Model description

The models define agent types where each agent type is a representative agent for that type defined by a set of parameters. Some of the models below define two or three types of agents in the population of players. The calibration procedure estimates the mix of different agent types.

Selfish rational agents

Investment: agent invests only if the investment leads to more earnings from extraction. Hence an upstream agent will invest if it's investment lead to an increase in the capacity of the infrastructure which will subsequently also lead to higher earnings from extraction. For example, if the infrastructure efficiency is 40 units an investment of 6 tokens by a selfish rational agent in position A leads to a capacity of 5 units of water per second, which leads to 10 tokens from crop production (250 units of water produces 10 tokens). Selfish agents in position D and E will never invest since selfish agents in positions A, B and C will never leave enough water for downstream agents to earn tokens from crop production.

Extraction: agent will always open their gate until 500 units of water are collected.

Altruistic agents

Investment: agent will always invest one fifth of the investment needed to reach a minimal infrastructure efficiency of 66.

Extraction: agent will keep gate open until one fifth of the water available during 50 seconds is collected.

Random decisions

Investment: agent invests an integer amount uniformly distributed in the interval [0 10].

Extraction: agent decides each second to open or close the gate with probability = 0.5.

Mixed null model

We allocate the distribution of the three types of agents. Agents can act selfish, altruistic or random with probability p_s (probability of being selfish), p_r (probability of being random) and $p_a = 1 - (p_s + p_r)$ (probability of being altruistic). After an agent is classified as selfish, altruistic or random, she follows the rules of investment and extraction previously described.

Conditional cooperation & reciprocity

This model is based on the observation that people cooperate if they expect and/or observe others will cooperate too (Ostrom, 1998; Van Lange et al. 2013). We assume that an agent *i* has the expectation EC that agent *i* will follow the cooperative norm.

Agents are assumed to have an initial level of expectations in the cooperation of others defined as EC_0. Based on expectations EC agents will behave either cooperatively or selfishly.

Let EC mean the expected level of cooperation by others. The initial level of expected cooperation is for simplicities same assumed to be the same for all agents and equal to EC_0. If the expected level of cooperation is lower than 0.5 the agent will make an investment decision using the selfish rational mode of decision, and otherwise are cooperative. We assume agents have a trembling hand in making decisions, and a noise term is added with standard deviation σ_T.

When agents collect water we assume that they have their gates open at the start of the 50 seconds, and each second they make a decision whether to close it. The higher the expected level of cooperation EC the earlier they close the gate. When communication is unlimited the water level reached that lead the agent to close the gate is defined as $W_C = 500 - 200 \cdot EC$. Hence if expected cooperation is 1 the agent collects the amount from the social optimum.

Besides the expected level of cooperation, agents have also an option to close the gate earlier, having a trembling hand, with probability $\frac{W^{\gamma_W}}{W^{\gamma_W}+W_C{}^{\gamma_W}}$. Figure 1 shows the relationship of the probability of closing the gate with the amount of water already collected, using W_C equal to 300, for different values of γ_W. The higher the value of γ_W the smaller the trembling of the hand.

