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A Survey on Dynamic Common Pool Resources : Theory and Experiment

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A Survey on Dynamic Common Pool Resources : Theory and Experiment

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Abstract

This paper provides a survey on the literature using dynamic games to analyse the decision-making processes of common pool resources (CPRs) users. The purpose of this paper is to shed some light on the application of dynamic games in laboratory experiments. In this way, we focus on articles presenting both a theoretical model with laboratory experiments, by making a distinction between discrete time and continuous time. Therefore, we put a particular attention to subjects' classification according to their observed behavior, the different channels by which cooperation can occur and the econometric tools used to analyse experimental data.

Keywords : Common Pool Resources; Dynamic games; Experimental Economics; Experimentics.

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1 Introduction

The issue of environmental protection remains a practical concern since no environmental aspect is untouched by human activity (Rose, 2002). Common pool resources (water, fisheries, forestry, pastures, etc) are natural resources for which the exclusion of users is difficult, and the use of the resource by one user reduces the available amount for other users. Given their non-excludability and their rivalrous nature, common pool resources are the locus of the "Tragedy of the Commons" (Hardin, 1968). In other words, common pool resource users are faced with dilemmas which can lead to a severe overexploitation when they are not solved, and even to the destruction of the resource. Without rules, resource users will engage in a race for its use (Janssen & Ostrom, 2006). To find solutions for the management of common pool resources (CPRs), the well understanding of resource users decision-making processes is required. Previous work on this problem focused on a static framework until the early 1970's from which a transition to a more realistic dynamic framework took place, with the use of dynamic programming, dynamic game theory and equilibrium analysis to solve people's decision-making problems (Dasgupta & Heal, 1979; Gisser & Sanchez, 1980; Clark, 1990; Basar & Olsder, 1999; Dockner et al., 2000; Haurie & Zaccour, 2005; Engwerda, 2005; Van Long, 2010).

Moreover, experimental economics is a powerful tool used to test theoretical models, and have with cognitive and social psychology challenged the rationality of individuals, leading to consider the influence of social interactions and the role of emotions in people's rational decision-making (Carlsson & Johansson-Stenman, 2012; Croson & Treich, 2014). Thanks to laboratory experiments, experimental economics is able to build a simplified economic situation for which the experimenter has control over all the variables. While there is an extensive theoretical literature on dynamic common pool resource management, the literature combining theory and experiments on dynamic common pool resource is very scarce, with some of the studies using continuous time, others using discrete time and others again making a mix of both continuous and discrete time. Notice however that a continuous time model have different predictions from a discrete time model, except if the latter is a discretization of the continuous time model.

This review aims to shed some light on the implementation of dynamic games in laboratory, especially on continuous time, to study the behavior of the users of CPRs. Hence, we are particularly interested in the research questions, the classification of subjects according to their behavior and the channels by which cooperation occurs. We would also like to know how the experimental instructions were presented to subjects. Another aspect we are interested in this survey is to know the different econometric models used in these articles to answer the questions

they ask. The behavioral benchmarks to which subjects are frequently compared in this survey are the social optimum equilibrium, the Nash feedback equilibrium and the myopic equilibrium. The social optimum equilibrium is equivalent to a joint maximization problem. In the Nash feedback equilibrium, each subject take into account the dynamics of the resource in his decision process. When behaving myopically, a subject ignores the dynamics of the resource in his decision process. In this survey, we contribute to highlight the different applications of dynamic games in the lab, as a tool for solving CPRs problems. We especially point out the place of continuous time, whose implementation in the laboratory is very recent. Our work is complementary to that of [Tasneem & Benchekroun \(2020\)](#) on dynamic games in environmental and resource economics, as we give a more detailed description of the reviewed articles, we also distinguish mixed time articles and provide a discussion on experimetrics.¹ Finally, in order to facilitate reading, we have endeavoured to harmonize the notations and terminology used. Appendices 6 provide a summary of the variables used.

In what follows, we present in the second section articles in discrete time. The third section is devoted to continuous time articles. In the fourth section we present articles having combined continuous and discrete time. One should keep in mind that when presenting the articles, we do not focus on the models used in the data analysis because, section five is devoted to a discussion of the econometric models used in the reviewed articles. The last section gives some concluding remarks.

2 Discrete Time Models of CPRs

The vast literature combining theory with experimentation in the management of common pool resources (CPRs) is in discrete time, since laboratory experiments have been successful in this framework. Discrete time offers the opportunity to experimental agents to make their decisions at the same time. It can also be assimilate to a repeated game in which a variable evolves over periods, which makes it easy to implement in the lab. However, repeated games are widely implemented in lab experimentation. They can be defined as static games which are repeated over a given number of periods without changing the conditions of the game. Repeated games differ from dynamic discrete time games, in which a state variable evolves over time an affects subjects' decision processes. Hence, the change in the conditions of the game is specific to discrete time, which is also called "supergame" ([Pénard, 1998](#)).

2.1 Externalities from the Use of CPRs

In the last five decades, a growing number of scholars have started to use the theory of dynamic games to model the dynamic interactions involving in the use of common pool resources. These interactions create externalities having mostly a time dependence structure. [Herr et al. \(1997\)](#) and [Mason & Phillips \(1997\)](#) discuss dynamic and static externalities related to costs in the use of CPRs, while [Gardner et al. \(1997\)](#) distinguish three kinds of dynamic externalities occurring in the use of groundwater. A strategic externality, that appears because the use of groundwater via ownership creates depletion. A congestion externality, that is due to the short distance between the wells allowing to pump groundwater, and creates a loss in efficiency. The last externality is stock externality, occurring because the use of water by an individual reduces the available amount for others, increasing their pumping costs.

[Herr et al. \(1997\)](#) investigate the effects on agents behaviors, of two types of externalities (static and dynamic) resulting from the use of a common non-renewable resource assimilated to a groundwater bassin. Time independent or static externalities are situations in which the current extraction of an agent leads only to an increase of the current extraction costs of other agents, whereas time dependent or dynamic externalities involve both an increase in current and future extraction costs of others. Supposing no discount rate, they used a linear quadratic finite horizon model where n agents share an access to a groundwater bassin. Each agent i has to maximize his net benefit function, which is the difference between the benefit function (B_{it}) and the cost function (C_{it}), under the dynamics of the marginal cost (c_t). The net benefit depends on the agent's extraction, x_{it} , at period t and the total group extraction X_t . The authors have defined three benchmark solutions that are the social optimum, the Nash feedback equilibrium and the myopic solution.

For time independent externalities, the marginal cost as well as the depth to water are reset to their initial values at each period, so that $c_t = c$. It is a static game repeated over T periods where in each period, the Nash equilibrium is obtained by maximizing equation (1). For time dependent externalities however, the marginal cost is linearly increasing by k as the depth to water becomes high, so that the Nash feedback equilibrium is given by maximizing equation (1) in each period, subject to equation (2) :

$$\max \sum_{t=0}^T \underbrace{ax_{it} - bx_{it}^2}_{Benefit} - \underbrace{x_{it}(c_t + kX_t/2)}_{Cost} \quad (1)$$

$$s.t \quad c_{t+1} = c_t + kX_t \quad (2)$$

The authors ran eight experimental sessions of a non contextualized experiment. These sessions involved five treatments : three time independent and two time dependent, and lasted about an hour and a half each. In each experimental session, the authors ran two training phases followed by two experiment phases called "series". When the treatment involved a time independent setting, an experiment phase consisted of 10 repetitions of a one-shot game where the marginal cost is reset to its original value each period. However, when the treatment involved a time dependent setting, an experiment phase consisted of a single 10 periods game where the marginal cost is linearly increasing over periods. In this case, it was possible that the phase stops before the 10th period, when the cost of the base token becomes so higher that positive profits disappear. In each experimental session, groups of two and five subjects had to individually and simultaneously with the other members of the group order entire values of tokens between a lower bound of zero and an upper bound according to the parameterization chosen by the authors. The cost incurred by an individual for a given period depends on both the number of tokens he has ordered and the total number of tokens ordered by the group. Subjects were given a benefits table showing them the total benefits they can individually earn. At each experiment phase, they were also informed of the total number of tokens ordered by the group, the average cost of a token and their individual profits. They had the ability to see at any time the results of previous periods.

The different size of the groups allowed the authors to measure the level of depletion of the resource. They found high depletion rates in the initial periods, with a large number of subjects. This initial depletion was higher in dynamic designs. They also found by applying a Mean Squared Deviation (MSD) to token orders, that individual token orders are more closed to the Nash equilibrium than to the social optimum when considering time independent externalities. However, they found in time dependent externalities a higher number of myopic subjects, which exacerbates the tragedy of the commons. The authors finally found significantly higher payoffs in time independent externalities compared to those in time dependent externalities.

