Experimenting Groundwater Governance Assessing Policy Performance through Lab-in-the-field Experiments in Kebili Oases (Tunisia)

Oussama Rhouma¹, Dimitri Dubois², Katrin Erdlenbruch², Emmanuelle Lavaine², Marc Willinger², Stefano Farolfi^{2,3,4}, Faten Khamassi⁵

¹ESI Medjez ElBab, Tunis, Tunisia.

²CEE-M, Univ Montpellier, CNRS, INRAE, Institut Agro, Montpellier, France.
 ³G-EAU, Univ Montpellier, AgroParisTech, CIRAD, INRAE, Institut Agro, IRD, Montpellier, France.
 ⁴CEEPA, University of Pretoria, Pretoria, South Africa.

⁵INAT, Tunis, Tunisia.







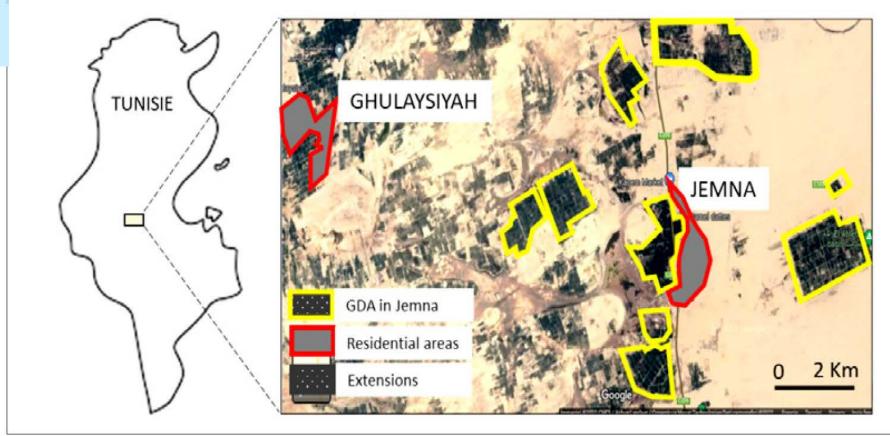


Background

- **Groundwater** is a crucial source for **irrigation** => over 70% of global water use (FAO, 2022).
- In North Africa, half of groundwater withdrawals exceed natural recharge rates (Mayaux et al., 2022).
- In Tunisia in recent decades, **public policies have driven rapid agricultural intensification** in the oases (Kadiri et al., 2022).
- In the Kebili region, **unregulated water extraction** is a major cause for groundwater overexploitation (Mekki et al., 2013, Ghazouani et al., 2009, Mekki et al., 2013).
- To combat groundwater overexploitation in the oases, **alternative and more effective governance tools** are urgently needed (Frija et al., 2015).



Figure 1 - Geographical location of Jemna oasis.



The Oases in Jemna, Kebili















Behavioural economics and public policy design

- **Behavioural economics** is now widely recognized as a valuable contributor to **public policy design**, including **water** management (Chetty, 2015, Correia and Roseta-Palma, 2014, Lunn, 2014)
- It offers new tools, **improving policy impact predictions**, and revealing new **welfare implications** (see (Chetty, 2015)
- Lunn and Choisdealbha (2018) emphasize the overlooked value of lab experiments in policymaking, compared to the **dominant focus on RCTs**. Lab studies, however, can **better isolate behavioural mechanisms** across contexts. The authors call for a complementary use of both approaches

Previous experiments for CPR issues

- Previous experiments have shown the relevance of **lab-in-the-field experiments to address commons issues**. (Cardenas and Ostrom, 2004, Gelcich et al., 2012, Hopfensitz et al., 2018, Raheem, 2015, Timilsina et al., 2017).
- Janssen et al. (2009) set up a **spatial and dynamic resource experiment to test different governance tools**. Tu et al. (2023) Investigated the role of shared goals among resource users in promoting sustainable resource exploitation, using a dynamic game-theoretic approach.
- We designed a framed lab-in-the-field experiment to investigate governance challenges related to the management of the Kebili aquifer. The experimental setup is based on a dynamic model of CPR extraction that incorporates both static and dynamic externalities, following Gardner et al. (1997)
- This combination of externalities exacerbates rivalry among users (Gardner et al., 1990, Walker et al., 1990, 2000), ultimately leading to a "tragedy of the commons" (Hardin, 1968).

