Appendix: Groundwater Commons Game ODD+D Model Documentation

Table A.1. ODD+D[1,2] model documentation for the Groundwater Commons Game

		Guiding questions	Description
I) Overview	**I.i Purpose**	**I.i.a What is the purpose of the study?**	To synthesise and extend existing work on human cooperation and collective action, to elucidate possible determinants and pathways to regulatory compliance in groundwater systems globally. We have designed the 'Groundwater Commons Game' (GCG) as a scientific instrument to systematically investigate mechanisms that may lead to compliance with groundwater conservation policies, taking into consideration human behavioural variables revealed by the World Values Survey. The study aims to: ● offer general insights that are applicable to aquifers everywhere ● parametrise agent behaviours using the most recent version of the World Values Survey ● develop GCG simulations for three real-world case studies; the Punjab (India/Pakistan), the Central Valley (USA), and the Murray-Darling Basin (Australia) ● assess the validity of results using surveys from the Murray-Darling Basin ● propose policy recommendations of global relevance More broadly, the systems understanding that we present here has general implications to any regulated resource that is accessed by many users, as in the case of fisheries, forests, wildlife and global climate.
		I.ii.b For whom is the model designed?	The model is designed for groundwater scientists, groundwater managers, decision and policy makers interested in natural resource management and regulatory compliance. The GCG can also be used for learning activities in undergraduate and graduate courses in environmental management. Water managers typically evaluate the performance of enforcement and compliance policies via manager experiences, outcomes from enforcement actions, field surveys and interviews. These instruments however may not reveal the true motivations and attitudes towards water regulation. The cost and time of conducting empirical research can be significant. These are major challenges for decision-makers searching for courses of action that lead to long-term compliance and extend economic activity in groundwater basins subject to depletion. Simulation-based approaches like the one proposed here can help water authorities overcome the difficulties of studying rule-breaking behaviour directly, and provide new insights on how human behaviour impacts resource conservation at the global scale.
	I.ii Entities, state variables, and scales	**I.ii.a What kinds of entities are in the model?**	• Individual farmers • A water authority/regulator • The groundwater resource—a physical entity • The agricultural region—defined by the number of farmers and the local economy

		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	**Farmer:** geographical location (determines depth to water table), irrigated acreage (ha), gross margins from crop ($/ha), behavioural strategy (B=boldness, P=punitiveness), pumping decision (comply, defect), mutation probability (probability that the agent will try a new strategy, fixed at 5%), Economic utility (E), Institutional utility (I), Social utility (S), overall Performance Index (PI=E*I*S), rule-follower (yes/no), grid/group scores (determined from the WVS, see Methods), pump efficiency (~80% for centrifugal pumps), returns ($/ha), irrigated area (ha) **Water authority:** Pumping cap (% of licensed allocations), % monitoring capacity (M, 0-50%), magnitude of monetary fines (F, representing the fraction of farmer profit forgone to pay a fine), risk-based management (yes/no), monitoring style (constant/adaptive), graduated sanctions (yes/no) **Groundwater:** model size (kmxkm), number of cells, cell dimensions (m), boundary conditions (no-flow, specified-flux), aquifer thickness (m), hydraulic conductivity (m/d), storativity, initial heads (m) **Agricultural region:** number of farmers (per/ha), crop parameters (type, price $/ton, yield ton/ha, water requirement ML/ha, energy price $/kWh, other variable costs $/ha)
		I.ii.c What are the exogenous factors / drivers of the model?	• Country-level Grid-Group scores determined from the World Values Survey • Level of monitoring (M) and fines (F) adopted by the water authority • % rule-followers in the population • Groundwater conditions (hydraulic parameters, boundary conditions)
		I.ii.d If applicable, how is space included in the model?	Explicitly through the location of each farm within the modelled domain. The depth to groundwater is spatially variable (following the hydraulics of groundwater flow), thus location determines the costs to extract groundwater, and the information each farmer has on his/her neighbour's strategies.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	Six-month timesteps over a period of 100 years. The first 50 years represent a burn-in period without management, followed by 50 years of groundwater regulation. Irrigation decisions are taken at the beginning of a season, i.e. once a year, except in the wheat-rice rotation in Punjab example where irrigation decisions are taken twice a year. The groundwater sub model represents a 10x10 km basin, discretised into 40x40 cells. The dimension of each cell is 200 m. Model boundary conditions are defined by a no-flow boundary to the North and South, and constant head boundary cells to the East and West; setting head values to create an East-West gradient of 1/1,000 representing typical conditions in regional aquifer systems. Groundwater is pumped from a semi-confined sand aquifer of 50 m thickness, hydraulic conductivity K=10 m/d and storativity St=1e-4.
	I.iii Process overview and scheduling	**I.iii.a What entity does what, and in what order?**	See Supplementary Figure 1 below
	II.i Theoretical and Empirical Background	**II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the**	Tipping points and critical transitions[3-5], theory of complexity and complex adaptive systems[6], groundwater hydraulics[7]. The link to complexity related to emergent patterns across the grid-group plane in the form of tipping points. This suggests that certain social interactions and nonlinearities in the system can be exploited