In line with [Herr et al. \(1997\)](#), [Mason & Phillips \(1997\)](#) were also interested in the study of static and dynamic externalities from the use of common pool resources. In their infinite horizon model, n agents assimilated to firms share an access to a renewable fishery, so that the authors tried to investigate the effect of industry size in the emergence of cooperation. Static and dynamic externalities are introduced through costs that are assumed to be additively separable. Each firm has to maximize his profit π_{it} , which is the difference between the benefit function and the cost function, under the dynamics of the stock, which evolves

according to a logistic growth function. The profit depends on the firm i 's harvest level, x_{it} , and the industry total harvest level, X_t . In both the static and the dynamic externalities, the authors computed the Nash and the social optimum predictions.

For their static cost externalities, the maximization problem is determined by equation (3), where c_1 is the static cost externality and c_2 is equal to zero. For their dynamic cost externalities, using the assumption of symmetry in which each firm i uses the same harvest strategy $x^e(S)$, the maximization problem described by equation (3) takes into account the dynamics of the stock (4), which evolves according to a logistic growth function, where c_2 reflects the dynamic cost externality and c_1 is equal to zero

$$\max_{x_{it}} \sum_{t=0}^{\infty} \rho^t \left[\overbrace{P(X_t)x_{it}}^{\text{Benefit}} - \underbrace{[c_f + c_1(X_t) + c_2(S_t)]x_{it}}_{\text{Costs}} \right] \quad (3)$$

$$s.t. S_{t+1} = S_t + RS_t \left[1 - \frac{S_t}{K} \right] - \sum_{i=1}^n x_{it}, \text{ with } x_t = x^e(S) \quad (4)$$

The discount factor is denoted by ρ , c_f is fixed costs, R is the intrinsic growth rate and K denotes the carrying capacity. The authors assumed that fish stock is perishable, so that all the stock (S_t) of a given period is sold in that period. They also assumed that firms' harvests are strategic substitutes and that the market price $P(X_t)$ in each period t is an inverse demand function of the harvests. In both the static and the dynamic externalities, the authors wanted to test the hypothesis that subjects will cooperate more than in the one-shot Nash prediction.

The authors ran eight experimental sessions involving four treatments of static externalities and four treatments of dynamic externalities. The treatments consisted with industry sizes of two, three, four and five firms, and each treatment lasted from about an hour and a half to two hours. In each experimental session, the authors ran a training phase to make sure that subjects well understand the experimental conditions. However, in sessions involving dynamic externalities, subjects also had to complete a question, allowing them to understand how their current harvest decisions affect futur costs. In each period, subjects had to make a harvest decision individually and simultaneously with the other members of their firm. The authors described a payoff table depending on the number of firms in the industry, so that it allowed subjects to know the calculated profit for each possible combination of harvest they might collectively make with their rivals. Each subject was informed of the choices and payoffs of the other members of his group.

The infinite horizon was simulated by applying a random termination rule. In this case, the discount factor can be interpreted as a continuation probability, allowing the authors to deduce the termination probability which is equal to 0.2. In other words, after 35 periods of play, the experiment stopped at the end of each period with a probability of 0.2. While static stock externalities were included in the payoff table given to subjects, dynamic cost externalities were implemented by giving to subjects a penalty table. This table provides them information about the adjustment of their payoffs, resulting from each of their choices. They were also given a detailed description of the link between costs and stock, as well as the current harvest and future stocks. Finally, to analyze potential extinction in the dynamic cost externality design with large industry size, the authors ran four supplementary sessions with industry of size five.

Using a learning or a partial adjustment model to analyze current harvest decisions, the authors found that subjects learn to adjust their actions over time in both the static and dynamic cost externalities.² Despite a faster convergence to the steady state in the dynamic framework than in the static framework, their results suggest highest cooperation in static cost externalities than in dynamic cost externalities, where they found more aggressive behavior. Moreover, they found an optimal industry size of four in the static treatment (which is larger than the optimal number of firms in the Nash prediction), while this number is three in the dynamic treatment (which is equal to the Nash prediction). They also found little evidence of extinction in the dynamic cost externalities.

Considering externalities resulting from the use of a non-renewable groundwater, [Gardner et al. \(1997\)](#) investigate the relationship between groundwater property rights doctrines and extraction behaviors of the users from 17 states in the American West.³ They distinguished four property rights doctrines. The absolute ownership doctrine, in which the owner of the land overlying an aquifer can extract the aquifer without limitation. The reasonable use doctrine, based on the same principle as the previous doctrine, except that it takes into account the fact that water can provide from the property of the neighbors. The correlative rights doctrine, in which landowners overlying the aquifer must use it reasonably, as the doctrine imposes an individual quota on the resource stock. Strategic externalities are suppressed under this doctrine but stock externalities persist. The last doctrine is the prior appropriation doctrine, which restricts the entrance to new pumpers by protecting reasonable pumping levels of senior appropriators.

Supposing no discount rate and using a linear quadratic finite horizon model in which n users share an access to a groundwater aquifer, each agent i has to maximize his net benefit function under the dynamics of the depth to water (d_t).

Water is used as an input in agricultural production. The net benefit function is the difference between the benefit function (B_{it}) and the cost function (C_{it}) and depends on the agent's extraction x_{it} , as well as the total group extraction X_t . The authors consider for their study three property rights that are the absolute ownership doctrine, the prior appropriation doctrine and the correlative rights doctrine. Under each doctrine, they compute the social optimum and the Nash equilibrium. For example in the absolute ownership doctrine, the social optimum maximization problem is given by equation (5) :

$$\max \sum_{i=1}^n \sum_{t=0}^T \overbrace{ax_{it} - bx_{it}^2}^{\text{Benefit}} - \underbrace{[(d_t + AX_t + B) x_{it}]}_{\text{Cost}} \quad (5)$$

$$\text{s.t } d_{t+1} = d_t - R + s \sum_{i=1}^n x_{it}$$

where a , b , A and B are positives parameters, s is a parameter depending on the size and the configuration of the aquifer and R denotes the constant recharge rate, which is equal to zero. The finite horizon, the no discount and the no resource recharge are the restrictive assumptions that the authors have made to simplify the model and the experiment, and focus subjects' attention on strategic and stock externalities.

Subjects participated in a non contextualized experiment involving three treatments. Each treatment include a set of three experiment phases. In the first two experiment phases, subjects were inexperienced in the decision environment, while the last experiment phase involved experienced subjects, randomly selected from the group of inexperienced. The baseline treatment, in which groups of 10 subjects played over 10 periods, illustrates the absolute ownership doctrine where no restriction is made on pumping levels. The second treatment illustrates the prior appropriation doctrine in which there is an entry restriction, limiting the number of subjects to groups of five. However, subjects played over 20 periods instead of 10 periods, in order to keep constant the maximal resource value. The last treatment, in which groups of 10 subjects played over 10 periods, illustrates the correlative rights doctrine where an individual stock quota of 25 is imposed. In each period, subjects had to individually and simultaneously with the other members of their groups, order entire values of tokens between a lower bound of zero and an upper bound according to the parameterization chosen by the authors in each treatment.

They were given the cost of a base token at the first period and were informed that this cost will increase by a given amount for each token ordered by the group, with the possibility that the experiment stops before the last period, when the token cost is so high that it no longer allows positive profits. In

the baseline treatment, the experiment stopped after three, two and four periods respectively in the two inexperienced groups and the experienced subjects. The experiment stopped after six, five and eight periods in the entry restriction treatment; and after seven, four and three periods in the stock quota treatment. After each period, subjects were informed of the total number of tokens ordered by the group, the token cost for this period, the new cost of base token for the next period and profits for the current period.⁴

In their analyzes, the authors compared the tokens ordered by subjects in the experiment to the theoretical social optimum and Nash feedback token orders. Considering the first decision periods in each treatment, they found under the absolute ownership doctrine (no restriction treatment), higher average token orders than the Nash feedback prediction. The average token orders under the prior appropriation doctrine (entry restriction treatment) was also higher than the Nash feedback prediction. However, this number was close to the Nash feedback prediction under the correlative rights doctrine (stock quota treatment). Analysing efficiency, the authors also found that restricting entry and applying a stock quota improve performance.

2.2 The Role of Information

From what we saw above, the use of common pool resources generates some externalities among the users, leading to a race for the resource which is intensified by myopic behavior. Otherwise, [Gardner et al. \(1997\)](#) have shown that imposing a quota could mitigate this situation. The question now is how would resource users behave in the absence of strategic interaction. This was the point for [Hey et al. \(2009\)](#).

