sell their patches of land when the cost of maintenance exceeds profits, e.g., due to crop infection. However, they may also choose to sell land to, say, a real estate company, with a certain probability if they see their neighbours selling land even if it is not profitable. Thus, ABM can model the *bounded rationality* of agents: rules can be specified to model rational behaviour based on available information and probabilities to model 'irrational', reactive behaviour (ibid.).

In the social sciences, computer simulations have aided important theoretical contributions by serving as 'proof of concept', i.e., to demonstrate that certain macro-outcomes are theoretically feasible with a given set of micro assumptions about agent behaviour (Janssen & Ostrom, 2006: 37). For example, Epstein (2006) showed that cooperation can emerge as a dominant strategy in a population whose pairwise interactions are dominated by the prisoner's dilemma structure, even though the Nash equilibrium in the two-player game is mutual defection. This result has profound implications for the understanding of human behaviour and is of particular relevance to CPR problems.

However, such models are highly abstract, and their practical validity is unclear without empirical evaluation. Increasing attention is being paid to developing empirically grounded models—both from the input side, i.e., basing parameter choice in robust empirical data, and the output side, i.e., testing the empirical validity of model results, assumptions, and mechanisms using data (Janssen & Ostrom, 2006).

5. Case study: Groundwater management in Andhra Pradesh, India

Groundwater is a particularly challenging CPR to manage because of its complicated dynamics and difficulties in monitoring use. Groundwater depletion poses a serious problem in many parts of the world, threatening access to water for vulnerable populations affected by climate change and erratic rainfall patterns (Meinzen-Dick et al., 2018).

In this study, I draw on the work of Meinzen-Dick et al (2018), who used role-playing games to gain behavioural insights into groundwater use for irrigation in the state of Andhra Pradesh in India. In Andhra Pradesh, groundwater pressure has increased in the last three decades, in great part due to farmers shifting from surface water (such as from lakes) to groundwater for irrigation. Groundwater extraction on a large scale has become possible only recently due to the proliferation of high-power tube wells. Thus, unlike in the case of surface water, traditional community governance institutions do not exist for groundwater use. This provides an ideal scenario for conducting empirical studies on the development of norms and institutions for community resource governance (ibid.).

In the study, groups of participants from farming communities of Andhra Pradesh were asked to choose between two crops: crop A, which yields lower profits but consumes less water, and crop B, which yields higher profits but consumes more water. Thus, in this game, the 'cooperation' strategy is to choose crop A and the 'defection' strategy to choose crop B. The game was played over multiple rounds. After every round, groundwater was replenished by a fixed amount. The players communicated their crop choices in secret to the game facilitator. The water level was shown graphically to the participants after every round (ibid.).

The researchers examined the role of various factors, including communication among participants and the level of trust in community, in affecting crop choice. According to Janssen and Ostrom (2006), data collected from role-playing games can be used as input for ABM. Thus, the insights into the motivations of actors faced with a collective-action dilemma from Meinzen-Dick et al. (2018) can serve as the empirical foundation for modelling micro-level behaviour in an agent-based model for community groundwater management.

6. Preliminary model

Groundwater levels are affected by both natural (such as rainfall) and social factors (such as individual choices and state policy). Due to the non-linear nature of these relationships, ABM is ideal for understanding the dynamics of groundwater management. Fig. 2 graphically shows the factors affecting individual behaviour, which in turn determine groundwater levels, and the relationships between them.