II) Design Concepts		**sub model(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?**	to trigger long-term resource conservation.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	Agents are bounded rational[8], use a form of inductive reasoning[9], rely on heuristics[10] and they have no foresight[11,12]. Agents engage in a process of trial and error to determine their best decision (how to update their strategies in terms of B and P) based on their experience with past strategies and the imitation of successful neighbours. This assumption is supported by recent work in the context of the role of imitation in land use change and the adoption of agricultural innovations, and work on imitation in spatial games{Gotts:2009td}—this research confirms that farmers are influenced toward adopting new land uses, techniques, or behaviours by the example of other farmers they know. Studies of the spatial characteristics of innovation diffusion also indicate that imitation of neighbours is important.
		II.i.c Why is a/are certain decision model(s) chosen?	The decision model of the water authority is based on real-world attributes of groundwater governance systems. The decision model of farmers builds on Robert Axelrod's seminal paper on the emergence of social norms[13]. Here, we adapt Axelrod's framework to study social norms in the context of compliance with groundwater conservation policies. The GCG is designed to be very general and the approach can be applied to any number of problems involving stressed groundwater systems. The structure and assumptions of the GCG can be easily tailored and/or extended to suit specific economic, institutional, social, and hydrogeological contexts. Key changes to Axelrod's original model are: 1. We consider local interactions between neighbouring agents, instead of a "soup" model as in Axelrod's model, where all agents interact with each other. In our model, monitoring and punishment is local instead of global; see[14]. 2. We incorporate the physics of groundwater flow as one of the drivers of agent behaviour. We explicitly quantify the economic damage (externality) imposed by defecting wells on other wells, which manifests as additional pumping costs incurred within a neighbourhood of the defecting well. The extent of this neighbourhood is determined by the local hydrogeological conditions and the magnitude of a breach. 3. We use a combined score metric to quantify 'fitness' of an agent at every moment, based on economic, institutional and social factors. In the Axelrod case, fitness is entirely driven by the social component. 4. We introduce variability in the magnitude of breaches, as we would expect in agricultural settings. 5. Breaches are not only enforced by agents, but also by a water authority: the water authority. Enforcement therefore occurs at the local and basin scales.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	Agent behaviour is parametrised using Grid-Group dimensions obtained from Wave 6 of the World Values Survey The hydraulic properties of the groundwater sub model are typical of groundwater basins in alluvial settings[15]. All hydrogeological parameters can be changed with frugal user intervention via the provided interface.

		II.i.e At which level of aggregation were the data available?	The WVS is conducted at the country-level and each wave represents a period of approximately four years.
	II.ii Individual Decision Making	**II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?**	Decision making is modelled at two levels: • The water authority decides about the cap on groundwater allocations, the level of monitoring and the severity of fines • The farmers decide about whether to comply with the allocations or not, and in doing so, the area of land that will be irrigated in a given year.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	Agents are assumed to employ a simple utility function to evaluate the social and economic implications of their actions. This utility function combines: an economic score (*E*) that quantifies the gross margins of crop production, considering pumping costs based on local groundwater drawdowns; an institutional score (*I*) that notionally represents the proportion (0-100%) of gross margins forgone to pay fines; and a social score (*S*) that notionally represents the loss of reputation (proportional to Group) and the social costs of reporting offenders (inversely proportional to Grid). These components are combined into an overall performance index $PI = E*I*S$, which agents use to compare and decide among competing strategies (B,P).
		II.ii.c How do agents make their decisions?	Agents rely on local information and operate on a simple heuristic to decide what do next: "*imitate* the strategy of whichever neighbour is doing best, *exploit* the current strategy if better, and *explore* a new strategy occasionally"[12] Decisions that are selected on the criterion of their recent performance within the neighbourhood of the land parcel concerned—as implemented in our model—is known as "Best-mean Imitation". Gotts et al.{Gotts:2009td} show that Best-mean imitation outperforms other forms of imitation in a wide range of settings.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes, they use the imitation heuristic described above to adapt their behavioural strategies (B,P), which in turn define whether or not they will comply with water allocations and whether they will report offending neighbours.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Indeed, our model focuses on a limited set of contextual factors that play a role in achieving community compliance—conservation policies, social norms, and cultural values. These factors have been identified as fundamental drivers of human cooperation[16,17] and collective action[18-20] in a wide range of settings. Cultural parameters are derived from the World Values Survey (see Methods)
		II.ii.f Do spatial aspects play a role in the decision process?	Yes because the imitation of neighbours and the drawdown propagation are spatial factors influencing decisions.
		II.ii.g Do temporal aspects play a role in the decision process?	In this study we assume that agents have no memory of past decisions; however this feature is implemented in the model (see Netlogo version of the model in Open ABM repository)
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Uncertainty is incorporated as agents are only aware of information about their immediate neighbourhood and not those further afield. Another source of uncertainty is the strategy mutation rate (fixed at 5%) which determines how often agent will choose to try a completely new strategy. This introduces novelty to the pool of strategies in the agent population.

	II.iii Learning	**II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?**	Learning occurs via a "best-mean imitation" heuristic{Gotts:2009td} based on past performance of strategies within the neighbourhood of the land parcel concerned. The heuristic is: *imitate* the strategy of whichever neighbour is doing best, *exploit* the current strategy if better, and *explore* a new strategy occasionally"[12]
		II.iii.b Is collective learning implemented in the model?	Collective learning is not implemented in the model but it is an emergent property of the system. The decision heuristic is a genetic algorithm which the agent population uses to discover and exploit decisions that provide the highest utility, considering the simultaneous decisions of the collective
	II.iv Individual Sensing	**II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?**	Individuals sense depth to water table, irrigation costs, yields and their budget. All these variables are known without error.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	A farmer can perceive the Performance Index (PI) and strategy (B,P) of its immediate neighbours (i.e., we assume they can look over the fence). The water authority can assess whether a farmer has complied or not with the allocated water, provided there is sufficient capacity and resources to send inspectors to the field (M determines the maximum number of farmers that can be audited in a given year) All these parameters and behaviours are known without error.
		II.iv.c What is the spatial scale of sensing?	Basin (water authority), immediate neighbourhood (farmers).
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Sensing is local, but information can spread across through farmer networks. The calculation total utility (PI) is modelled explicitly (as a weighted average of social, institutional and economic utilities). All other variables are just known by the agents.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No
	II.v Individual Prediction	**II.v.a Which data uses the agent to predict future conditions?**	Agents have no ability to predict future conditions
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	No specific models
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Agents' predictions/decisions are erroneous because of unknown variability of other's decisions. Agents neither know about the strategies, performance and decisions of agents beyond their immediate neighbourhood.

