Managing Groundwater under Uncertain Seasonal Recharge

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ABSTRACT

Managing water resources is one of the most pressing environmental challenges of the coming decades. With a changing climate, growing population and change of land use, the stress on water resources has dramatically increased [1]. Whereas policies are emerging on the use of surface water, groundwater is still lacking sustainable exploitation strategies. Designing optimal policies for groundwater extraction is challenging, particularly because of the uncertainties on the climate, subsurface and human behavior. In this study, we approach a simplified groundwater management problem with the formalism of Markov Decision Processes (MDPs). We only consider the uncertainty about the rainfall. We attempt well-established algorithms for sequential decision making, and compare the obtained policies with the global optimal policy found with brute force exploration assuming full knowledge of the future rain. We conclude that algorithms are promising but require a great amount of domain knowledge in order to converge to optimal policies.

1. Introduction

Optimal groundwater resources management has become crucial over the last decades with changing weather pattern and increased stress on the resource. The risks from suboptimal management are multiple, from saltwater intrusion in coastal aquifer to land subsidence [2]. The challenge with groundwater resides in the difficulty to gather direct information on the aquifer. Indeed, estimating just the amount of water available or the level of the aquifer is subject to many uncertainties, making the formulation of an adequate policy challenging [3]. The objective of such policy is to maximize the groundwater production to match the needs of the population without any environmental impacts. There are various uncertainties involved in this decision-making process. The rock permeability that controls the water level, the rainfall that dictates the recharge of the aquifer or the pressure gradient that creates the flux are some of many examples of uncertain variables that play a crucial role in the groundwater usage. Under these conditions, it becomes challenging to optimize the pumping of groundwater over space and time. This paper focuses on the creation of optimal pumping policy in an unconfined aquifer over 12 months. The recharge of the aquifer (constrained by the rainfall) is varying over time. A single water user is extracting water out of the aquifer under some constraints. The amount of water available for pumping is either partially or fully known through observations wells. Given this (lack of) information, the user must make the optimal decision at each time step.

The formalism of Markov Decision Process (MDP) has been adopted to describe this sequential decision making problem. Two approaches have been adopted in this paper: 1) a MDP with unknown transition model and 2) a Partially Observable MDP (POMDP) where the states are not fully observable. The MDPs are described in the following section, as well as the generative model used and the algorithms developed to solve then. The different results are then presented and compared to an optimal solution computed under assumption of full knowledge. Possible improvements are then discussed.

2. Methodology

In this section, we give an overview of the groundwater model used in this work, formulate the POMDP of groundwater management, and present the global optimal policy for the problem, which will be used for evaluating the performance of the attempted algorithms.

2.1. Groundwater model

A generative model was implemented using Flopy, a python script of `MODFLOW`, a 3D finite-difference groundwater simulator developed by the U.S. Geological Survey [6]. The model takes as input a hydraulic head map (i.e. pressure map), a pumping rate, and recharge from the rain, and outputs the hydraulic head after a month of pumping. The flow dynamics depend on rock properties such as hydraulic conductivity and porosity. These were filled from a vertical section of a 3D model known as Stanford V [4] illustrated in Figure 1.

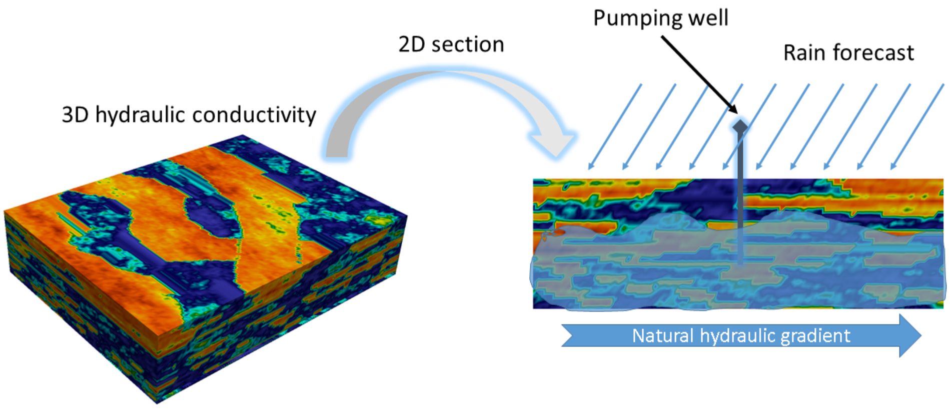

Figure 1: Groundwater flow model illustrating single pumping well, recharge from the rain, natural hydraulic gradient and subsurface properties.