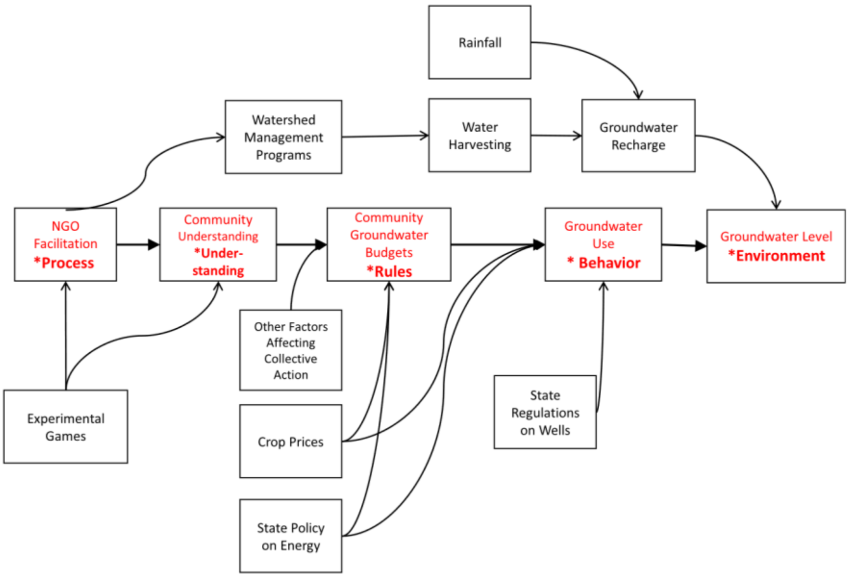


Fig. 2. Factors affecting groundwater levels (Meinzen-Dick et al, 2018: 43).

Here, I develop a preliminary agent-based model of the dynamics of groundwater use in agrarian communities of Andhra Pradesh, India based on the results of Meinzen-Dick et al. (2018). From a CPR management perspective, the most relevant parameters are the ones that determine whether actors choose to cooperate or defect, which in this case correspond to choosing the low and high water-consuming crop, respectively. Of the twelve factors that were identified in affecting crop choice (such as initial water level, education level, and gender), I model only three—inter-agent communication (a community-level parameter), level of trust (an individual-level parameter), and initial groundwater level (an environmental parameter)—for simplicity.

The aim of this study is to develop a very basic model founded in empirical data to aid a preliminary *qualitative* exploration of groundwater CPR dynamics. At this stage, the model is highly abstract with a number of simplifying assumptions. In Section 8, I propose the further development and potential applications of the model.

6.1. Model description

The model, implemented in the software NetLogo, consists of agents who own a finite amount of land. For the sake of simplicity, it is assumed that all agents have the same amount of land and the same capacity to extract groundwater (e.g., the same density of tube wells) per unit area of land. This assumption was also adopted in the game used by Meinzen-Dick et al. (2018).

The simulation begins with an initial groundwater level. The groundwater level changes after every round as a function of crop choice and a fixed replenishment amount (e.g., through rainfall). In each round, agents choose to plant either crop A (which consumes 1 unit of groundwater and earns 3 units of profit) or crop B (which consumes 3 units of groundwater and earns 5 units of profit), depending on three parameters: the trust index (which captures the level of trust in community) of the individual, whether communication takes place in the community, and the initial groundwater level. Once the groundwater level goes below 10 units, crops cannot be sustained anymore. (Numbers adopted from Meinzen-Dick et al. (2018)).

Monitors are added to track the following variables of interest: (i) variation of groundwater level over iterations and (ii) wealth distribution in the population.

6.2. Parameters affecting crop choice

i. *Trust index*

The trust index was developed by Meinzen-Dick et al. (2018) as a measure of the level of trust that an individual has in other community members. It was determined empirically for each participant through surveys and normalized to a value between 0 and 1.

In the model, I assume the trust index to follow a standard normal distribution in the population around a variable mean value, ‘trust-index-mean’, which can be changed by a slider in the NetLogo interface. A lower mean implies a lower average level of trust in the population. A higher ‘trust-index-mean’ is thus expected to have a positive effect on the tendency to cooperate because the individual is also more likely to trust that other community members will cooperate. s

To ensure that the trust index remains in the range of [0,1], I use a bounded standard normal distribution, which simply discards any values beyond this range. Thus, as the mean is changed, the standard normal shifts horizontally and is truncated at 0 or 1 (Fig. 3).

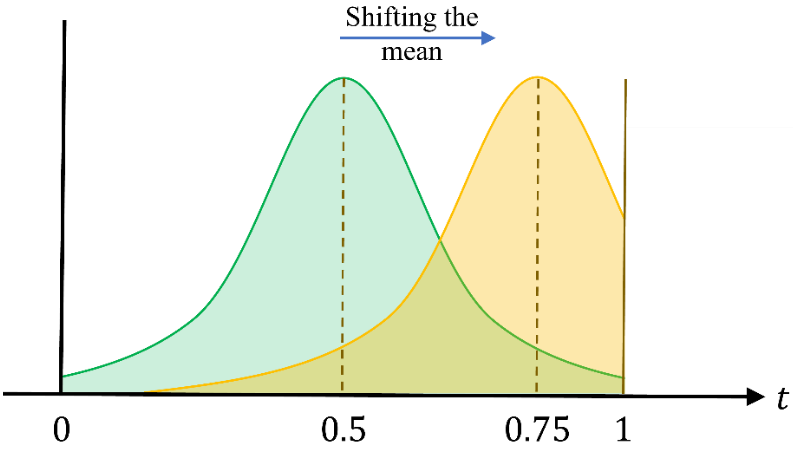


Fig. 3. Distribution of trust index t in population: Bounded normal.