In a single agent finite horizon model, they investigate the role that information about the stock and the growth function of a renewable resource can have on agents' harvesting decisions. Assimilating the resource to a fishery, the authors assume zero costs with prices normalized to one. Each fisherman has to maximize his extraction x_t , which is the difference between the stock before and the stock after extraction, under the dynamics of the stock, which evolves according to a logistic growth function :

$$\begin{aligned} \max \sum_{t=0}^T \rho^t x_t &= \max \sum_{t=0}^T x_t & (6) \\ \text{s.t } S_{t+1} &= S_t - x_{it} + RS_t \left[1 - \frac{S_t}{K} \right], \text{ with } S_0 = K \end{aligned}$$

The discount factor is denoted by ρ , which is equal to unity. R is the intrinsic growth factor and K is the carrying capacity. Thus, the optimal solution is the

most rapid approach to the Maximum Sustainable Yield (MSY), with an extinction at the last period.⁵

A total number of 121 subjects participated in two experimental sessions of a non contextualized experiment.⁶ These sessions involved four treatments and lasted about an hour. A first treatment with a stock information and an accurate signal about the number of existing resource units. A second treatment with information on the growth function and a noisy signal on the number of existing resource units. In other words, the noisy signal means that the stock was multiplied by a random number pulled from a uniform distribution. The third treatment is a full information treatment in which information on both the stock and the growth function were given to subjects. They received in addition an accurate signal on the existing number of resource units. The last treatment was a zero information treatment, with a noisy signal on the existing number of resource units. Unlike other subjects, subjects in the second and the third treatments were given an on-screen facility, allowing them to anticipate the consequences of their extraction choices before confirming their decisions.

In each treatment, the authors tried to determine the optimal theoretical strategy. In all the treatments but the full information treatment, they were not able to derive optimal strategies. That's why they numerically defined for these treatments, reasonable theoretical strategies which are "prudent"; i.e. extraction strategies leading to a pre-mature extinction of the resource are excluded.⁷ In each treatment, subjects had to decide one hundred times the number of units they wanted to transfer from a fictitious resource to their savings account, so that a logistic growth function was applied to the remaining units. The dynamics of the resource was then determined by the remaining stock and the initial stock was equal to the carrying capacity K . Subjects had to exhaust the resource at the last period, but in case of pre-mature exhaustion the experiment ends instantaneously. However in each treatment, subjects were warned when they choose an extraction of zero units or when the number of units extracted exceeds the stock signal.

From the experiment the authors found by applying a binomial test on the distribution of over-harvesters and under-harvesters, that a higher percentage of subjects under-harvest the resource when they do not receive any information.⁸ In terms of behavioral patterns, the authors found that subjects tried to control the dynamic system by holding constant the stock or their extraction level when they received accurate information on stocks. Furthermore, subjects who received a noisy stock information had a misperception of feedback, leading them to adopt a pulse extraction by alternating periods of extraction and periods of non-extraction. This allowed the resource to build up. Finally with no information, subjects tend to under-exploit the resource because they misperceive the non-linearity of the growth function. In other words, as subjects have in mind a

linear relationship between the stock and the growth, they believe it would make sense to let the stock grow and harvest at the end the profit maximizing the stock size (as they think that growth increases with the stock size). For a deeper understanding of this misperception, see [Sterman \(1994\)](#) and [Moxnes \(1998\)](#).

2.3 Taking Into Account Spatial Characteristics

Problems of groundwater allocation have mostly been studied by using relatively simple models, sometimes to make it easy to understand and sometimes because of the difficulties to obtain actual data on pumping decisions. These models may mischaracterize the nature of the predicted resource use by ignoring the possibility for users behaviors to diverge from social optimum and myopic predictions. However, there is another part of the literature that in order to overcome the shortcomings of the traditional model, takes into account the spatial effects of groundwater pumping ([Gisser & Sanchez, 1980](#); [Feinerman & Knapp, 1983](#); [Rubio & Casino, 2003](#)). Moreover, even if these studies take into account the spatial characteristics of groundwater, they find a rather paradoxical result known as the Gisser-Sanchez's effect (GSE). The GSE, discovered by [Gisser & Sanchez \(1980\)](#), suggests that the social benefits of optimal groundwater management are insignificant, because as the storage capacity of the groundwater increases, the difference between optimal management and private exploitation becomes negligible. This is even more when we consider that the optimal management is not costless.

[Suter et al. \(2012\)](#) analyze the impact of hydrogeologic characteristics of the aquifer on users behavior and pumping rates by using an infinite time horizon model. They defined and compared two theoretical models that are a traditional bathtub model and a spatially explicit model, in which the spatial characteristics of the aquifer are taken into account. n users share a common groundwater and must choose individually at each period, a pumping rate that maximizes their profit, which is the difference between benefit and costs, taking into account the dynamics of the depth to water d_t .

In the bathtub model, the authors assumed that pumping made by a user increases equally in the next period the depth to water for all the users, while in the spatially explicit model it is the specific hydrogeologic characteristics of the aquifer (transmissivity, storativity, the distance between wells, and time) that determine how the depth to water is influenced by pumping in future periods.⁹ In each model they defined three benchmarks that are the social optimum, the Nash feedback and the myopic solution. The corresponding social optimum problem for the bathtub model is given by equation (7) and by equation (8) for the spatially explicit model :

$$\max \sum_{i=1}^n \left(\sum_{t=0}^{\infty} \rho^t \left(\underbrace{ax_{it} - \frac{b}{2}x_{it}^2}_{Benefit} - \overbrace{c_0 d_t x_{it}}^{Costs} \right) \right) \quad (7)$$

$$\text{s.t } d_{t+1} = d_t + \frac{\sum_{i=1}^n x_{it} - R}{AS}$$

$$\max \sum_{i=1}^n \left(\sum_{t=0}^{\infty} \rho^t \left(\underbrace{ax_{it} - \frac{b}{2}x_{it}^2}_{Benefit} - \overbrace{c_0 d_t x_{it}}^{Costs} \right) \right) \quad (8)$$

$$\text{s.t } d_{it+1} = \sum_{k=1}^t \sum_{j=1}^n \frac{x_{ik} - x_{jk-1}}{4\pi T_r} \times w(t - k + 1, v(i, j)) - \frac{(t+1)R}{AS}$$

R is the recharge rate and AS denotes the area time the storativity of the aquifer, ρ is the discount factor, b is the slope of the demande curve, a is the intercept of the demande curve, x is the quantity of groundwater pumped, c_0 is a cost parameter and r is the discount rate. $v(i, j)$ is the radial distance between well i and well j , T_r is the transmissivity and $w(t, v)$ is the well function. Solving the problem by means of the Hamiltonian and using the approximation of [Feinerman & Knapp \(1983\)](#) the authors are able to determine the optimal and the Nash feedback quantity of pumping in both the bathtub and the spatially explicit model.¹⁰ They found similar myopic pumping levels for the spatially explicit model and the bathtub model. The authors also found that both in the bathtub and the spatially explicit model, a higher storativity value leads to the reduction of the overall effect of pumping on the future depth to water.¹¹ In addition, the ratio of private to external costs increases with higher storativity values when transmissivity is low, and vice-versa.

A total number of 96 subjects participated in eight experimental sessions involving four treatments. The first treatment denoted Bathtub, illustrates a common bathub model. The second treatment denoted Spatial 1, illustrates a spatially explicit model with a low storativity. The third treatment denoted Spatial 2, illustrates a spatially explicit model with a high storativity. The last treatment denoted Individual Bathtub, illustrates an optimal control treatment in which a single user exploits the groundwater and where future costs of pumping are entirely private. There is no interaction between subjects in this thaatment. The experiment was contextualized to an aquifer commonly shared by groups of six subjects. The aquifer was divided into six plots in which each subject has to operate one of the well located in the middle of a plot, in order to make an individual and anonymous pumping decisions in each period. The authors have

intentionally made instructions vague to reflect the real-life groundwater dynamics which is not exactly known. Thus, they chose a discount factor and a transmissivity value that represent real-world cases.