The model is discretized into 100×30 grid cells. Examples of hydraulic head maps produced by a constant pumping policy are illustrated in Figure 2. In general, hydraulic maps are difficult to predict due to the heterogeneity of the rock and the recharge from the rain. Figure 2 shows the top cells becoming "dry" under high pumping and low recharge and the same cells turning "wet" when the recharge overcomes the pumping.

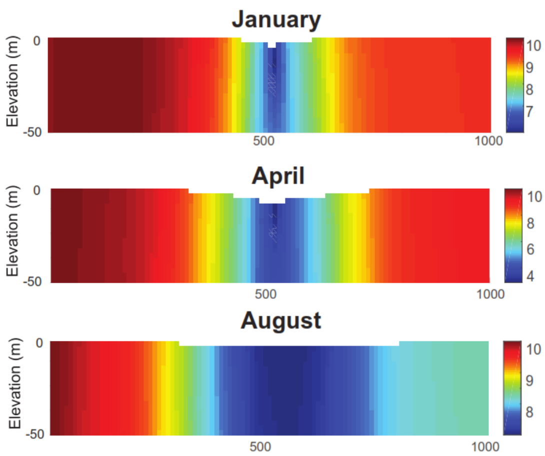

Figure 2: Example of hydraulic heads distribution under different pumping rates.

In Figure 3, we illustrate an example of 12 water tables under various pumping rates. These water tables are extracted from the previous head maps. The blue sub-horizontal water table correspond to the initial condition of the model and therefore does not present any pumping depression.

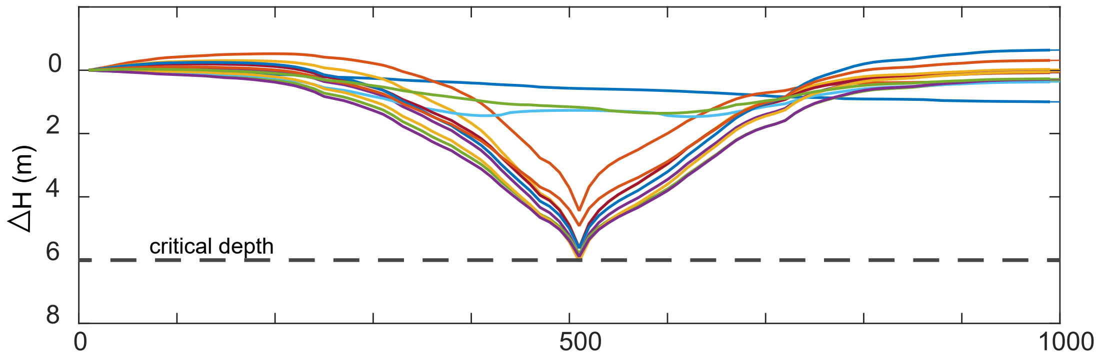

Figure 3: Example of water table evolution over 12 months under various pumping rates. The critical depth indicated correspond to a penalty in the reward model. The vertical axis represent the difference between the hydraulic head and the elevation of the top layer. Negative values correspond to the confined part of the aquifer.

2.2. Formulation of the (PO)MDP

An optimal pumping policy must be chosen that maximizes the profit of a single agent operating under a set of constraints imposed by the government. The agent is allowed to extract water from the aquifer to attend the demand of the local community but it cannot do so if the water table is depleted below a specified average depth. The law also specifies a discrete set of permitted pumping rates ranging from no-pumping (q_o), low pumping (q_l), mid pumping (q_m) and high pumping (q_h). These pumping ranges from 0 to 35 cubic meters per day. Given our current belief about the state of the aquifer and water table measurements in neighboring observation wells, we have to make a decision about which pumping rate to adopt today without knowing the rainfall in the upcoming months. The decision network for this sequential decision making problem is illustrated in Figure 4.

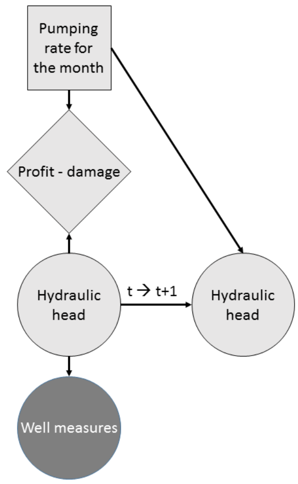

Figure 4: Decision network of groundwater management.