	II.vi Interaction	**II.vi.a Are interactions among agents and entities assumed as direct or indirect?**	Direct via Best-mean imitation Indirect through groundwater extraction and the topology/superposition of pumping cones of depression.
		II.vi.b On what do the interactions depend?	Location of agents within the basin
		II.vi.c If the interactions involve communication, how are such communications represented?	There is no communication, agents essentially perceive the performance and strategies of other agents by 'best-mean imitation'[14]
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	The topology of the agent network is determined by the number of agents per hectare, as revealed by the FAOSTAT database (see Extended Data Figure 3)
	II.vii Collectives	**II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?**	No
		II.vii.b How are collectives represented?	There are no collectives in this model
	II.viii Heterogeneity	**II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?**	No
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	The agents are not heterogeneous in their decision-making, but we impose no constraints on the strategies that they choose.
	II.ix Stochasticity	**II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?**	Individual agents are assigned a strategy (B,P), with each component independently drawn at random from a [0,1] uniform distribution. No correlation between B and P is assumed, although this may be an emergent property of the system. Also, when an agent chooses to try a new strategy, either B or P (with 50% chance) is replaced by a random number drawn from a [0,1] uniform distribution.
	II.x Observation	**II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?**	The data collected is: • Compliance (% of agents that comply), • Strength of social norms, SN=mean P – mean B • Gini coefficient (statistical measure of income inequality) • Mean water table drawdown below surface (m) • Total volume of breaches (ML) • Mean B • Mean P • Mean cumulative profits of agents

			This data is collected at each time step and is available in time series format.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	Our main finding is that collective attitudes towards groundwater conservation policies are governed by tipping points.
II) Details	**II.i Implementation Details**	**III.i.a How has the model been implemented?**	The coupled agent-based groundwater model was developed using FlowLogo[21] (Extended Data Fig. 2), a software platform developed in Netlogo specifically for this purpose[21].
		III.i.b Is the model accessible and if so where?	Yes, in the OpenABM library (www.openabm.org) of the 'Network for Computational Modelling for SocioEcological Science' (CoMSES) at: *https://www.openabm.org/model/5634/version/1/view*
	III.ii Initialization	**III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?**	For our three case studies and for each possible combination of grid and group scores (9 grid scores x 9 group scores = 81 combinations), we initialised 100 'unregulated' (*M*=0, *F*=0) runs. In each run, individual agents were assigned a strategy (B,P) with each variable drawn at random from a [0,1] uniform distribution. No correlation between B and P is assumed. The possible grid-group scores are grid=0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9 group=0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9 and their permutations. The step between scores are arbitrarily chosen, but a finer resolution is probably not necessary. The groundwater model was set up using hydrogeological parameters characteristic of regional flow conditions in alluvial settings (see below). In each run, and after a 50-year burn-in period, we activated groundwater management scenarios (setting *M*,*F*≠0) with allocations arbitrarily set at 20% (to represent an extreme scenario of groundwater conservation). This assumption also reflects the fact that it is politically challenging to implement regulations in the real-world, and once regulations are introduced they are often hard to adjust over time. We then simulated the evolution of the system over 50 years. Four combinations of discrete values of M (monitoring) and F (fines) were chosen to develop four specific scenarios (see Extended Data Figure 4): • lax enforcement: M=0.1, F=0.1 • low monitoring: M=0.1, F=0.9 • low fines: M=0.5, F=0.1 • full enforcement: M=0.5, F=0.9 The biggest assumption here is M=0.5. The logic for not using a higher value for monitoring is because from our experience, it will be unlikely that the water authority will be able to monitor more than half of water users. The four scenarios chosen here are in our opinion sufficient to understand the general effects of regulation on the tipping points.

		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	To account for uncertainty and stochasticity, we report the mean and standard deviation of 100 independent realisations. In each realisation, agents are initialised with a strategy (B,P), with each component independently drawn at random from a [0,1] uniform distribution. No correlation between B and P is assumed
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Gross margin data was determined from published agro economic statistics (see Supplementary Table 1) Cultural parameters were determined from Wave 6 of the World Values Survey.
	III.iii Input Data	**III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?**	The model uses Grid-Group scores of cultural dimensions obtained from Wave 6 of the World Values Survey. Agroeconomic data for the three case studies (Supplementary Table 1) is included in the code, but could be read from external data files.
	III.iv Submodels	**III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?**	• Institutional submodel • Agent decision submodel • Economic submodel • Social submodel • Groundwater submodel
		III.iv.b What are the model parameters, their dimensions and reference values?	See: • Supplementary Table 1 • Extended Data Tables 1 & 2 • Extended Data Figures 1, 3 & 4 • Figure 1
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	See text below

Institutional submodel

Agents represent farmers in a groundwater basin where a primary crop is grown, e.g., cotton, almonds, wheat, etc. The problem is intentionally designed to be water-limited. Rainfall is not sufficient to irrigate crops and the underlying aquifer is used to supplement irrigation demands. Drought and overexploitation have also led to additional restrictions on groundwater withdrawals. To overcome this situation, the water authority imposes a cap on groundwater entitlements which applies equally to all agents. Capped groundwater withdrawals constrain farmers' profits, which have to cut back from the ideal levels of irrigation that maximize crop yields and irrigated acreage.

Groundwater allocations are implemented as a system of non-transferable entitlements or water rights. Our focus is exclusively on the role of social norms, thus we do not consider trading of these entitlements, as this would incorporate an additional and unnecessary level of complexity to the analysis. Trading rules, however, could be easily implemented in our model.

Farmers agents have the option of behaving opportunistically by pumping more water than the allocated limit (i.e., the cap imposed by the water authority). The consequences of their decisions are modelled with an institutional utility function, I, which notionally represents the proportion of gross margins forgone to pay fines when an agent is caught breaking the rules, according to the following relationship:

$$I = \begin{cases} 1, & if\ an\ audited\ farmer\ cooperated \\ 1 - F, & if\ an\ audited\ farmer\ was\ caught\ defecting \end{cases}$$

Where F (0-1) is the severity of fines implemented by the water authority. The larger F is, the greater proportions of profits need to be used to pay a fine.