ii. *Communication*

In Meinzen-Dick et al. (2018), communication is a binary community-level variable: it is either present or absent. The parameter 'comm-allowed' is introduced as a binary switch in the NetLogo model: 0 and 1 indicate that communication is allowed and not allowed, respectively. Allowing communication is expected to have a positive effect on the tendency to cooperate because communication enables rules and institutions to be developed.

iii. *Initial groundwater level*

It is hypothesized that agents get more conservative with their water usage if the initial groundwater level is lower, i.e., they tend to plant crop A more. I model the relationship between the probability of planting crop A (p_A) and the initial groundwater level (i) as a linear, monotonically decreasing one (Fig. 4).

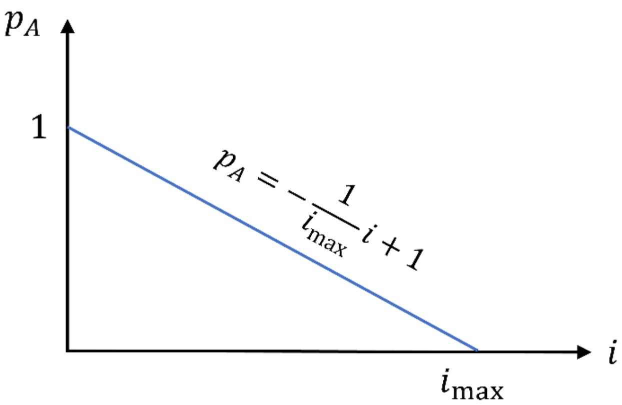


Fig. 4. Relation between probability of planting low water-consumptive crop (p_A) and initial groundwater level (i).

Meinzen-Dick et al. (2018) used logistic regression to determine the degree of dependence of crop choice on the variables. Their results were sensitive to small changes in the game structure. The experiment was repeated in two consecutive years with slight changes in the rules of game, and all three parameters considered in the were significant in one of the games but not the other.

As the model proposed here is intended to aid qualitative exploration, the precise numerical form of the dependence of crop choice on these parameters is not important. To simplify the model, I assign equal weights to all three parameters. The final equation determining crop choice of an *individual agent* is as follows:

$$p_A = \frac{1}{3}t + \frac{1}{3}c + \frac{1}{3}\left(-\frac{1}{i_{max}}i + 1\right), \qquad \text{(II)}$$

where p_A is the probability of planting the low water-consumptive crop (crop A), t is the agent's trust index, c is the binary communication variable in the community, and i is the initial groundwater level.

6.3. Assumptions and limitations

i. *No spatiality*

The model does not incorporate any spatial element of groundwater dynamics. Groundwater withdrawn from one region is assumed to lower the water table equally throughout the farm area. This assumption is valid in small regions or over sufficiently large time scales. However, to investigate larger regions, such as the entire state of Andhra Pradesh, and/or smaller time scales, such as in a single season, it is necessary to consider the spatial dimensions of groundwater diffusion by modelling the physical characteristics of the soil and substrate. For example, the water table may get lowered more in a patch of farmland with high withdrawal rates than in its surrounding farms.

When considering spatiality, the geographical distribution of farmland among agents also becomes relevant. Thus, it is necessary to have a spatial map of the entire farm area with different sections of the land assigned to different agents.

ii. *No inequality*

In the current model, it is assumed that all agents have equal land and resources for cropping and irrigation. However, in reality, the distribution of land among farmers is highly unequal following the traditional Indian caste structure (Meinzen-Dick et al., 2018: 43–44). Thus, it is necessary to incorporate the unequal land distribution to more accurately understand the resulting wealth distribution and differential role of big and small landowners in groundwater depletion and management.

iii. *Dependence of crop choice on parameters*

The crop choice function (equation II) in its present form is highly abstract. While it allows the exploration of the qualitative features of groundwater management, its quantitative foundations are not rigorous. In the experiments conducted by Meinzen-Dick et al. (2018), the dependence of crop choice on parameters such as the trust index is very sensitive to the structure of the game. Thus, it is difficult to come up with accurate weights for these parameters in the function based on data from this study alone. Moreover, the assumed form of t (normal variation) and dependence of p_A on i (linear) are arbitrary and not based on empirical data.