Our Experimental Approach LEEM **FIELD** LAB Experiments

A simple dynamic CPR model (Gardner et al.,1997)

Extraction =
$$X_t = \sum_{i=1}^n x_{it}$$
.
Water depth = $D_{t+1} = D_t + X_t$,
Benefits = $B_{it} = ax_{it} - bx_{it}^2$,

$$Costs = C_{it} = x_{it}(c + kX_t + D_t),$$
Utility = $U_{it} = ax_{it} - bx_{it}^2 - x_{it}(c + kX_t + D_t)$.

Parameters: $a = 220, b = 5, c = 0.5, D_1 = 0, k = 0.5.$

N=5; T=5

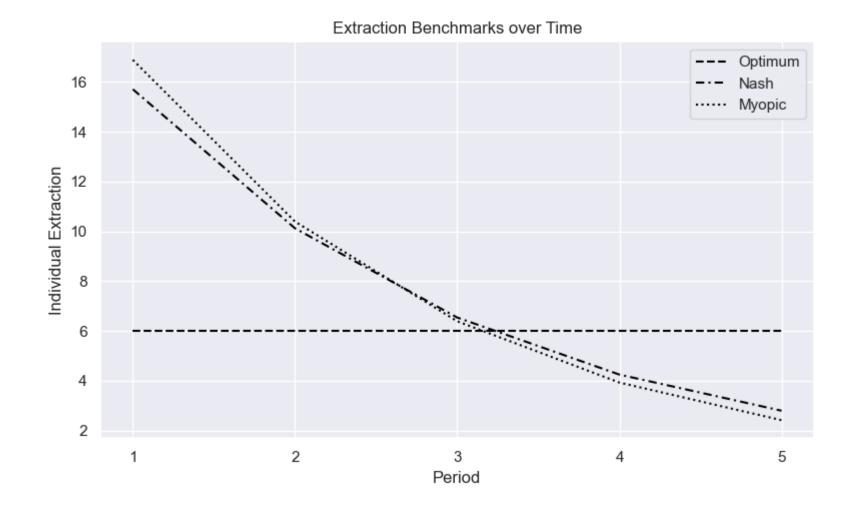
Solutions

Optimum =
$$\max_{xi} \sum_{t=1}^{T} \sum_{i=1}^{n} U_{it}$$

Nash =
$$\max_{xi} \sum_{t=1}^{T} U_{it}$$

$$Myopic = \max_{xi} U_{it}, \qquad D_t \quad given.$$

Conditional optimal strategy : the Expert Based on Dt



Experimental Design

• The experiment was conducted in **laboratories** in Montpellier (France) and Tunis (Tunisia), as well as in the **field** in Tunisia (Kebili).

Parts

- Part 1: Common-Pool Resource Extraction Game
- Part 2: Experimental Treatments
- Part 3: Number Line Estimation (NLE)

Questionnaires

- Risk and Time Preferences: Assesses participants' self-perceived risk-taking tendencies
- Contextual Risk-Taking: Evaluates participants' risk preferences in specific domains
- Socio-Demographic

CPR Extraction game (Part 1)

- Groups of five.
- The game consists of five periods.
- In **each period**, every participant decides **how many tokens to extract** from a common resource shared by all group members. The extraction amount can range from 0 to 25 tokens. Each extracted token generates a benefit but also incurs a cost.
- The **benefit** function is strictly increasing up to 22 tokens and then decreasing.
- The extraction **cost** depends on individual and group extractions as well as a scarcity index D, which represents the cumulative extraction of the group in previous periods.
- **Participants are informed** of the benefit and cost structure before making their decisions. The payoff for each period is computed as the difference between the benefit and the extraction cost.
- **Before Part 1** begins, participants complete a five-period training phase under identical rules, but payoffs from this phase do not contribute to their final earnings.