Agent decision submodel

An agent's strategy has two dimensions: the propensity to defect (boldness, B), and the propensity to act in a punitive manner (punitiveness, P). B and P are continuous variables between 0 and 1. For instance, an agent with B=0.8 and P=0.8 is very likely to defect, but also very likely to punish other farmers breaching the seasonal allocation. On the other hand, an agent with B=0 and P=1 could be considered as a strong rule-follower. Many combinations are possible. The population averages of B and P define the presence or absence of a social norm (SN). Following Axelrod's definition: a social norm of compliance emerges when B~0 and P~1 become a stable and long-term condition among agents.

The emergence of a norm is modelled by allowing farmers modifying their strategies (B,P) based on the evolutionary principles of imitation and exploration. At the end of each growing season, agents look at their neighbours and copy (imitate) the most successful strategy of that year, using a fitness metric as a basis of comparison: we define this metric as the farmer's performance index (PI, see below). If an agent scores higher than its neighbours, he maintains the current strategy for the following year. With a given probability (mutation), agents change their boldness and punitiveness level to a random value, overriding the imitation mechanism. In other words, agents occasionally explore completely new strategies (either B or P); with 50% chance is replaced by a random number drawn from a [0,1] uniform distribution. This heuristic is commonly known as "best-mean imitation"[14]. As in Axelrod's work, we do not impose any constraint or make any a priori assumption or correlation about the boldness (B) or punitiveness (P) of agents.

The GCG simulates the evolution of norms of compliance with allocations as evolutionary process. The strength of a norm is the difference between the population averages of B and P. If B is significantly higher than P, or if there is not much difference between them, we have a weak norm (most agents are pumping more water than they are supposed to, and not punishing breaches). On the other hand, when agents consistently select strategies having high P and low B, we can say that a norm of compliance has emerged. The GCG can be used to investigate the stability, growth and decay of these norms and the different conditions under which this happens.

The consequences of agent decisions and interactions are captured and quantified in the farmer's performance index (PI=E*I*S). The goal of formulating PI=E*I*S is to construct a simple index that captures the interaction of three broad indicators of farmer success: economic profitability (E), good relationships with the water authority or institution (I), and prolific social interactions (S). Each indicator is represented (quantified) by a utility function (see above and below). For generality, we have kept the functional forms of utility as simple as possible. Supplementary Figure 3a illustrates the interaction between any two agents, showing the benefits (+) and costs (-) that apply in the neighbourhood of a breach.

Another way to think about the dynamics of the GCG is to consider that each growing season farmers simultaneously play two games: *defect-or-not* and *punish-or-not*. The former is driven by the farmers' boldness B, the latter by their punitiveness P. Supplementary Figure 3b represents the three components of the farmer score (economic, institutional, social) as 'forces' pulling agent decisions in different directions. The objective of our model is to propose mechanisms that 'pull' the decisions of the majority of farmers towards compliance.

The main assumption of our agent's PI is equal weighting of the three indicators to produce the final index. Equal weighting is the most parsimonious approach, as it avoids introducing complexity (weight coefficients) without clear justification[22]. Practice tends to support this method, unless there are compelling reasons for differential weighting: the burden of proof should be on the differential weighting, and equal weighting should be the norm[23]. Also, equal weighting is used in a number of highly reputable social indices, such as the Human Development Index (United Nations), the Political Rights Index (Freedom House), the Basic Capabilities Index (Social Watch), the E-Government Index (United Nations), and the

Fragile States Index (Fund for Peace), among others [24]. Other approaches to assigning indicator weights may be implemented—such as theoretically categorised, schematic, or variable weights [23]. Although application of these methods is beyond the scope of this work, users of the GCG could derive and test other forms of weighting (if data is available) on a case-by-case basis.

Economic submodel

We assumed that prior to regulation, farmers irrigate crops at full nominal water requirement (Extended Data Table 1). For simplicity, we also assumed that farmers do not engage in deficit irrigation, meaning that under pumping restrictions they are forced to reduce their irrigated acreage. If a farmer (agent) cooperates, it only irrigates a fraction of land equivalent to the pumping allocation (i.e., if the allocation is 20% of the full license, the farmer irrigates 20% of his land). If the agent defects, it pumps a fraction of illegal water proportional to his boldness. For example, for a 20% allocation, a defecting farmer (agent) with boldness B=0.1 would irrigate 20%+80%*0.1=28% of his land; one with boldness B=0.8 would irrigate 20%+80%*0.8=84% of his land, and so on.

We calculated gross margin budgets (Extended Data Table 1) using reported and published agro-economic statistics for Bollgard II R cotton in the Murray-Darling basin (2015 Australian Cotton Production Manual, http://www.cottoninfo.com.au/publications), almonds in the southern Central Valley (UC Davis Agricultural and Crop Economics; http://coststudies.ucdavis.edu), and the wheat-rice rotation in the Punjab[25,26]. Gross margins were calculated as total revenue minus total costs, not including the energy costs of pumping groundwater. Pumping costs were calculated and incorporated to the agent objective function at simulation runtime using depths to water table from the groundwater submodel, based on the equation for power consumed by a centrifugal pump set:

$$PC = \frac{P_e g(WR)H}{\eta}$$

Where *PC* is the pumping cost in US$/ha, *Pe* is the price of electricity in US$/kWh, *g* is gravity, *WR* is the crop's water requirement in ML/ha, and *H* is the dynamic pumping lift of the pump in m.

The current version of the model could be extended to include a more detailed description of the farm enterprise (e.g., crop rotations, deficit irrigation, etc.). Here however, we develop a simple model with flexible and customizable input data, which can be used as a basis for applications in specific farming contexts.

We also assume that decisions are only related to water pumping and not crop choice. Farmers may indeed choose to switch to a different crop when allocations are reduced. Yet, this option is not always available to water users. This is the case, for example, with tree crops such as almonds, cherries, oranges, grapes etc. (important in California) and many others. These crops are a long-term investment: they take many years to grow and reach their optimal yields and become profitable to farmers. Soils and climate can also limit crop choice. Specialisation can also play an important role in cases where farmers have heavily invested in crop-specific machinery (e.g., cotton ginners, wheat reapers/binders, etc. can cost hundreds of thousands of dollars).