Before the beginning of each session, subjects had to answer several comprehension questions. An experimental session was divided into a training phase followed by four experiment phases. After each phase, the groups of six subjects were randomly match. The infinite horizon was simulated by applying a stochastic termination rule. The discount factor is then interpreted as a continuation probability (85%), allowing the authors to deduce the termination probability which is equal to 15%. This allowed the authors to find an expectation of 6.67 periods per experiment phase. Thus, the four experiment phases were respectively of six, ten, five and seven periods. The authors derived three predictions including subpredictions for each. The first prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in pumping" levels. In other words, depending on the treatment, pumping levels are higher or lower.¹² The second prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in the pumping strategy types used by participants". This prediction explains that the frequency with which subjects adopt a behavior (myopic, Nash feedback or optimal) depends on the treatment. The final prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in the observed social efficiency". In other words, depending on the treatment, observed social efficiency is higher or lower.

The authors found support for all their predictions. Regressing pumping levels on myopic pumping in each treatment to analyse myopic behavior, they found on average more myopic in the Bathtub than in the Individual Bathtub treatment (single agent). Even if subjects pump less in the Individual Bathtub treatment on average, they pump more than the level that maximizes the discounted net benefits. The authors also found on average that subjects' behavior in the two Spatial treatments are between optimal and Nash feedback predictions. Furthermore, analysing individual myopic behavior in each treatment, they found the fewest number of myopic subjects in the Individual Bathtub treatment. They also found few myopic subjects in the two Spatial treatments, with a high number of myopic subjects in the Bathtub treatment.¹³

With a social efficiency of 80%, and the resulting efficiency if all the subjects were myopic lying in the range of [50% – 80%], results suggest that efficiency gains from the management of pumping levels are less sufficient to offset the cost of implementing such a policy. This seems to be in line with the Gisser-Sanchez's effect (GSE). While the authors did not find robust results on learning effects (resulting from the stochastic termination rule), they observed a reduction of pumping levels in the third experiment phase compared to the previous two phases.¹⁴ Table 1 summarizes the discrete time articles we reviewed.

Table 1 – A summary of discrete time models

Paper	Research question	Nature of the resource	Theoretical model	Experiment	Data analysis	Main results
Herr et al. (1997)	Behavior in time dependent vs. time independent cost externalities	Non-renewable groundwater	Finite horizon NF ¹ , myopic, SO	No contextualization Static : token cost reset Dynamic : linear increasing token cost	Parametric & non-parametric tests	More myopic in time dependent externality
Mason & Phillips (1997)	Effect of industry size in static vs. dynamic cost externalities	Renewable fishery	Infinite horizon Comparison to NF outcome	No contextualization Random termination Industry size : two three, four & five firms	Parametric tests	High cooperation : static externality with industry size of four
Gardner et al. (1997)	Property rights & behavior	Non-renewable groundwater	Finite horizon NF & SO	No contextualization No restriction, quota & entry restriction	Parametric tests	Efficiency improvement : quota & entry restriction
Hey et al. (2009)	Behavior & information structure	Renewable fishery	Finite horizon Sole agent	No contextualization Information structure : full, stock no & growth	Parametric & non-parametric tests	No information : 90% under harvest the resource
Suter et al. (2012)	Effect of hydrologic properties on behavior	Renewable groundwater	Bathub vs. spatial models Infinite horizon NF, myopic & SO	Contextualization Stochastic termination Bathub : sole agent + n-agents	Parametric tests	Few myopic : spatial & sole agent treatments

3 Continuous Time Challenges

Another possible way to analyze subjects decisions in the use of common pool resources is to use continuous time, which emphasizes the non stop evolution of CPRs. Although there is a growing literature on the implementation of continuous time models in experiments, it is still quite recent. Few examples of continuous time situations in real life, with quick interactions can be electricity markets with high-frequency bidding, financial markets with high-frequency computerized trading (Bigoni et al., 2015).

We can find in the literature two ways of implementing continuous time in lab experiments : by using extensive form games and by using differential games. The first way is in line with Simon & Stinchcombe (1989) who suggested a general model of games played in continuous time. They considered discrete grids in the time interval $[0, 1)$ for games with finite numbers of players and actions. Thus, they obtained under some technical conditions (for example, keeping uniformly bounded for each player, the number of strategy switches) in the limit as the grid interval approaches zero, well-defined games in continuous time. Therefore, articles using this method are qualified as quasi-continuous time articles (Friedman & Oprea, 2012; Oprea et al., 2014; Bigoni et al., 2015; Leng et al., 2018). The second way is in line with Tasneem et al. (2017, 2019) who used dynamic models.

3.1 "Quasi-continuous" time Experiments

In this subsection, we provide a short review of quasi-continuous time articles. For instance, Friedman & Oprea (2012) study a prisoner's dilemma in a finite horizon to measure the tension between efficient cooperation and inefficient defection. In addition to their continuous time treatment, they implemented a one-shot treatment and a discrete time treatment. They found, using a pairwise Mann-Whitney test on subject's median cooperation rates, that continuous time gives the highest level of cooperation. Cooperation was never appears in the one-shot treatment and was heterogeneous in the discrete time treatment. Bigoni et al. (2015) also study cooperation in a repeated prisoner's dilemma, with different termination rules (deterministic and stochastic time horizons) and different durations (long and short). They ran two deterministic treatments (long and short durations), two stochastic treatments (long and short durations) and one deterministic treatment with variable durations across supergames. By analysing median and mean cooperation rates, they found significantly high cooperation rates with short duration deterministic time horizon.¹⁵ However, they found similar cooperation rates with long duration, both for deterministic and stochastic time

¹⁵NF : Nash Feedback equilibrium. SO : social optimum equilibrium.

horizons.

[Oprea et al. \(2014\)](#), in a finite horizon framework, crossed time protocol (continuous vs. discrete time) and communication protocol (no communication vs. unrestricted communication) to get four treatments through which they study subject's contributions in a public good game. By analysing median and mean cooperation, they found high contributions in continuous than in discrete time. However, the results suggested that without communication continuous time does not perform better than discrete time. Similar results have been found by [Leng et al. \(2018\)](#) who studied a minimum effort game by crossing time protocol (continuous vs. discrete time) and information feedback (group minimum effort level vs. each member of the group effort level) to measure cooperation in a minimum effort game, also called a weak-link game.¹⁶ Analysing the minimum and the average effort levels to measure cooperation, the authors used a two-sided Mann Whitney rank sum test and found contrary to their expectations that when the number of subjects become larger, continuous time without communication or an additional feedback information have no significant impact, because subjects hardly coordinate to increase the group minimum effort within a period. They also found no significant difference in the minimum effort level between continuous time and discrete time.

3.2 Real Time : A Feature of Continuous Time

In continuous time, interactions among agents are made in real time and imply an uninterrupted update of information in the lab. Thus, some recent experimental studies have tried to introduce more realism (mimic field settings) by taking into account spatial and temporal dimensions in the study of renewable social ecological systems. For example, [Janssen et al. \(2010\)](#) study the impact of communication and costly punishment in the governance of a renewable resource assimilate to a 29-by-29 grid of cells from which subjects have to harvest tokens. The resource dynamics is represented by the renewal rate, which depends on the density. They mainly found that communication allows the regeneration of the resource by reducing its exploitation. However, without communication, costly punishment does not allow the increase of the group payoff.¹⁷ Moreover, [Cerutti \(2017\)](#) revisited the experiment proposed by [Janssen et al. \(2010\)](#) to study the effects on subjects' behavior, of introducing a spatial representation of the resource. The author compared the baseline version of the experiment to a blind version. In the baseline version, the resource is assimilated to a grid of 18×18 cells from which subjects have to harvest tokens. Contrary to [Janssen et al. \(2010\)](#) there was neither communication nor costly punishment, but a bar representing the current amount of tokens. In the blind version, only the bar representing the current amount of tokens could be seen by subjects. The resource dynamics,

represented by the renewal rate, depends only on the total amount of tokens in the grid. The main result was that, contrary to the baseline version, the blind version gives results close to the social optimum. The authors derive the social optimum equilibrium by simulating the behavior of ten thousand groups behaving cooperatively. Their finding was that in the social optimum, subjects allowed the resource to cover up to 50% before harvesting above this threshold.