Treatments (Part 2)

- Baseline: Replicates the structure of Part 1 without any additional decision-support mechanisms.
- *Simulator*: Participants have access to a simulator that allows them to **visualize potential future payoffs** based on their extraction levels and the total extraction of the other players in their group.
- *Communication*: In addition to the simulator, participants can **communicate with their group members through a chat interface**. The discussion is unrestricted but must not include identifying information or offensive language. Eight predefined messages are available to facilitate coordination.

Communication takes place for 3 minutes before every round.

• *Expert*: Participants have access to both the simulator and an **external expert's advice**. The expert provides, for **each period**, **the optimal group extraction level** that maximizes collective payoffs for the remainder of the game.



Hypotheses

- **H1**. Under "laissez-faire", subjects' extraction behavior leads to an **inefficient extraction path** (Gardner et al., 1997).
- **H2**. In the baseline treatment, subjects' extraction behavior is **close to both, the Nash extraction path and the myopic extraction path** (which are close to each other). Herr et al. (1997) for example showed that extraction behavior is closest to the myopic path.
- **H3**. Introducing the simulator would not change significantly subjects' behavior wrt the baseline (Apesteguia, 2006). The better information on future payoffs will not be sufficient to move subjects' extractions away from the Nash or Myopic extraction pattern.
- **H4**. **Communication will lead to Pareto improvements**. Indeed, Janssen et al. (2009) showed that communication treatments in resource experiments lead to more cooperative behavior and less resource extraction.
- H5. The expert treatment will lead to Pareto improvements, bringing subjects closer to the optimal extraction and earning patterns (Janssen, 2013). As in Brucks and Mosler (2011) the expert treatment introduces information about the state of the resource and a sort of nudge that is informative and mildly normative for the players (Buckley and Llerena, 2022), suggesting at each round what would be the optimal extraction for the group, without any obligation to follow it.

Samples

630 subjects (126 groups)

460 subjets (92 groups) in the Lab: 240 in France, 220 in Tunisia

170 subjects (34 groups) in the Field

Treatment	# Participants	# Groups	% Student	% Female	\mathbf{Age}
Lab					
Baseline	145	29	92.41	64.14	23.29
Simulator	100	20	90.00	44.00	22.53
Communication	100	20	91.00	56.00	22.97
Expert	115	23	91.30	53.91	21.83
Field					
Baseline	40	8	0	0	51.60
Simulator	40	8	0	0	51.92
Communication	40	8	0	0	46.15
Expert	50	10	0	0	50.92

Table 5: Summary of participant characteristics

Empirical strategy

• To compare the average extraction levels between each treatment and the baseline after the treatment is introduced, we estimate a *difference-in-differences* empirical model.

$$Y_{grc} = \alpha_0 + \beta_1 Post * Treat_{grc} + \beta_2 Treat_{gc} + \beta_3 Post_r + \alpha_r + \varphi Country_c + \xi_{my}$$

Y = Extraction or Payoff $Post = 1 ext{ if round} = 11 ext{ onward (Part2)}$ $Treat = 1 ext{ if group received treatment}$ $\alpha r = fixed round ext{ effects}$ $Country = 1 ext{ if country} = Tunisia ext{ (in Lab samples)}$