Including crop choice to our model would add an additional layer of complexity and make our goal of revealing factors that trigger compliance more difficult. For this reason, the current version of the GCG only takes a strictly limited subset of variables into account which are relevant to our research questions. The subset of variables/drivers chosen are essentially those identified by previous studies as key drivers of human cooperation: cultural values, social norms, bounded rationality, altruistic punishment, etc.[12,13,27,28].

Social submodel

Social utility function *S* provides a numeric representation of individual benefits and costs that agents derive from their interactions. *S* was constructed based on the following requirements:

- *S* allows agents' utilities to be put on a common scale and compared.
- *S* follows a Cobb-Douglas functional form which is commonly used in welfare economics and the construction of social indices; see Happy Planet Index (http://happyplanetindex.org) and the Human Development Index (http://hdr.undp.org/en))

- The intrinsic cost of reporting non-compliant neighbours decreases with increasing grid score [22], and increases each time the agent chooses to report a non-compliant neighbour.
- The intrinsic cost of developing a bad reputation decreases with increasing group score[22], and increases each time the agent is seen by others extracting water illegally (a neighbour might see a breach, but choose not to report it; in this case, the offender's reputation is still affected)

Each season, agents face the decision of whether to cooperate with the allocations (pump a fraction of their entitlement as required by the water authority) or to defect (pump more than the allocation). Each opportunity to defect comes with a probability of neighbouring farmers seeing that breach and reporting it to the water authority. This opportunity is represented by the probability of punitiveness Prob(P). Prob(P) is drawn from a random uniform distribution on the interval [0,1], at every turn for each agent. When P < Prob(P) an agent chooses to punish a defector. Similarly, there is a probability that an agent with defect, Prob(B). If B < Prob(B) the probability of defecting is higher than the agent's boldness and therefore it decides to defect, otherwise it cooperates. We quantify social utility using the following relationship:

$$S = (1 - grid)^m group^n$$

Where m = number of times an agent reports a neighbour that takes water illegally; n = number of times an agent is seen taking water illegally

In this functional form of S, grid and group are the normalised (0-1) mean grid group scores from Extended Data Figure 3 The scores were normalised based on the minimum and maximum scores in the cohort.

Groundwater flow submodel

The coupled agent-based groundwater model was developed using FlowLogo[21] (Extended Data Fig. 2), a software platform developed by the authors specifically for this purpose. The groundwater submodel represents a 10x10 km basin, discretised into 40x40 cells. The dimension of each cell is 200 m. Model boundary conditions are defined by a no-flow boundary to the North and South, and constant head boundary cells to the East and West; setting head values to create an East-West gradient of 1/1,000 representing typical conditions in regional aquifer systems. Underlying this basin is a semi-confined sand aquifer of 50 m thickness, hydraulic conductivity K=10 m/d and storativity S=1e-4. The model is transient with a time step of six months. We used a steady-state run with no pumping stresses as the initial condition for each simulation.