3.3 Taking Into Account Strategies in CPRs

This subsection reviews continuous time article using differential games. To our knowledge, [Tasneem et al. \(2017\)](#) was the first article that have tried to implement differential games in the lab. The peculiarity of the articles reviewed here and in the following subsection is that the authors analyse agents' behavior according to Markovian strategies (state dependent strategies). [Tasneem et al. \(2017\)](#) investigates the choice of extraction strategies between linear and non linear, resulting from the use of a common renewable resource assimilated to a fishery. Using a linear quadratic infinite horizon model, they consider groups of two identical agents, who individually and simultaneously exploit the fishery. Assuming zero costs, each agent i has to maximize the present value of his discounted payoff, which depends only on his extraction rate $x_i(t)$, under the dynamics of the stock, which evolves according to a logistic growth function $F(S(t))$. The maximization problem is given by equation (9) :

$$\begin{aligned} & \max \int_0^{\infty} \exp^{-rt} x_i(t) - \frac{x_i(t)^2}{2} dt & (9) \\ & \text{s.t } \begin{cases} \dot{S}(t) = F(S(t)) - x_i(t) - x_j(t) \\ S(0) = S_0 \\ x_i(t) \geq 0 \end{cases} \\ & \text{with } F(S) = \begin{cases} RS & \text{for } S \leq S_{th} \\ RS_{th} \left(\frac{K - S}{K - S_{th}} \right) & \text{for } S > S_{th} \end{cases} \end{aligned}$$

where r is the discount rate, R is the replenishing rate, RS_{th} denotes the maximum sustainable yield and K is the carrying capacity. This problem admits a piecewise linear Markov-perfect equilibrium and also a continuum of nonlinear local Markov-perfect equilibria which differs in terms of the aggressiveness of the resource exploitation.

A total number of 134 subjects participated in nineteen experimental sessions of a contextualized experiment. Each session lasted about two hours, with groups of two subjects randomly formed at the beginning of each session and remaining the same during the session. To make sure that subjects well understand the Markovian environment, they had to succeed to a test before the beginning of a session, in which they learned how to manage their extraction rate. The test consisted in choosing an extraction rate to increase and keep the stock constant at this new level, then in decreasing and holding the stock constant to another level. This was called "constant rate".¹⁸ Subjects were given fifteen tries. They were dismissed in case of failure and received ten dollars show up fees. A total of 25 subjects failed this test.

In each experimental session, each subject, assimilated to a fisherman, had to decide in real time and simultaneously with the other member of his group, the speed at which he wants to harvest a fishery. The authors chose the replenishing rate R , the discount rate r and the initial stock, so that the time required to reach the steady state does not exceed four minutes. An experimental session consisted in four training phases followed by six phases for pay. A phase stops after four minutes, or with a stock level of zero or after 30 seconds of inactivity because a steady state is supposed to be reached. Continuous time has been implemented by updating all information every second and allowing subjects to take their decision at any time by using a graduated slider from zero to an upper bound, according to the parameterization chosen. Moreover, the infinite horizon has been simulated by discounting payoffs over a fixed period and computing a continuation payoff as if the phase went forever, assuming that the last extraction rate of the group remains constant. This computation also takes into account the probability the stock level could drop to zero. After making a decision, subjects could see the dynamics of the stock in real time, as well as other information (their extraction rate, the group extraction rate, the time elapsed). At each phase, the authors set both the starting stock level and the initial extraction rate. They varied the design according to two dimensions. First, by varying the initial extraction, with constant initial stock. This allowed them to analyse whether initial conditions affect subjects' extraction behavior. Second, by keeping constant the strategies resulting from initial extractions, they ran two treatments with a low initial stock and a high initial stock.

Analysing their experimental data, the authors found that when focusing on linear strategies, subjects's extraction rates reach the best possible steady state. However, taking into account non linear strategies allow them to find other possible steady states including those leading to the exhaustion of the stock. To analyse if a pair reached a steady state, they used a steady state detection algorithm called MSER-5.¹⁹ By investigating the effects of initial conditions, they found that different initial extraction rates did not affect subjects' behavior. Fur-

thermore, grouping in each treatment all the phases for pay and applying a two-sample Kolmogorov-Smirnov test, the authors found that the steady state total extraction distribution in the second treatment (high initial stock) contains larger values than that of the first treatment (low initial stock).

Finally, to investigate whether subjects' decision-making are susceptible to be affected by other variables, the authors ran for each phase for pay a subject-by-subject individual Tobit regression on the general model shown by equation (10) :

$$x_t = \beta_0 + \beta_1 S_t + \beta_2 (S_t)^2 + \beta_3 x_{t-1} + \beta_4 x_{other, t-1} + \beta_5 t + e_t \quad (10)$$

where x_t denotes the current extraction rate of a subject, x_{t-1} is his lagged extraction rate, the time in seconds for a decision is denoted by t , $x_{other, t-1}$ is the lagged extraction rate of the other subject of the group, e_t denotes the error term, and S_t is the current stock level.²⁰ They found that half of the strategies condition on time and that about half of the extraction strategies condition on the extraction rate of the other player of the group. Their results also shown that a high percentage of the models selected were non-linear strategies, and that a less but not negligible percentage were "rule-of-thumb" strategies, which do not depend on the stock level. The rule-of-thumb strategy is close to the social optimum equilibrium in the sense that it consists of choosing a zero or a very low extraction rate, in order to quickly increase the stock to the level allowing the highest extraction rate.

3.4 Sustainability in CPRs

Following [Tasneem et al. \(2017\)](#), [Tasneem et al. \(2019\)](#) investigate a private management of a renewable resource. More precisely, they want to know to what extent a single agent can manage a private fishery in a sustainable and efficient way. Assuming zero costs, each agent has to maximize the discounted sum of his instantaneous payoffs, which depends on his extraction rate $x(t)$, taking into account the dynamics of the stock $S(t)$. Using a linear quadratic infinite horizon model, the maximization problem is given by (11) :

$$\max_{x(t)} \int_0^{\infty} \exp^{-rt} x(t) - \frac{x(t)^2}{2} dt \quad (11)$$

$$\text{s.t } \begin{cases} \dot{S}(t) = RS(t) - x(t) \\ S(0) = S_0 \\ x(t) \geq 0 \end{cases}$$

where r is the discount rate and R is the replenishing rate. The optimal solution is a piecewise extraction rate function composed of three regimes. The first regime consists in a null extraction regime allowing the stock to grow. In the second regime, the extraction rate is a linear function of the stock and the last regime is a steady state regime with the maximum extraction rate.

A total number of 31 subjects participated in three experimental sessions of a contextualized experiment. Each session lasted about two hours, where each subject had to decide in real time the speed at which he wants to harvest exclusively a fishery. The authors chose the discount rate r , the replenishing rate R and the initial stock, so that the time required to reach the steady state does not exceed two minutes. An experimental session consisted in ten training phases with the same initial stock, followed by twenty phases for pay with different randomly increasing initial stocks within the range of the optimal solution. During a phase, the computer checked whether the stock would drop to zero or not and computed the discounted sum of future payoffs till infinity. In case of 30 seconds of inactivity, the computer assumes a steady state is reached and the phase stops. The phase also stops after two minutes, or with a lower stock level of zero or when the stock reaches its maximum level. The infinite horizon and continuous time were also implemented as in [Tasneem et al. \(2017\)](#), with the difference that all the information were updated every half second, which is faster enough to simulate continuous time. After making a decision, subjects could see the dynamics of the stock in real time, as well as other information (their extraction rate, the constant rate, their instantaneous and cumulative payoffs).²¹ The payoff in the experiment depends on both the quantity of fish extracted by a subject and the time of the extraction.

Adopting the same procedure as [Tasneem et al. \(2017\)](#) to analyse their experimental data, the authors, by using the steady state detection algorithm called MSER-5, checked whether an extraction behavior results in a steady state.²² To analyse the relationship between stock and extraction, the authors compared subjects' extraction behaviors to the optimal extraction policy. They did it because their design admits a cross-sectional analysis of initial extraction rates, as they chose their parameters in the range of the optimal extraction policy. Thus, in their phases for pay, and for nine different half seconds in time, the authors regressed subjects' extraction rates on the stock level according to equation (12).

$$x_{ij} = \alpha_0 + \alpha_1 S_{ij} + e_{ij} \quad (12)$$

where i denotes the order of a phase for pay and j denotes the order of a subject (one up to thirty one). Comparing the regression to the optimal policy, they found that even below a certain stock level, subjects still tend to extract the resource when they should not. Investigating whether there was an improvement in subjects extraction behavior, the authors found that the tradeoff between instantaneous payoff and the future sum of payoffs created by the discount factor, leads to initial overextraction of the resource which persists over sessions.²³ They also checked for the model that best describes the behavior of subjects in the different phases for pay, by estimating a more general model (13) with three subspecifications.²⁴

$$x_t = \beta_0 + \beta_1 S_t + \beta_2 (S_t^2) + \beta_3 x_{t-1} + \beta_4 t + e_t \quad (13)$$

The first subspecification includes the current stock (S_t) and the lagged extraction rate (x_{t-1}). The second subspecification includes the time (t) in half seconds in the first subspecification, while the last subspecification includes the square root of the current stock (S_t^2) in the first subspecification. The results suggested that linear model better explains extraction rate than non linear model, and that the second subspecification was the most selected by subjects. Table 2 summarizes the continuous time articles we reviewed in subsections (3.3) and (3.4).