An important caveat is that even with further refinement, the usefulness of the model for making accurate quantitative predictions will always be limited because agent behaviour in this problem is highly context-sensitive and difficult to predict, especially given the scarcity available behavioural data. Rather, the utility of the model is that it allows one to investigate the possibilities with different interventions and institutional arrangements. Thus, the model can serve as a guide for practical policy design.

In Section 8, I will discuss how the model can be modified to overcome these limitations.

7. Results and discussion

The emergent macro dynamics of the system resulting from the micro-level agent modelling described in Section 6 are discussed here. The model parameters are presented in Table 1:

Table 1. Model parameters.

Parameter	Range	Default value
Initial groundwater level (‘init-gw-level’)	0–500	250
Number of agents (‘num-agents’)	0–50	10
Mean trust index (‘trust-index-mean’)	0–1	0.5
Communication (‘comm-allowed’)	Boolean	1

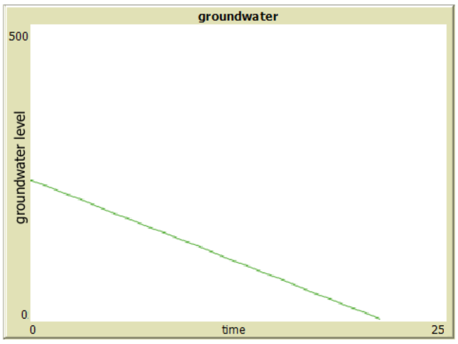
The system dynamics are investigated by varying each of the parameters while holding the others constant.

i. *Initial groundwater level*

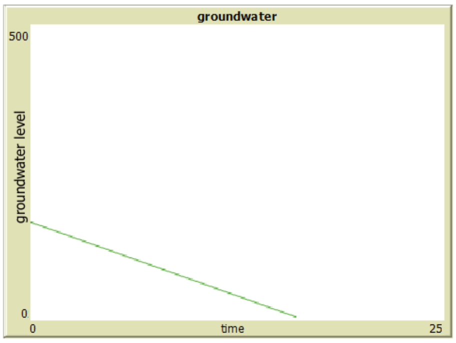
The initial groundwater level has a two-fold influence on the model—it is both the starting value of the simulation and a parameter in the crop selection function (II). At the default value of 250, the groundwater is depleted in about 20–25 time steps. As the initial groundwater level is decreased, the number of steps it takes to deplete groundwater decreases almost linearly. However, when the initial groundwater level is increased from 250, the time taken for depletion does not continue to increase linearly but rather saturates at a point, specifically around 30 time steps at an initial groundwater level of ~350.

This suggests that up to a point, the effect of the decreasing initial reserve of groundwater outpaces the effect of cautious crop choice. However, at a certain threshold, the latter catches up and the effects of the two factors balance each other out.

Some representative plots are shown in Fig. 5. The dynamics are very stable, i.e., the number of time steps to reach groundwater depletion does not vary much for different iterations with the same set of parameter values despite the stochastic element introduced in the trust index.



(a)



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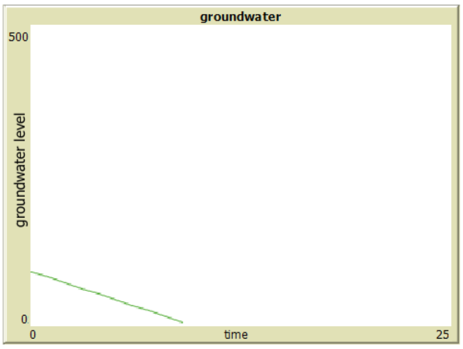

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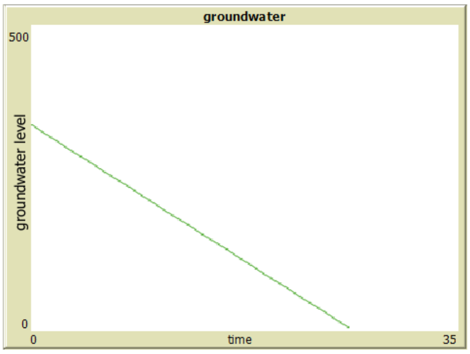