ODD+D model documentation references

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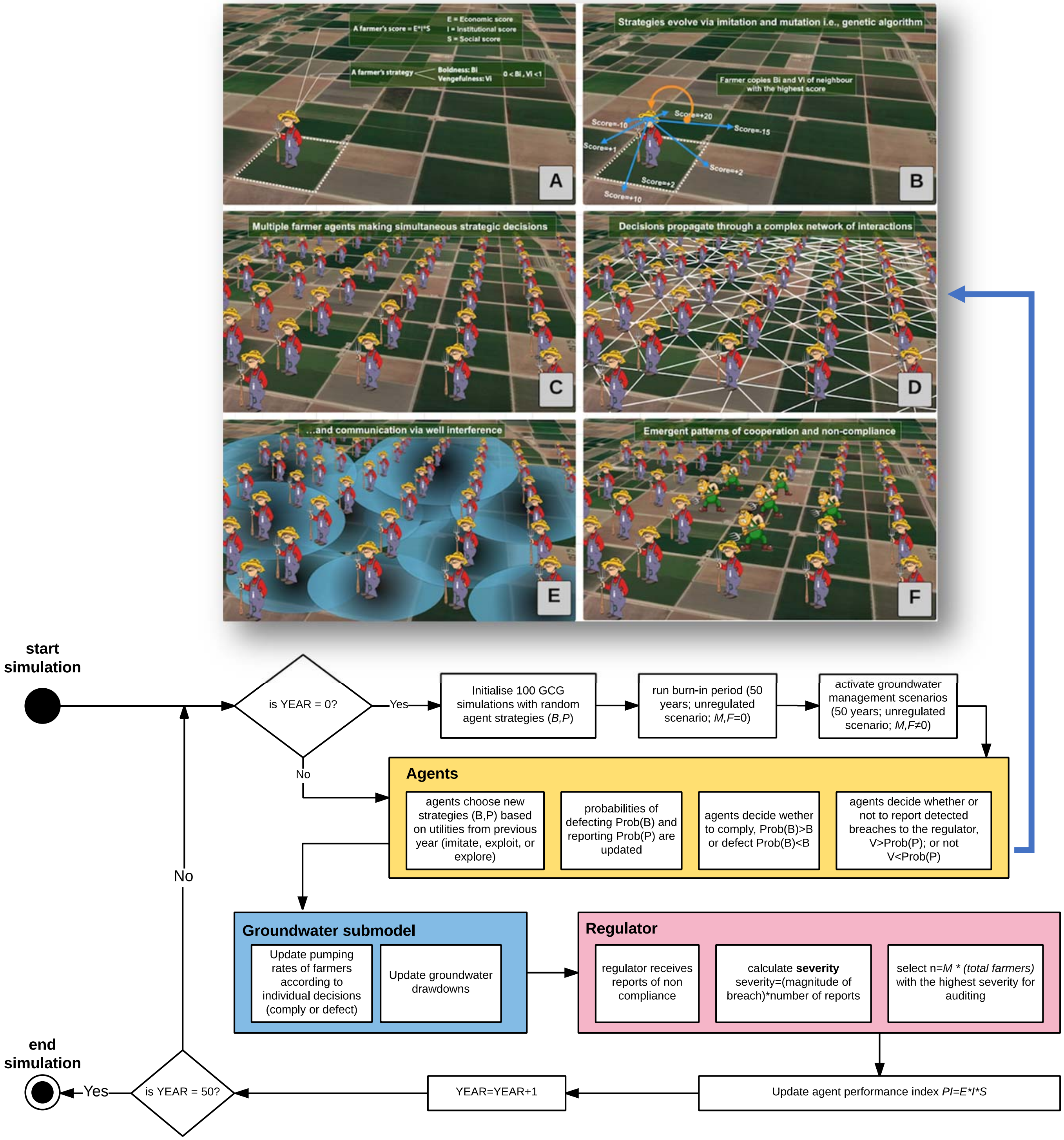
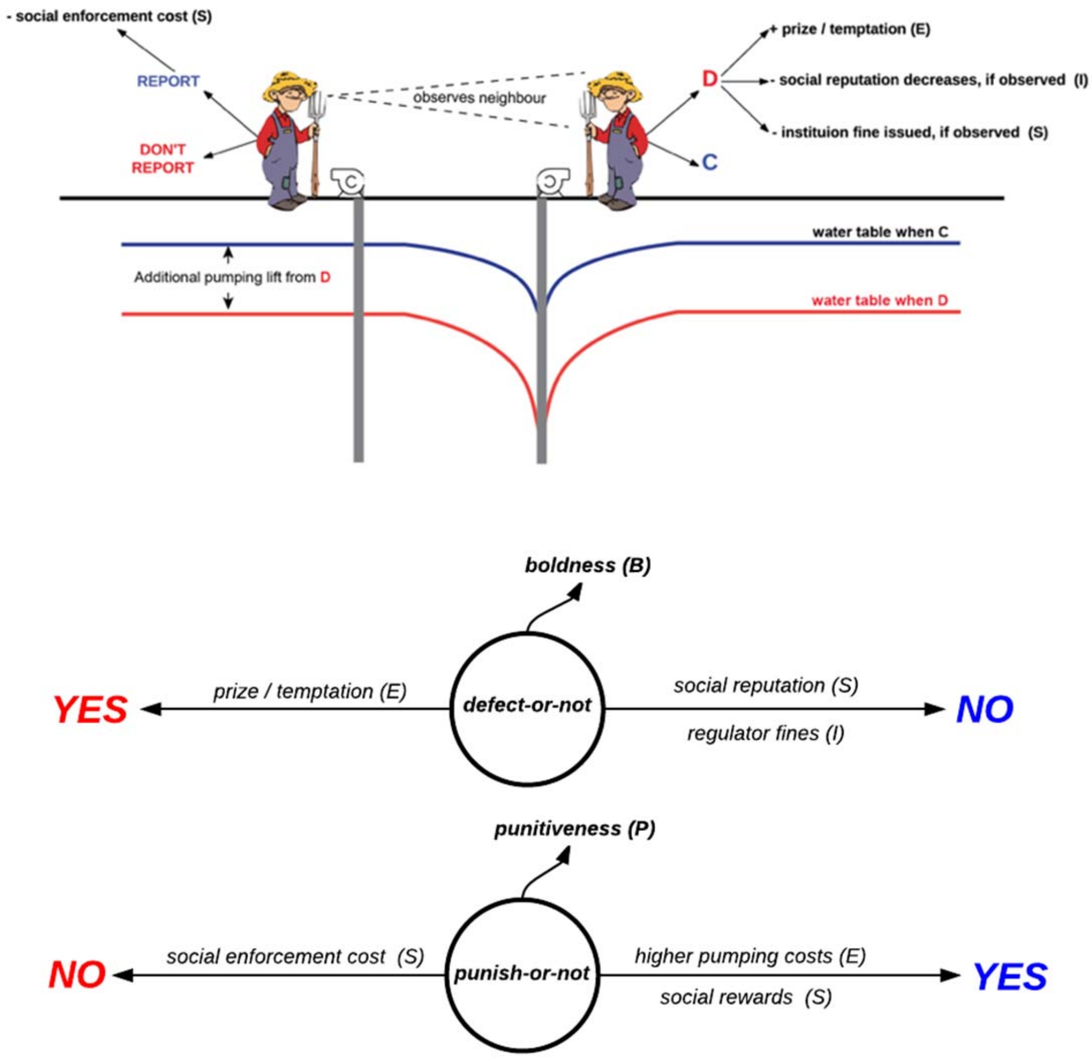
ODD+D Model Documentation Figures