Table 2 – A summary of continuous time models

Paper	Research question	Nature of the resource	Theoretical model	Experiment	Data analysis	Main results
Tasneem et al. (2017)	Choice of strategies : linear vs. non linear	Renewable fishery	Markovian strategies Infinite horizon	Contextualization Information update every second Continuation payoff	Parametric & non-parametric tests	Steady state : 41.5% non linear vs. 19% linear
Tasneem et al. (2019)	Efficient & sustainable management	Renewable fishery	Markovian strategies Infinite horizon Sole agent	Contextualization Information update every half second Continuation payoff	Parametric & non-parametric tests	Suboptimal behavior : initial overextraction

4 Mixed Time CPRs Models

As it is obvious from sections 2 and 3, the literature emphasizes the management of common pool resources either in discrete time or in continuous time. However, a small but significant part of the literature has studied CPRs by combining continuous and discrete time for various reasons (Noussair et al., 2015). Most of the time in these articles, continuous time is used for the theoretical model, while discrete time is used for the experiment. One of these reasons could be the fact that the implementation of continuous time in the lab is relatively recent and a bit difficult, while discrete time is quite simple and more rational. This property of discrete time makes it easy to implement in the lab. Another reason could be that using a very small discretization in time, continuous time can be approximated by discrete time, which avoids the difficulty of implementing continuous time in the lab.

Laboratory experiments (in vitro), despite their relative simplicity and the reliability of the data obtained thanks to the control exerted by the experimenter, have been widely criticized for their lack of external validity (Loewenstein, 1999). Field experiments (in vivo) could be an alternative in providing external validity and can be divided into three main groups. Artefactual field experiments, which are identical to laboratory experiments, but are carried out with subjects representative of the active population. Framed field experiments, which are artefactual field experiments with realistic environment and information. Natural field experiments, also identical to framed field experiments except that the studied environment is the one in which subjects perform their tasks and they ignore that they are participating in an experiment. For precise details about experimental economics, see Serra (2012).

4.1 An Example of Field Experiment

Framed field experiments have the advantage of testing the influence of context elements on agents' behavior. Based on this framework, Noussair et al. (2015) try to investigate cooperation among the users of a common renewable resource. Departing from the canonical model of Schaefer (1957), the authors defined a continuous time finite horizon model in which n agents share a fishery. Assuming zero costs, each agent i has to maximize his catch $x_i(t)$ under the dynamics of the stock $S(t)$, which is renewed according to a logistic growth function $F(S(t))$. Then, the authors derived two benchmarks that are the Nash and the social optimum outcomes. The corresponding social optimum problem is given by equation (14) :

$$\begin{aligned}
& \max_{x_i(t)} \int_{t=0}^T \sum_{i=1}^n \exp^{-rt} \bar{p} \underbrace{\alpha E_i(t) S(t)}_{x_i(t)} dt \quad (14) \\
& \text{s.t. } \dot{S}(t) = \overbrace{RS(t) \left(1 - \frac{S(t)}{K}\right)}^{F(S(t))} - \sum_{i=1}^n \underbrace{\alpha E_i(t) S(t)}_{x_i(t)} \text{ with } S_0 = K
\end{aligned}$$

where $E_i(t)$ denotes the harvesting effort and \bar{E} is the maximum amount of effort an agent can provide. R is the intrinsic growth, K is the carrying capacity and \bar{p} is the marginal value of an extracted resource unit.

Eight fixed groups of four subjects participated in two experimental sessions of a recreational fishing. To make sure that all the subjects well understand the game, they had to answer test questions before the start of a session. Each session consisted in four periods of one hour each and each member of a same group wore a colored ribbon to indicate to which group he belongs. The authors implemented their experiment by making a discrete approximation of the dynamics of the stock as shown by equation (15) :

$$S_{t+1} = S_t - X_t + F(S_t - X_t) \quad (15)$$

where $X_t = \sum_{i=1}^n x_{it}$ denotes the total catch. In the experiment, the stock size is also called the "allowable catch remaining" (ACR) at the beginning of period t . At the beginning of the first period, experimenters released into a pond 38 rainbow trout including a supplementary six trout, so that each subject can catch 2 trout. Then, as long as the total catch did not exceed the available amount for the group, each participant could harvest as many fish as he liked. Regeneration was simulated by adding at the end of each period and for groups that have not exhausted their stock, an amount of fish equals to the amount harvested in the previous period. This aimed to have the same amount of fish at the beginning of each period. At the end of each period, subjects were given all information to begin a new period, but in case of resource exhaustion before the last period, they had to leave the pond. To avoid the problem of negative marginal utility, subjects were allowed to take home all the fish they caught and received in addition five euros for each fish caught. The authors derived two main predictions to distinguish cooperation from non-cooperation. The first prediction is that the social optimum equilibrium is reached when the logistic growth function equals the discount rate. Given their parameterization, subjects should quickly harvest the stock until it remain four fish, stop catching for the stock to regenerate up

to eight fish, and quickly catch again four fish. Thus, the fishing effort will depend on the remaining group stock under cooperation. The second prediction is that, contrary to the first prediction, subjects' will not modify their harvest over the four periods under the Nash equilibrium, which involves the depletion of the stock within the first period.

Although they found a lack of cooperation, consistent with the standard economic theory, the authors emphasize the importance of contextualization when testing the canonical renewable resource model. A Wilcoxon test on the distribution of the average group effort between the first and the fourth period, allowed them to find support to their second prediction. And applying a fixed effects regression confirmed that harvesting effort does not differ statistically regardless of the stock size.²⁵ Table 3 summarizes the mixed time article we reviewed in this subsection.

Table 3 – A summary of mixed time models

Paper	Research question	Nature of the resource	Theoretical model	Experiment	Data analysis	Main results
Noussair et al. (2015)	Cooperation among subjects	Renewable fishery	Continuous time Finite horizon Nash, SO	Framed field Discrete time	Parametric & non-parametric tests	Lack of cooperation

5 Empirical Methods used in the Studied Articles

Another crucial step in the study of the behavior of common pool resource users is data analysis, as it is based on these results that policy implications can emerge to ensure the effective management of CPRs. Experimental data collected in the studies we reviewed are generally panel data. That is, they contain several observations for the same individual over a period of time, and therefore have two dimensions : an individual dimension (cross-sectional) and a temporal dimension (time series). However, one of the key elements for the analysis of experimental data lies in the choice between parametric and non-parametric methods. Parametric methods are based on distributional assumptions (most commonly, the normality of the outcome variable) which holds if the analyzed variables are cardinal. Nevertheless, experimental data do not always satisfy normality condition, so that non-parametric methods seem to provide a compelling alternative to parametric methods.²⁶ Most of the articles studied in this survey adopted non-parametric methods, some used parametric methods and others made a combination of both. In this section, we will review the main methods frequently used by the authors to analyze their data.

The first category of empirical methods that we will examine is that of statistical indicators. Some authors compare the mean to the median because they are positional measures that give a quick idea of the characteristics of the study sample. They have the advantage of simplicity, are intuitive, the median is robust to extreme values, and they could therefore be a good beginning for further analysis. For instance, [Oprea et al. \(2014\)](#) used this method to compare contribution levels to a public good in quasi-continuous time to those in discrete time. This was also the case for [Bigoni et al. \(2015\)](#), for the determination of cooperation levels in their repeated prisoner's dilemma game.

The research question most frequently addressed in this review was the determination of the theoretical behavior to which experimental subjects are closest. To do this, a simplest parametric method is to compute the Mean Squared Deviation (MSD), which is a dispersion parameter used to accurately estimate the difference between the optimal and the observed behavior ([Herr et al., 1997](#)).²⁷ One should keep in mind that the MSD is only relevant if it is compared to another value of MSD. Suppose for example that we want to know whether a subject's behavior is closer to myopic or to optimal behavior. We should therefore compute the myopic MSD and the optimal MSD. Thus, the lowest value of MSD (close to zero) will determine the behavior to which the subject is closest. However, using the MSD as the only criterion for classifying behaviors could give misleading results, as the MSD allows for a global classification of subjects' behavior, without taking into account the fact that subjects may deviate from the

theoretical solution. It is therefore necessary to combine the MSD with a regression method to obtain an accurate classification. See [Djiguemde et al. \(2019\)](#) for a detailed explanation.