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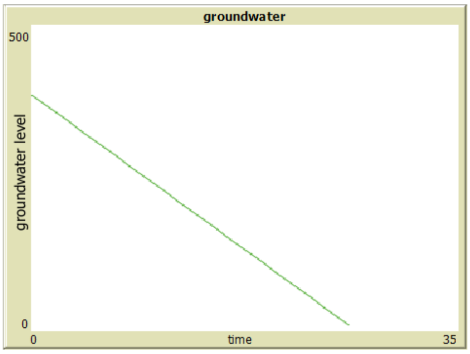
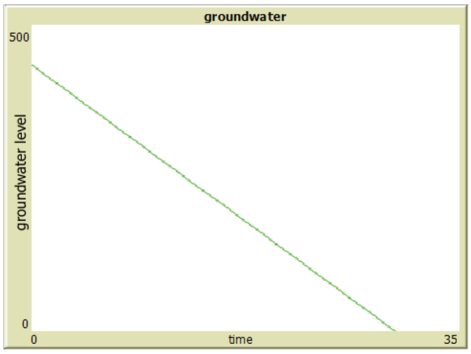


(e)



(f)

Fig. 5. Effect of initial groundwater level ('init-gw-level').

(a) init-gw-level = 250; number of steps for groundwater depletion = 22
(b) init-gw-level = 175; number of steps for groundwater depletion = 17
(c) init-gw-level = 100; number of steps for groundwater depletion = 10
(d) init-gw-level = 300; number of steps for groundwater depletion = 27
(e) init-gw-level = 350; number of steps for groundwater depletion = 27
(f) init-gw-level = 400; number of steps for groundwater depletion = 31

ii. *Number of agents*

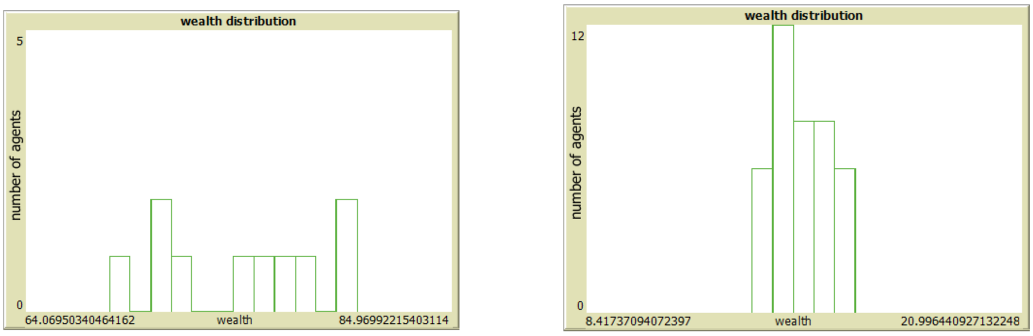
The number of steps it takes for groundwater to deplete for different values of ‘num-agents’ is presented in Table 2.

Table 2. Effect of number of agents.

‘num-agents’	**Number of time steps to ‘gw-level’ = 10**
5	~ 90
7	~ 40
10	~ 20
15	~ 12
20	~ 10
30	6
40	5
50	4

Thus, the effect is non-linear: at lower ‘num-agents’, the system outcome is highly sensitive to changes in the parameter, but at higher ‘num-agents’, sensitivity decreases. This is because with increasing ‘num-agents’, groundwater usage saturates due to the finite amount of initial groundwater. Note that the entire land (i.e., groundwater capacity) is not divided equally among the agents; rather, each agent has a fixed capacity for groundwater withdrawal irrespective of the initial groundwater level.

As ‘num-agents’ increases, the wealth distribution starts approaching a normal distribution because of the higher sample size, reflecting the normal distribution of the trust index. Below a threshold of ~30, it is difficult to discern a pattern in the shape of the wealth distribution. Some sample results are presented in Fig. 6.