The reward follows the model described in Equation 1:

$$\text{Reward} = \begin{cases} aV - bV^2 - cDV & \text{if } D < 6 \\ -100 & \text{otherwise} \end{cases} \tag{1}$$

where V is the volume of water extracted, D the depth to water and a, b, c parameters of the reward model. These parameters have been adjusted so that the reward varies substantially for the given groundwater model and pumping rates.

2.3. Optimal policy

In order to measure the efficiency of our algorithms, a metric is necessary. As we are dealing with online methods (the computation is limited to reachable states), an online optimal policy has been computed. To calculate this policy, we assumed full knowledge of the rain for all upcoming months. The optimal policy is plotted in Figure 5 and Figure 6.

3. Results

3.1. MDP

The first step to solve the MDP with unknown transition model is to create a state-action-state matrix. Such a matrix has been created by running the generative model over 10,000 times. Each state corresponds to a water table. In order to limit the number of state, the water tables have been discretized. This discretization is varying along the aquifer extent. For example, a coarse grid is sufficient close to the boundaries of the aquifer, as the water tables do not vary much (as illustrated by Figure 3). A finer grid is used close to the pumping well. Each state has been reduced to a vector of 100 integers. A Q-Learning algorithm with eligibility traces has been implemented to find an optimal policy. The results are presented in Figure 5.

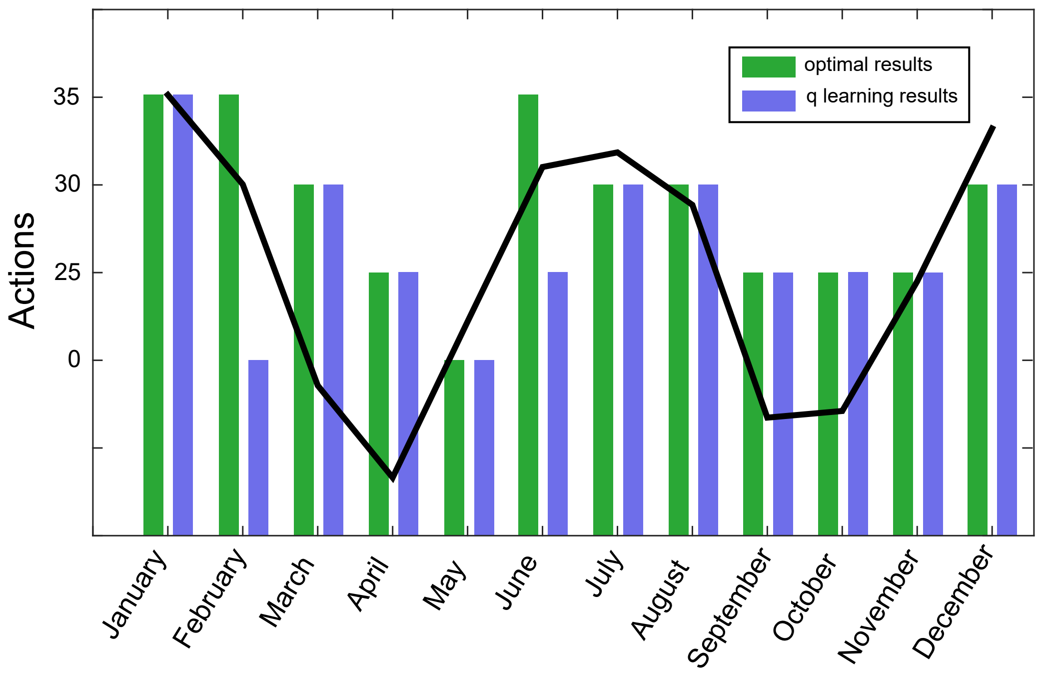

Figure 5: Comparison of the Q-learning results and the optimal results. The monthly recharge is plotted.

The optimal policy consists in pumping with a high rates when the recharge is high and the aquifer full of water. When the recharge diminishes, the optimal rates diminish as well. The optimal agent even stops pumping to let the aquifer recharge. We observe that Q-Learning provides similar actions except for the months of February and June when the pumping rates are lower than the optimal ones.

3.2. POMDP

For solving the POMDP formulation illustrated in Figure 4 we applied "Partially Observable Monte Carlo Planning" (POMCP) described in Silver et al [5] and implemented by Sunberg et al in POMCP.jl[1]. The variant with "Double Progressive Widening" was used given the complexity of groundwater flow dynamics.