Finally, the last criterion we found is efficiency. Determined by almost all the authors, efficiency is defined as the ratio of the total observed payoffs to the optimal payoff. ([Herr et al., 1997](#); [Suter et al., 2012](#); [Tasneem et al., 2017, 2019](#)). [Tasneem et al. \(2019\)](#) found that average efficiency increases with the initial stock of the resource and the experience of subjects. Otherwise, [Gardner et al. \(1997\)](#) defined efficiency as the coefficient of resource utilization (CRU). But unlike previous authors, [Hey et al. \(2009\)](#) defined efficiency by the ratio of observed extraction to optimal extraction, and used it for the calculation of payoffs, which they defined as the product between efficiency and a premium specific to each of their four treatments.

The second category of methods, the most commonly used by the authors, is a non-parametric test of comparison called the Mann Whitney test.²⁸ This test is a non-parametric alternative to the Student t-test, used to compare two paired groups, by calculating and analyzing the difference between each set of pairs. ([Herr et al., 1997](#); [Oprea et al., 2014](#); [Noussair et al., 2015](#); [Leng et al., 2018](#)). The two-sample Kolmogorov-Smirnov test is similar to the Mann Whitney test, as it allows to test whether two samples come from the same distribution ([Tasneem et al., 2017](#)). However, in case of more than two independent samples, the Kruskal-Wallis test is used as an extension of the Wilcoxon Rank-Sum test, but is replaced by the Jonckheere-Terpstra test of ordered alternatives when there is an expected order to the group medians ([Hey et al., 2009](#)).

The third category of empirical methods deals with estimation methods. One of the most widely used estimation method nowadays is the Maximum Likelihood (ML) method, whose goal is to find the parameter that maximizes the probability of observing the sample actually observed, by assuming a conditional distribution of the explained variable with respect to the explanatory variables ([Mason & Phillips, 1997](#)). It can be applied to linear regression and under some assumptions like the Gaussian assumption (normality of errors), the Maximum Likelihood gives the same estimations as the Ordinary Least Squares (OLS).²⁹ The Maximum Likelihood also allows the estimation of qualitative variables (most often dichotomous). However, in the case of qualitative variables, the dependent variable is not always observable (latent). The Tobit model, intermediate between linear and dichotomous models, is then adapted for this type of analysis, because it is a censored regression model that describes the relationship between a limited dependent variable (which is continuous but can only be observed over a certain interval) and one or more independent variables.³⁰ When the dependent

variable is limited by two bounds, the model used is a two-limit Tobit (Tasneem et al., 2017, 2019).

In economics, the use of simple dynamic regression models such as partial adjustment models dates back to Nerlove (1958), who used this type of model to investigate the lags in farmers' response to price changes. In econometrics, partial adjustment models are used to justify taking into account one or more lags of the dependent variable in a regression function. It has been used by Mason & Phillips (1997) to study the decision-making of experimental subjects. However, the problem with the partial adjustment model is that the OLS estimator, although convergent, is biased. Hence the use of alternative methods such as the Feasible Generalized Least Squares (FGLS), which is an implementable version of the Generalized Least Squares (GLS), used when the covariance of the errors is unknown. FGLS is built in two stages : the model is firstly estimated by Ordinary Least Squares (OLS) to build a consistent estimator of the errors covariance matrix with the residuals. Using secondly this consistent estimator, one can implement Weighted Least Squares (WLS). GLS is a generalization of OLS technique, used to estimate the parameters of a model in case of serial correlation and/or heteroskedasticity (the errors can have different variances), while WLS is a special case of GLS where covariance matrix is diagonal, i.e. the error terms are uncorrelated. Feasible Generalized Least Squares were also used by Suter et al. (2012), but with the Prais-Winsten procedure, to analyse individual myopic behavior in each of their four treatments. This procedure is a modification of the Cochrane-Orcutt estimation and is a special case of Feasible Generalized Least Squares, taking into account the serial correlation of type AR(1) (autoregressive-1) in a linear model.³¹

6 Conclusion

In this survey, we attempted to bring an overview of the recent literature using dynamic games to examine the issues of common pool resources throughout experiments. Our goal was to identify the different steps for the implementation of these games into the lab. This leads us to distinguish continuous time from discrete time, finite from infinite horizon and provide a discussion on experimentics. We found that most of the articles were in discrete time, due to its relative simplicity of implementation in the lab compared to continuous time. The time horizon over which the study is conducted is also very determining, since it strongly influences the results. We thus found that the finite horizon was the most implemented for several reasons including its simplicity. For Hey et al. (2009) for instance, «infinite horizon cannot be implemented in laboratory». Moreover, implementing finite horizon instead of infinite horizon seems logical,

since «... the earth does not exist indefinitely... ».

Therefore, we paid special attention to continuous time and infinite horizon for two reasons. First, their implementation in the lab is in its infancy, as they are very challenging. Continuous time makes it possible to simulate the real evolution of common pool resources, which takes place without interruption over time. As for the infinite horizon, it is simple to implement from a theoretical point of view and allows to obtain predictions over a very very large time interval. From an experimental point of view, the infinite horizon ensures the sustainability of the resource, because it allows experimental subjects to have a projection of the consequences of their decision making on the resource up to infinity. This stimulates them to adopt a less myopic behavior. Furthermore, although people don't live forever, they may care about their offspring, by taking care of the resource. Second, we wanted to contribute to the growing literature on the study of the behavior of CPR users. We wanted to do that, simultaneously in a simple dynamic environment without interactions first and second by allowing for strategic interactions between users, in order to analyze potential differences (Djiguemde et al., 2019). This allowed us to distinguish continuous time using differential games (Tasneem et al., 2017, 2019) from quasi-continuous time using extensive form games (Friedman & Oprea, 2012; Oprea et al., 2014; Bigoni et al., 2015; Leng et al., 2018).³²

However, we found that the ability of continuous time to foster cooperation seems mixed, so that some authors suggest supplementary mechanisms like punishment, communication, regulation, voting processes to improve cooperation (Gardner et al., 1997; Noussair et al., 2015; Leng et al., 2018). We also found two ways of implementing infinite horizon : either by imposing a random termination rule (Mason & Phillips, 1997; Suter et al., 2012); or, by discounting payoffs over a fixed period while adding a continuation payoff, which computes the payoff that subjects would have obtained if the experimentation pursue indefinitely with the last conditions remaining constant (Tasneem et al., 2017, 2019). We suggest the use of the second alternative, because unlike the random termination rule, it allows to get rid of the use of a continuation probability. Moreover, it ensures all players the same end of experiment. The main finding in this survey was that, when taking into account the dynamics of the resource, suboptimal behavior (myopic) is a frequent outcome (Herr et al., 1997; Mason & Phillips, 1997; Tasneem et al., 2019). However, Hey et al. (2009) found contrary to the literature, that subjects tend to underexploit the resource when they have no information, neither on the stock, nor on the growth function. Therefore, the dynamic environment created by common pool resources does not always promote virtuous behavior from the users of these resources. Hence the need to pay particular attention to the design of the experiment.

Thus, we propose three key elements to anyone wishing to carry out an ex-

perimental study on dynamic CPRs. Note however that these key elements can be extended to other types of studies such as those relating to public goods. The first key element is the framing of the experiment, as it greatly influences the results. When choosing to contextualize an experiment, one must pay attention to the framing effects, which could bias the behavior of experimental subjects (Désolé, 2011; Cerutti, 2017). The importance of contextualization was also stressed by Noussair et al. (2015). We recommend contextualisation for very specific CPRs studies for which simulation of the natural environment allows to capture the attention of experimental subjects. However, although contextualization provides a fairly accurate representation of real life, it must be ensured that framing effects do not bias the results obtained. The second key element is to ensure experimental subjects fully understand the complex dynamic environment. This requires the implementation of a comprehension questionnaire and even several training phases before the beginning of the experiment. This was done by almost all the reviewed articles, with however the special cases of Bigoni et al. (2015); Leng et al. (2018) and Tasneem et al. (2017), for whom the participation to the experiment was conditional on passing a test. Although the test allow the elimination of outliers in the data collected, it can however be criticized because all the users of CPRs in real life do not have a perfect knowledge of the resource they harvest. The last key element one should keep in mind is data analysis, as it will determine the results obtained. Parametric and/or non parametric methods can be applied depending on the research question.

Although there has been considerable progress in the implementation of dynamic games in the lab, more research is needed to improve and facilitate the implementation of continuous time and infinite horizon, which are still very recent. In addition, methods or a combination of data analysis methods, sufficiently harmonized for the study of common pool resources are needed. All these improvements will facilitate the establishment of much more targeted policies for the efficient management of common pool resources.³³

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Notes

¹Experimentics is a word used to designate the different econometric techniques customized to analyse experimental data.