(a) *(b)*

Fig. 6. Wealth distribution at ‘num-agents’ = (a) 10 and (b) 40.

iii. *Mean trust index*

Surprisingly, changing the 'trust-index-mean' from 0 to 1 while holding the other parameters constant has no effect on the system outcomes. The number of time steps to reach 'gw-level' = 10 remains the same. This does not change even after assigning a higher weight to the trust index parameter in crop choice. This may be because the truncated normal distribution does not impart a high sensitivity of the crop selection function to the mean, or that the cumulative effect of selecting the lower water-consumptive crop somehow cancels out when over multiple rounds of the game. This result is puzzling and requires a thorough analysis.

iv. *Communication*

Switching communication off reduces the time taken to reach groundwater depletion by an offset, as expected. This is a straightforward result because communication is encoded in the crop selection function as a binary variable. Thus, this does not reveal any interesting insights into system behaviour but is a test of consistency. The 'comm' variable may be an interesting swich when introducing more parameters in future model development.

The system exhibits a high degree of convergence: there is little variation in the time curve of groundwater (which is highly linear) for different runs with the same parameter settings. This is because of the low stochasticity in the model; the only element that incorporates stochasticity is 'trust-index-mean', and as discussed in this section, this parameter does not have a noticeable effect on the dynamics. Thus, future model development must incorporate more stochasticity to accurately model real-world scenarios.

8. Further model development

8.1. Parameters

The current model has many limiting assumptions, as discussed in Section 6.3. Here, I propose potential modifications and further refinements to overcome these limitations.

i. *Incorporating spatiality*

As discussed in Section 4.1, one advantage of ABM is that it can incorporate spatiality through cellular automata. The model presented in Section 6 lacks a spatial element in that groundwater withdrawal in one region is assumed to lower the water table in the entire area equally. This is a valid assumption for sufficiently small areas or sufficiently large time scales so that the water level equilibrates throughout the area.

To investigate larger areas (such as the entire state of Andhra Pradesh in this example) or smaller time scales (such as variations within a single growing season), it is important to consider spatiality by incorporating the physical features of the soil and other environmental factors affecting groundwater. For this, the model will include a lattice of grids representing patches of farmland.

The spatial and temporal aspects of groundwater diffusion can be taken into account by using Fick's law, which describes the dynamics of the flow of material as a function of its concentration gradient (Conlisk, 2013: 43):

$$J = -D\frac{d\Phi}{dx}, \tag{III}$$

where J is the diffusion flux (total current per unit time through a cross-section of flow), D is the diffusion constant, and $\frac{d\Phi}{dx}$ is the concentration gradient of the material (in this case, the gradient of the water table).

D is an empirically determined material property that will be dependent on the soil composition. The relevant values of the parameters D can be determined from reported values in the literature. The starting (equilibrium) gradient ($\frac{d\Phi}{dx}$) at the beginning of the simulation is the natural water table of the region, which will depend on physical factors such as topography and natural water sources and human activity such as past water pumping. This can also be determined from empirical studies of groundwater distribution in the region.

When water is pumped in one patch of farmland for irrigation, the equilibrium is disturbed, i.e., $\frac{d\Phi}{dx}$ changes. Thus, a water current begins to flow until the system regains equilibrium and the water table stabilizes. Thus, this parameter will be relevant for if the time scale for attaining steady state is of comparable order of magnitude to the cropping period, depending on D and the total area of the farmland. Note that for a two-dimensional groundwater model, the two-dimensional form of (III) must be used.

After solving (III) with the relevant boundary conditions, a part of the spatial grid in the model may look similar to Fig. 7. Here, the intensity of the green colour represents the height of the water table—a darker green represents a higher water table—and red represents unviable patches. Thus, the spatial model will be an abstract representation of the relevant geographical features of the region based on empirical data.

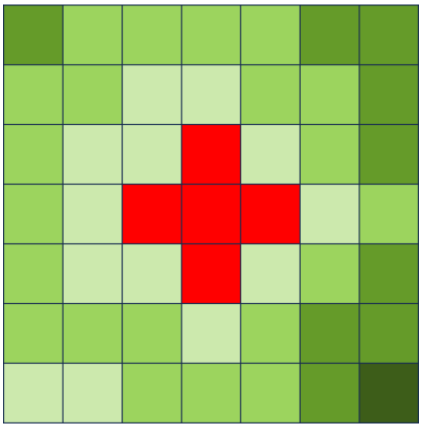


Fig. 7. Spatial grid of farm patches in model. Darker greens represent patches with higher water tables; red represents patches that cannot sustain crops.

ii. *Incorporating inequalities*

In the present model, inequalities in land distribution are not considered. It is assumed that every agent has equal area and equal technological capacity for crop planation and irrigation. In reality, the distribution of land in Andhra Pradesh is highly unequal and strongly follows traditional Indian caste structures (Meinzen-Dick et al., 2018: 43–44).