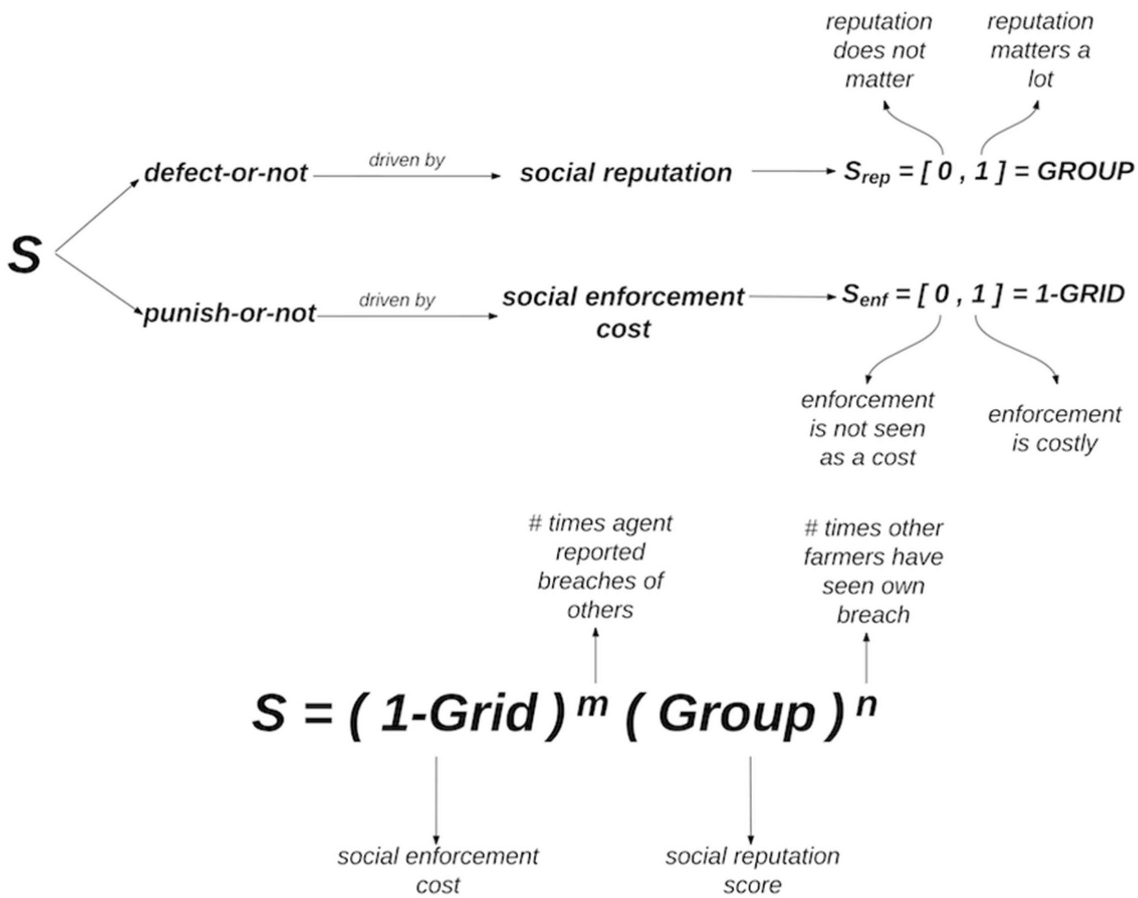


Supplementary Figure 1 | GCG main processes. (top) schematic of agent dynamics (bottom) scheduling of agent and groundwater processes.

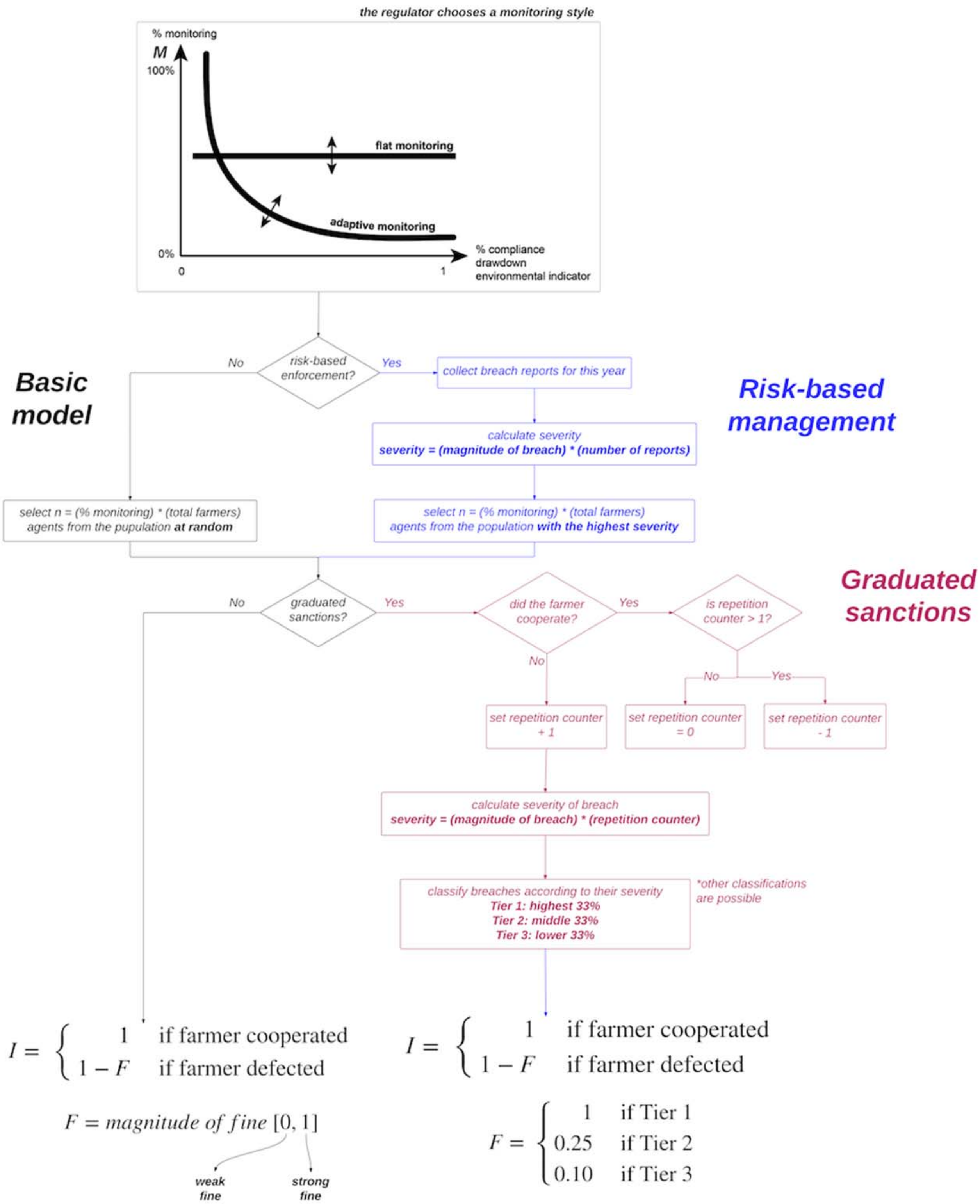
Supplementary Figure 2 | Agent-based implementation of the GCG. User interface for one of our case studies. Model window shows time series and histograms coupled social-groundwater output; sliders and switches to set base parameters for agents; controls for cultural variables and policy intervention mechanisms.