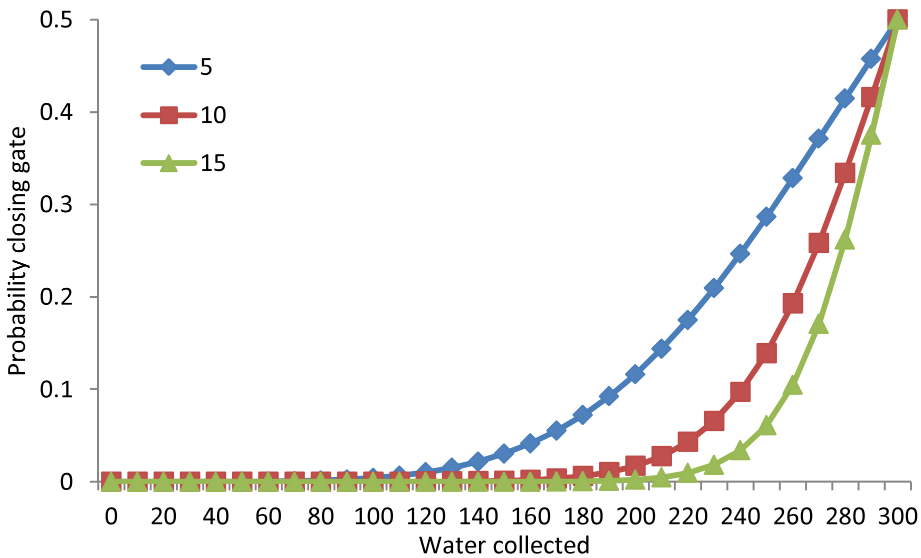

Figure 1. Relationship of between probability of closing gate and W_C for different values of γ_W.

Communication is assumed to affect the expected level of cooperation by others. In fact, communication is an imperfect way to evaluate the real intensions of the participants. The expected level of cooperation before agents can invest is influenced by direction communication (comC for constrained communication and comU for unconstrained communication). The parameter λ represent the level in which communication has an influence on updating EC. EC is updated by the following equation for constrained communication:

$$EC = (1 - \lambda) * EC + \lambda * comC$$

For unconstrained communication we expect that the effect of communication on expected cooperation is maximal, and is thus formulated as below. This means that comC can be interpret as the relative value of constrained communication compared the unconstrained communication.

$$EC = (1 - \lambda) * EC + \lambda$$

The expected level of cooperation is found to decrease when the agents experience more inequality in earnings from extracting water (Anderies et al., 2013). We capture this by assuming that EC is updated by the relative extraction compared to the mean extraction. If participations have limited vision they may have not have correct observations of the mean extraction, but they can observe how much water participants upstream leave for them. For simplicities sake we assume they can make a correct estimate of the mean crop harvest. We use a parameter γ_E to indicate that there might be a nonlinear effect of inequality.

$$EC = (1 - \lambda_E) * EC + \lambda_E * min\left(1, \frac{E}{\bar{E}}\right)$$

After the agents have invested, EC is updated. Like the update of EC for extraction of water, we assume an update rate λ_I and a simple estimate for inequality

$$EC = (1 - \lambda_I) * EC + \lambda_I * min\left(1, \frac{I}{\bar{I}}\right)$$

Table 2: Parameters of the model

Parameter	Range	Calibrated
Mean expected level of cooperation EC_0	[0, 1]	0.19
Standard deviation of noise σ_T	[0, 1]	0.39
Parameter defining the strength of trembling hand γ_W	[0, 10]	7.1
Relative update of EC due to communication λ	[0, 1]	0.71
Impact of constrained communication on EC, comC	[0, 1]	0.17
Relative update of EC due to extraction, λ_E	[0,1]	0.55
Relative update of EC due to investment, λ_I	[0,1]	0.96

<u>Social value orientation – Other Regarding Preferences</u>

This model is based on agents defining the utility of their actions. If they are satisfied they continue those decisions, and otherwise they reconsider their decisions. In defining the utility of the agents we assume agents have diverse social value orientations (Van Lange, 1999). In calculating the utility of the agents, we build upon the work on other-regarding preferences in behavioral economics (e.g., Charness and Rabin 2002; Camerer 2003; Arifovic and Ledyard 2012). We assume agents having other-regarding preferences, and all have the same values for f α and β defining the utility u_i:

$$u_i = z_i - \alpha_i \cdot \max(z_i - \bar{z}_{-i}, 0) + \beta_i \cdot \max(\bar{z}_{-i} - z_i, 0)$$

where α_i and β_i are drawn from the interval [-1,1], z_i is agent i's earnings, and $\bar{z}_{-i}$ is the average earnings of the other agents in the group. α can be regarded as the strength of an individual's aversion to exploiting others, and β can be regarded as an individual's degree of altruistic tendency. A lower value of β compared to α implies that a player gives a larger weight to his own payoff when his payoff is smaller than the average payoff of others compared to when it is larger. In line with Charness and Rabin (2002), we can define the following cases for $\beta \leq \alpha \leq 1$:

Case 1: When $\beta \leq \alpha \leq 0$, the player is highly competitive. Case 2: When $\beta<0<\alpha \leq 1$, the player prefers payoffs among all players to be equal. Case 3: When $0<\beta \leq \alpha \leq 1$. The player feels guilt earning more than others, and gains a sense of pride in acting altruistic. Case 4: if $\alpha=\beta=0$, we have the condition in which a player cares only about his or her own welfare.

An agent is satisfied with the earning if $u_i \geq u_{min}$ in the previous round. For the first round we have to assume whether agents are satisfied or not, and we assume that a fraction δ is satisfied. If the agent is satisfied the decision of last round is repeated, otherwise the agent will explore all 11 possible investment decisions. Agent calculates utility for the 11 possible investment decisions assuming others do the same as previous round.
Agent takes a probabilistic decision of investing an amount x in the public fund given by

$$\Pr(x) = \frac{\exp(\tau \cdot u(x))}{\sum_X \exp(\tau \cdot u(X))}$$

where τ is the weight given to the utility values. If τ is 0 all options have an equal probability, while if τ is equal to infinity the agents choose the option with the highest expected utility.

When agents can open and close gates they make their decisions on the expected utility derived from collecting water, hence excluding the returns derived from the investment decision. The agent decides each second to open or close the gate. The agent opens the gate if the agent is dissatisfied, and closes it if it is satisfied. Obviously upstream agents have first choice in implementing the decision and getting what they want.

Table 3: Parameters of the model on Social value orientation

Description	Parameter range	Calibrated
Strength of aversion to exploiting others α	[-1, 1]	0.98
Degree of altruistic tendency β	[-1, 1]	0.79
Weight for different utility values τ	[0, 20]	0.72
Minimum utility to be satisfied u_{min}	[0, 30]	15.5
Fraction of agents initially to be satisfied δ	[0, 1]	0.21

Defining the fit

The fit between the model and the data is based on the normalized square-root deviation between simulated and observed data. We first calculate the square root of the mean of the squared differences of observations and simulations. Then we normalize those metrics my dividing the metric by the maximum possible value (while the minimum value is our metrics is always 0). Hence for each of the metrics included, we have an error measure between 0 and 1. In order to derive a metric that is a composite of all six types of data used, we multiply 1 – the normalized square root deviation for each metric. This is a conservative approach penalizing more heavily high error levels. In sum our fitness score for the quality of the fit between the data and the model is

$$f = \prod_{i=1}^{6} \left(1 - \sqrt{\frac{\sum_{j=1}^{n_{i,j}} \left(s_{ij} - d_{ij}\right)^2}{n_{i,j}}} \Big/ d_{j,max} \right)$$

Where the data of metric j, d_{ij}, and simulations, s_{ij}, are compared for n_{ij} observations. The maximum value of the data is $d_{j,max}$.

The metrics used to evaluate the performance of the model include:

- Average infrastructure efficiency level for each round
- The average contribution per position for each round
- The average collection per position for each round.
- The average Gini coefficient of contributions for each round
- The average Gini coefficient of collected tokens for each round
- The distribution of changes in investments between rounds.

For unknown reasons groups over invest in the beginning of the experiment and we do not capture this overinvestment in our models. The overinvestment might be caused by an imperfect understanding of the dynamics of the infrastructure (Croson et al. 2009). We do not aim to explain this anomaly in the model.

We calibrate the models described on the experimental data. We use the standard genetic algorithm of *BehaviorSearch.org* for the model that is implemented in Netlogo 5.0.4. For the fitness evaluation of each parameter configuration we run the model 1000 times and compare the outcomes of the simulations with the actual values reported during the experiments for all 44 groups