These inequalities can be incorporated into the model by assigning agents different land areas, i.e., different capacity for groundwater extraction. The land distribution can be modelled to follow a *power law distribution* with the power law index calibrated with census data from the state. This can be taken further by considering government data for the number of tube wells installed by different groups of landowners. Land distribution can be incorporated into the spatial model proposed under '*Incorporating spatiality*' by assigning a collection of adjacent patches to a single agent.

Incorporating unequal land distribution into the model can help understand the different roles of landowners in affecting groundwater according to their land ownership. The of crop choice on land ownership as probed by Meinzen-Dick et al. (2018) may also be considered. Finally, it will be interesting to see the effects of unequal land distribution on wealth distribution.

iii. *Refining the crop selection function*

Agent behaviour in the CPR model is captured in the crop selection function (II) (Section 6.2.1); hence, selecting the relevant parameters and their weights and determining the appropriate form of the dependence of p_A on these parameters are both crucial and challenging. This needs to be tackled along the following dimensions:

a. Determine *which parameters are significant*: Meinzen-Dick et al. (2018) identified twelve factors that influence behaviour. However, whether some parameters, such as communication, are statistically significant depends greatly on the specific features of the game structure. Thus, it may not be useful to rely on the logistic regression results as mathematically precise weights. Rather, the function of the model, i.e., the balance between quantitative precision and qualitative features, must be further clarified.
   In particular, the form of the 'trust-index' function must be investigated further with a sound empirical basis. In the present model, this parameter has little effect on system outcomes; thus, the bounded normal distribution may not be appropriate to model this variable.
b. As *behavioural data* for the specific case of groundwater management in Andhra Pradesh is limited, generalizable behavioural data from other case studies can be used for the initial modelling. The empirical validity of the assumptions made needs to then be rigorously evaluated as described in Janssen and Ostrom (2006).
c. Behavioural data from Meinzen-Dick et al. (2018) can be combined with other types of data such as from remote sensing, surveys, and censuses. This kind of a *hybrid approach*, called case-study analysis, is common in ABM in agricultural economics (Janssen & Ostrom, 2006: 36–37).

Finally, all the numerical values in the present model need to be rigorously evaluated against empirical data so that they accurately represent the real-world dynamics of the problem. Further, higher system stochasticity needs to be incorporated as discussed in Section 7.

8.2. Applications

The model may be developed for two distinct applications.

i. *Research and policy design*

The modelling approach discussed so far in this paper was aimed at developing it as a tool for research. As discussed earlier, the model is likely to have limited utility for providing precise quantitative predictions unless more data is collected on agent behaviour for the specific case study. However, it may be useful to explore the possible outcomes of different policy interventions, e.g., setting up self-governance institutions, subsidy design for irrigation, land tax, etc. The different outcomes resulting from different policies may then be compared fruitfully with qualitative exploration as enabled by the present model.

ii. *Interactive game*

The second application is to develop an interactive game to aid behavioural experiments and interventions, e.g., a digital version of the game used by Meinzen-Dick et al. (2018).

Hence, no behavioural agent modelling is required for this application. Instead, an interactive platform will be designed through which participants can enter their crop choices in every round of the game. The digital platform has the following advantages over the analogue game:

a. A larger number of participants can be included by playing the game virtually, thereby increasing the sample size of behavioural data.
b. A greater number of parameters with more complex relationships can be included as the computation of groundwater level is done by a computer and not manually.
c. Spatiality can be incorporated.
d. Participants can visually see results on the interactive platform. This can potentially aid in better understanding of groundwater dynamics.

9. Conclusion

In conclusion, this paper proposed an agent-based model for collective groundwater management in the context of irrigation in Andhra Pradesh, India based on empirical behavioural research. The ontological foundations of complex systems economics and methodology of agent-based modelling were discussed to provide theoretical grounding to the proposed model. Then, a preliminary model was developed and its results analysed. Finally, avenues for further development and refinement of the model were discussed.

It is hoped that the ideas developed in this study can serve as the starting point for building a robust, empirically founded agent-based model for groundwater management in peninsular India and in other contexts. This can aid the qualitative exploration of the outcomes of various policy alternatives. Another potential application is to develop an interactive online role-playing game that can be used for further behavioural research and interventions.

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