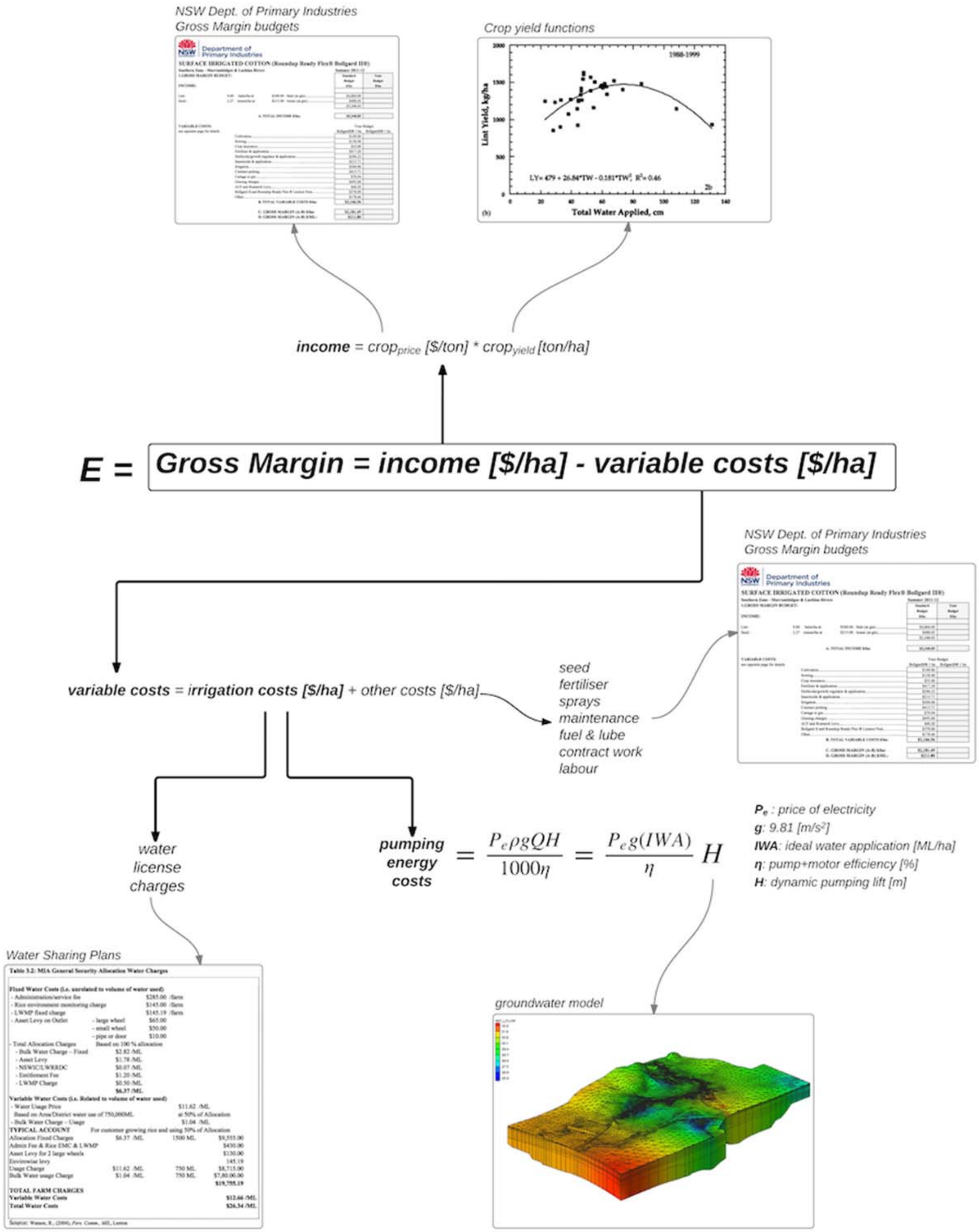
Supplementary Figure 3 | Socio-economic dynamics in the GCG represented as 'forces' pulling agent decisions in opposite directions.



Supplementary Figure 4 | Functional form of the social utility function of agents in the GCG.



Supplementary Figure 5 | Schematic of compliance and enforcement strategies of a typical water authority[29-31] and functional form of the institutional utility function of agents in the GCG.



Supplementary Figure 6 | Functional form of the economic utility function of agents in the GCG.

ODD+D Model Documentation Tables

Supplementary Table 1 | Agro-economic data for the three case studies.

	Australia	United States	India-Pakistan	
Representative region	Murray-Darling Basin (Lower Namoi)†	Southern San Joaquin Valley‡	Punjab§	
Crop	Bollgard R II cotton	Almonds	Rice	Wheat
Average farm size	362 ha	74 ha	4 ha	4 ha
Yield	10.5 bales/ha	6930.7 lb/ha	6960.0 kg/ha	5525.0 kg/ha
Price	580 AUD/bale	1.5 USD/lb	0.11 USD/kg	0.12 USD/kg
Revenue	6090 AUD/ha	10396 USD/ha	766 USD/ha	663 USD/ha
Total costs	3395 AUD/ha	6101 USD/ha	411 USD/ha	216 USD/ha
Costs of irrigation	570 AUD/ha	1351 USD/ha	89 USD/ha	27 USD/ha
Irrigation water requirement	9.5 ML/ha	13.2 ML/ha	13.52 ML/ha	4.1 ML/ha
Electricity price	0.20 AUD/kWh	0.15 USD/kWh	0.016 USD/kWh	0.016 USD/kWh
Total costs minus irrigation	2825 AUD/ha	4750 USD/ha	322 USD/ha	189 USD/ha
Gross margin*	3265 AUD/ha	5646 USD/ha	444 USD/ha	474 USD/ha

* gross margins do not include electricity pumping costs (computed at runtime, based on drawdowns obtained from the groundwater submodel)

† 2015 Australian Cotton Production Manual; http://www.cottoninfo.com.au/publications

‡ UC Davis Agricultural and Crop Economics; http://coststudies.ucdavis.edu

§ see[25,26]