Treatment — Baseline — Simulator — Communication — Expert



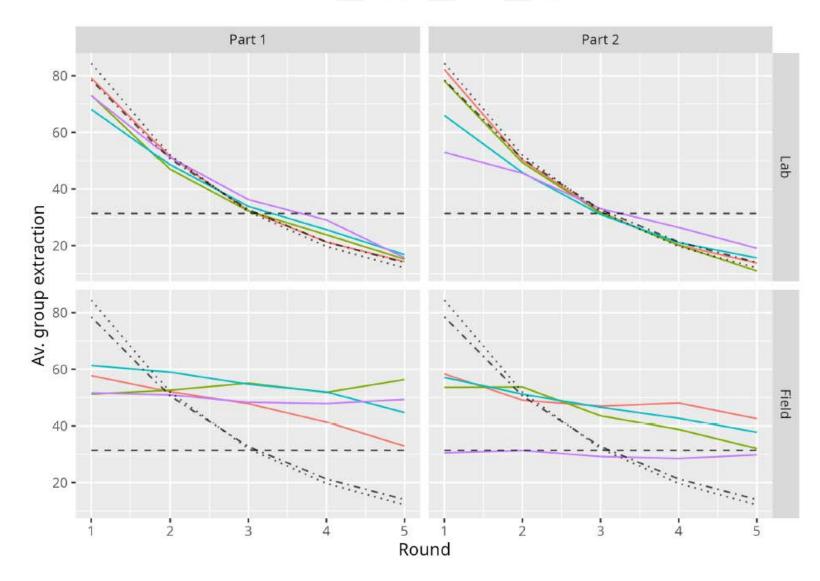


Table 6: Payoff and Extraction Efficiency by Treatments in Part 2

Benchmark	Cumulative Earnings	Efficiency	Cumulative Extraction	Extraction / Optimum
Optimum	17175.00	100%	150.00	100%
Nash	13393.00	78%	197.11	131%
Myopic	12520.00	73%	200.13	133%
LAB				
Baseline	10780.72	63%	198.97	133%
Simulator	11753.55	68%	190.15	127%
Communication	12991.95	76%	178.55	119%
Expert	14098.61	82%	177.43	118%
FIELD				
Baseline	6649.50	39%	245.25	164%
Simulator	8959.38	52%	221.75	148%
Communication	5122.12	30%	235.50	157%
Expert	15575.20	91%	149.30	100%

Table 6: Payoff and Extraction Efficiency by Treatments in Part 2

Benchmark	Cumulative Earnings	Efficiency	Cumulative Extraction	Extraction / Optimum
Optimum	17175.00	100%	150.00	100%
Nash	13393.00	78%	197.11	131%
Myopic	12520.00	73%	200.13	133%
LAB				
Baseline	10780.72	63%	198.97	133%
Simulator	11753.55	68%	190.15	127%
Communication	12991.95	76%	178.55	119%
Expert	14098.61	82%	177.43	118%
FIELD				
Baseline	6649.50	39%	245.25	164%
Simulator	8959.38	52%	221.75	148%
Communication	5122.12	30%	235.50	157%
Expert	15575.20	91%	149.30	100%

Table 6: Payoff and Extraction Efficiency by Treatments in Part 2

Benchmark	Cumulative Earnings	Efficiency	Cumulative Extraction	Extraction / Optimum
Optimum	17175.00	100%	150.00	100%
Nash	13393.00	78%	197.11	131%
Myopic	12520.00	73%	200.13	133%
LAB				
Baseline	10780.72	63%	198.97	133%
Simulator	11753.55	68%	190.15	127%
Communication	12991.95	76%	178.55	119%
Expert	14098.61	82%	177.43	118%
FIELD				
Baseline	6649.50	39%	245.25	164%
Simulator	8959.38	52%	221.75	148%
Communication	5122.12	30%	235.50	157%
Expert	15575.20	91%	149.30	100%

Table 6: Payoff and Extraction Efficiency by Treatments in Part 2

Benchmark	Cumulative Earnings	Efficiency	Cumulative Extraction	Extraction / Optimum
Optimum	17175.00	100%	150.00	100%
Nash	13393.00	78%	197.11	131%
Myopic	12520.00	73%	200.13	133%
LAB				
Baseline	10780.72	63%	198.97	133%
Simulator	11753.55	68%	190.15	127%
Communication	12991.95	76%	178.55	119%
Expert	14098.61	82%	177.43	118%
FIELD				
Baseline	6649.50	39%	245.25	164%
Simulator	8959.38	52%	221.75	148%
Communication	5122.12	30%	235.50	157%
Expert	15575.20	91%	149.30	100%

Table 6: Payoff and Extraction Efficiency by Treatments in Part 2

Benchmark	Cumulative Earnings	Efficiency	Cumulative Extraction	Extraction / Optimum
Optimum	17175.00	100%	150.00	100%
Nash	13393.00	78%	197.11	131%
Myopic	12520.00	73%	200.13	133%
LAB				
Baseline	10780.72	63%	198.97	133%
Simulator	11753.55	68%	190.15	127%
Communication	12991.95	76%	178.55	119%
Expert	14098.61	82%	177.43	118%
FIELD				
Baseline	6649.50	39%	245.25	164%
Simulator	8959.38	52%	221.75	148%
Communication	5122.12	30%	235.50	157%
Expert	15575.20	91%	149.30	100%

Figure 2: Comparison Lab/Field of the effect of each treatment on average group extraction.