²See section 5 for a detailed explanation of the partial adjustment model.

³The 17 states are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Texas, Utah, Washington, Wyoming.

- ⁴ • The token cost for an individual is equal to the average cost of the token for this period \times the total number of tokens ordered for this period.
- The new cost of base token is equal to : $(1 + \text{the total number of tokens ordered in previous periods}) \times \text{the amount of the increase}$.

⁵the Maximum Sustainable Yield (MSY), is the largest extraction an agent can achieve from a given stock.

⁶The non contextualization was to avoid an emotional bias related to the pity subjects will feel when confronted with the slaughter of fish.

⁷To provide these prudent benchmarks, the authors used for the first treatment, a "hill-climbing algorithm" to identify the stock level inducing the maximum growth. For the second treatment, they applied a "Monte-Carlo simulation" on extraction excluding a pre-mature extinction of the resource. In the zero information treatment, they applied a combination of the two previous methods.

⁸In case of only two categories (here, over-harvesters and under-harvesters), the binomial test allows the comparison between the observed distribution and the theoretical distribution.

⁹The main difference between the spatially explicit model and the bathtub model is that in the spatially explicit model, the depth to water variable is specific to the location and depends on both the distance of the sequence of pumping occurred in all previous periods. Another difference between the two models lies in the memory of the system, meaning that the impact on well j of pumping in well i in period t is very small in period $t + 1$, but larger in later periods.

¹⁰This approximation assumes that the costate variable λ is stationary, implying that future pumping is equal to current pumping. Thus, with $\lambda_t = \lambda_{t+1} = \lambda$, the first order condition gives $\lambda = nc_0x_t/(\rho - 1)$. Substituting it and solving for x_t gives the optimal quantity of pumping.

¹¹The storativity estimates the relation between pumping and its effect on the future depth to water, while transmissivity estimates the distance between wells. A low transmissivity value indicates that wells are more evenly spaced. When the transmissivity tends to infinity, the spatially explicit model converges to the bathtub model.

¹²Here, authors made numerical predictions by regressing in each period the predicted pumping rates on treatment-specific indicator variables and also on the treatment indicators interacted with the period number.

¹³While a higher number of myopic subjects was found in the Bathtub treatment, the authors found on average that subjects in that treatment adopt a Nash feedback behavior. This difference in results can be explained by the fact that the fewest subjects exploiting less than the myopic prediction, allow the groundwater to grow, leading on average to a Nash feedback behavior.

¹⁴All along their analyses, the authors have clustered standard errors either at participant level or at group level.

¹⁵In long duration treatments, subjects played supergames lasting 60 seconds each; whereas in short duration treatments, the supergame lasted 20 seconds.

¹⁶The minimum effort game is a coordination game having multiple Pareto-ranked Nash equilibria and where players coordinate on the less efficient equilibrium by choosing low effort, because of the high strategic uncertainty associated with the choice of a high effort which leads to the more efficient equilibrium. For more detailed information about the minimum effort game, see [Cartwright \(2018\)](#).

¹⁷The social optimum equilibrium is consistent with maintaining for most of the decision process a 50% density of token and harvesting at the end of the decision process the remaining tokens.

¹⁸Knowing the replenishment rate and using the constant rate, subjects learned how to keep the stock at a constant level.

¹⁹For more details about the the MSER-5 (Mean Squared Error Reduction ou Marginal Standard Error Rule) algorithm, see their "Appendix C : Steady state analysis".

²⁰Authors used the "general-to-specific" modeling approach, consisting in detecting the best model. See their "Appendix D : General-to-specific algorithm" for more details.

²¹The constant rate is the extraction rate allowing the stock level to be constant. The instantaneous payoff is a quadratic function of the extraction rate, where the maximum is reached for an extraction rate of one. The cumulative payoff is the sum of the discounted instantaneous payoffs, obtained by multiplying instantaneous payoffs by \exp^{-rt} .

²²To compute the MSER-5, the authors do not take into consideration situations involving a minimum stock of zero or a maximum stock of twenty five. For more details about this algorithm, refer to their Appendix 5 : Identifying Steady States in the Choice Data.

²³To find this result, the authors regressed the difference between the initial extraction rate and the optimal extraction rate, on the order of the phases for pay, by controlling for the stock level and clustering standard errors by subjects. Given the panel structure of the data, there is a correlation between some observations, hence the necessity to adjust standard errors before any analysis in order to get a good specification.

²⁴In each phase for pay, the authors applied a multi-path search general to specific model selection approach to estimate the best-fitting extraction policy. See Their Appendix C : General-to-Specific Algorithm, for more details about this approach. Then, they estimated a two limit Tobit panel model with an upper bound of two and a lower bound of zero, where each subject is a panel unit, to find the three subspecifications.

²⁵While theoretical predictions and the experimental earnings are mainly based on the number of fish caught, the harvesting effort is measured through the amount of times a fisherman casts his rod.

²⁶See [Moffatt \(2015\)](#) for a clear overview of econometric methods in experimental economics.

²⁷Let's n be the size of the sample, x_{it}^{obs} the observed behavior and x_{it}^{pred} the predicted or the theoretical behavior. The Mean Squared Deviation (MSD) is obtained through this formula :

$$MSD = \frac{\sum_i \sum_t (x_{it}^{obs} - x_{it}^{pred})^2}{n}$$

²⁸The Mann Whitney test is also known under various names such as : the Mann Whitney U test, the two-sided Mann Whitney rank sum test, the pairwise Mann Whitney test, the Mann-Whitney-Wilcoxon test, the Wilcoxon-Mann-Whitney test, the Wilcoxon rank-sum test and the Wilcoxon signed rank test.

²⁹The Maximum Likelihood (ML) method requires to know the distribution law of the parameters beforehand, unlike the Ordinary Least Squares (OLS) method. OLS is a linear regression method that estimates the relationship between independent and dependent variables by minimizing the sum of squared errors from the data.

³⁰In censored models, the entire sample contains observations of the explanatory variables.

³¹The Prais-Winsten estimation is a modification of the Cochrane-Orcutt estimation because it does not lose the first observation, thus providing a more efficient result.

³²An innovative aspect in the implementation of (quasi) continuous time in the lab by [Bigoni et al. \(2015\)](#), was the use of touch screens instead of a computer mouse in subjects' decision-making processes. This allowed the switch of decisions, not to be heard by the other members of the group.

³³For a supplementary review on groundwater management, see [Koundouri \(2004\)](#) and [Foley et al. \(2012\)](#) for habitat-fisheries.

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Appendices

Table 4 – Variables for game articles

Variables	Description
x_{it}	An agent's extraction (an agent's extraction rate in continuous time)
x_{jt}	Other agent's extraction rate (in continuous time)
X_t	Total group extraction
B_{it}	Benefit function
π	Profit
C_{it}	Total extraction cost function
c_t	Marginal cost
c_0	Cost parameter
c_f	Fixed costs
c_{op}	Opportunity cost
c_1	Static crowding externality
c_2	Dynamic externality
P	Price
k	Incremental cost parameter
V	Value function
d_t	Depth to water
s	Parameter on the size and configuration of the aquifer
S_t	Stock of the resource
S_{th}	Threshold stock
$F(S)$	Logistic growth function
n	Number of users
i	Index of users
T	Finite time horizon
r	Discount rate
ρ	Discount factor (in discrete time)
\exp^{-r}	Discount factor (in continuous time)
R	Recharge rate or replenishment rate or intrinsic growth rate
K	Carrying capacity
MSY	Maximum Sustainable Yield
E	Extraction effort
E_0	Per period effort endowment
\bar{E}	Maximum amount of extraction effort
α	Extraction technology
\bar{p}	Marginal value of an extracted resource unit
AS	Area times storativity of the aquifer
Tr	Transmissivity
$v(g, h)$	Radial distance between well g and well h
$w(t, v)$	The well function

Table 5 – Variables for optimal control articles

Variables	Description
x_t	An agent's extraction (an agent's extraction rate in continuous time)
S_t	Stock of the resource
$F(S_t)$	Logistic growth function
n	Number of users
i	Index of users
T	Finite time horizon
r	Discount rate
ρ	Discount factor (in discrete time)
\exp^{-r}	Discount factor (in continuous time)
R	Recharge rate or replenishment rate or intrinsic growth
K	Carrying capacity
MSY	Maximum Sustainable Yield

Remark : In this survey, **extraction, harvesting, pumping, catch** or **fishing** refer to the same concept.

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