We implemented a custom particle filter following the POMDPs.jl specification for performing belief updates over continuous hydraulic maps. Our initial belief drawn from a repository of plausible hydraulic heads generated with thousands of groundwater flow runs is updated in two steps. In the first step, all particles are forward in parallel with the generative model $G(s, a) \to s_p$ and observations of water table o_p are made for each. Based on the actual observed water table o, we compute new weights for the particles with a simple exponential model $\exp(-\|o_p - o\|)$. In the second step, we resample the particles using the weights and reestablish a uniform distribution for the next iteration.

POMCP results with a maximum depth of 12 steps are illustrated in Figure 6. The obtained policy is shown along with the rain profile for each month of the year.

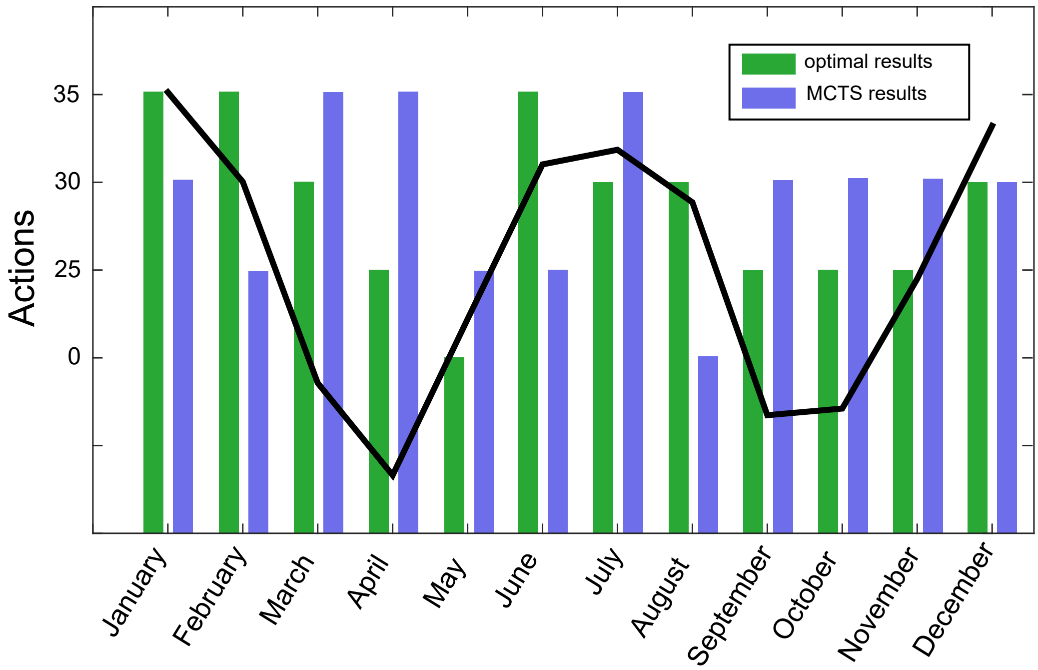

Figure 6: Comparison of the POMCP with DPW results and the optimal results. The monthly recharge is plotted.

4. Discussion

The results of the Q-Learning algorithm are close to the optimal policy. The differences for February and March can probably be overcome with either a better initialization of the state-action matrix and a longer learning. Since in groundwater management one can never have access to the full state of the aquifer, no additional time was used for fixing the mismatch.

In the realistic scenario in which only observations of water table are made at neighboring wells, POMCP with DPW fails to find a good policy. Although the method is suitable for large state spaces, it has rarely been applied to problems where states are as large as continuous pressure maps. Possible causes for the failure include a poor initialization of the belief and/or the low information content of sparse water table measurements.

[1] https://github.com/JuliaPOMDP/POMCP.jl

5. Conclusion

In this paper, we framed groundwater management as a (PO)MDP and applied two different online methods for solving a simplified 2D problem where a single agent tries to maximize profit constrained to government laws on water resources. Although simplified, the problem is quite challenging for state-of-art sequential decision making methods discussed in the literature. We conclude that a great amount of domain knowledge needs to be incorporated in order to improve on current pumping policies.

For future work, we suggest the design of a less expensive belief update by using reduced physics (e.g. streamline solvers) and a clever initialization of the belief from fundamental concepts in hydrology. If results are promising, one can start considering other sources of uncertainty such as subsurface uncertainty and uncertainty on the demand of water.

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Group contribution

Júlio took the class for 4 units. Thomas for 3 units.
Groundwater model: Júlio and Thomas (15h - 10h respectively)
Reward model: Thomas (2h)
Optimization: Thomas (5h)
MDPs: Thomas (10h)
POMDPs: Júlio (40h)