DiD

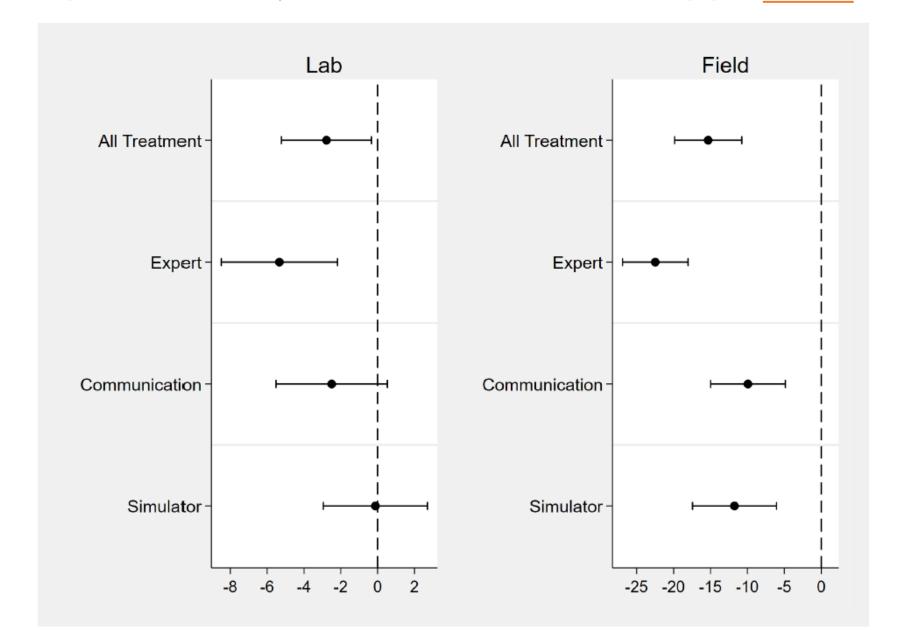
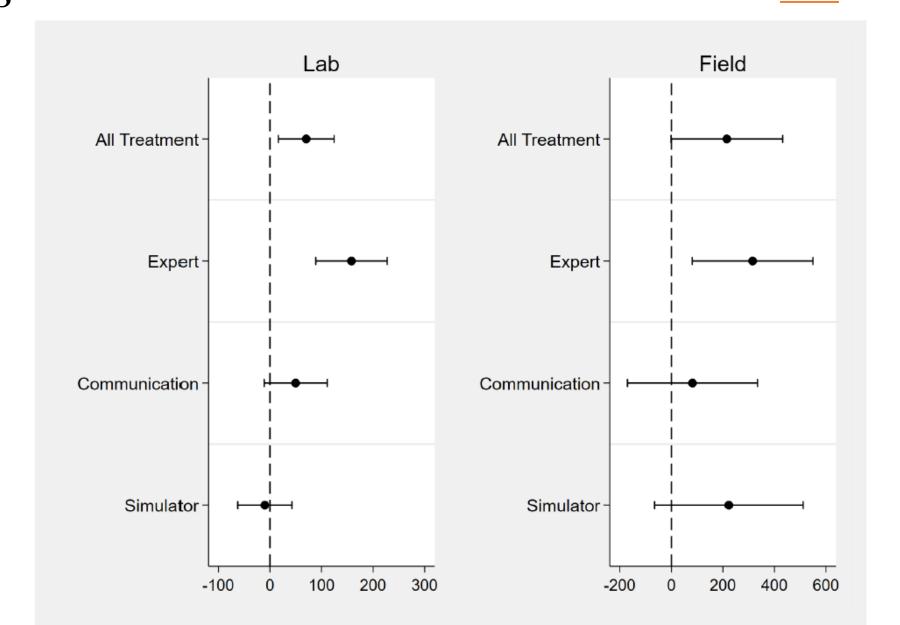


Figure 3: Comparison Lab/Field of the effect of each treatment on average group payoff.

DiD



Discussion

- Under "laissez-faire", subjects' extraction behavior leads to an **inefficient extraction path** (H1), **close to both, the Nash extraction path and the myopic extraction path** (H2)
- Simulator does not have a significant effect (H3)
- Introducing communication within groups did not produce the expected treatment effect (H4)
 - This result does not align with the principles espoused by Elinor Ostrom
 - In the Kebili area, social capital and collective action for groundwater management is low (Frija et al., 2015)
- The **Expert treatment triggered significant reductions** in the overall level of extraction both in the lab and in the field (H5)
- In the field, the Expert treatment effect is more significant and sustained all over the sessions

Discussion (contd.)

- Policy implications:
- Effectiveness of a policy based on an informed advice coming from a reliable source external to the farmers' associations => CRDA
 - CRDA could use an algorithm similar to the one used in this experiment to calculate the 'optimal extraction' and disseminate this information to the users.
 - The delivery of this information could take place **through information and communication technologies** (**ICT**), which are increasingly used in the African agricultural sector (Mansour, 2023, Mapiye et al., 2023, Mauti et al., 2021, Sarku et al., 2025)
- The proposed protocol, combining lab experiments and lab in the field experiments after having discussed with local stakeholders and decision makers the policy measures to test, proved useful and sound in order to get quantitative results in terms of policy tools to propose for implementation to the local actors.
- A final step of our protocol will consist of presenting the experimental results to the local actors in order to discuss the effectiveness and acceptability of the proposed policy tools. In this phase, **facilitation tools and approaches** such as participatory role-playing games (Barreteau et al., 2012).

• Limits:

- length and costs (human and financial) associated with the protocol.
- lab in the field was implemented **only in the Kebili** region

Thank you for your attention











Closest Benchmark per Treatment and Period (Lab Data)



Closest Benchmark per Treatment and Period (Field Data)

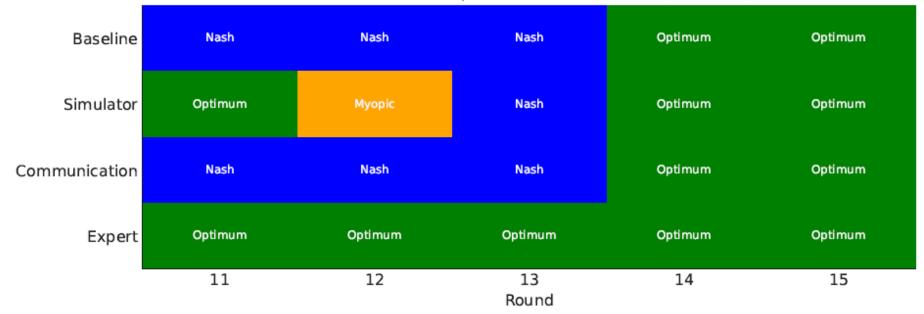


Table 13: Did group total extraction under communication

	(1)	(2)
	Group Total Extraction	
postcommunication	-7.000	-6.840
	(-1.22)	(-1.07)
rl	16.62**	16.63**
	(2.91)	(3.07)
r2	14.25*	14.25**
	(2.49)	(2.63)
r3	10.000	10.00
	(1.75)	(1.84)
r4	7.250	7.250
14	(1.27)	(1.34)
rš	0	0
To .	_	_
	(.)	(.)
16	19.38***	14.31
	(3.39)	(1.91)
r7	13.50*	13.20*
	(2.36)	(2.43)
т8	8.875	6.623
	(1.55)	(1.21)
r9	5.000	6.603
19	(0.87)	(1.21)
	(u.br)	(1.21)
r10	0	0
	(.)	(.)
num coop		-0.919
		(-0.79)
пит посоор		4.275*
mani_motoop		(2.34)
_cons	44.75***	44.75***
_ tomas	(7.66)	(7.62)
N	80	80

t statistics in parenthous

^{*} p < 0.05, ** p < 0.01, *** p < 0.001