NOTES AND INSIGHTS

Measure more or report faster? Effect of information perception on management of commons

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Syst. Dyn. Rev. **37**, 72–92 (2021)

Introduction

Like any other human actors, regulators and managers of common-pool resources (CPRs) often make decisions based upon *previously reported* or *perceived* information. As such, important decisions such as capital investments or resource use in CPR-dependent societies can be influenced by the availability of information and the information's temporal characteristics. These characteristics depend on the *perception* process that includes measurement, reporting, analysis, identification of actions, and effectively undertaking such actions in the system. The perception process could distort or delay the actions required for effective management of commons, a phenomenon that is often called "misperception" (Moxnes, 2000; Sterman, 1989b) and that usually leads to overshoot and collapse of CPR extraction and economic outputs that rely on it. This overshoot-and-collapse mode of behavior, observed in many cases such as depletion of common groundwater resources (Arvanitidis *et al.*, 2015), is known in the literature as the *tragedy of the commons* (Hardin, 1968). The literature of CPR management considers the information perception only as an aggregate delay process that adds to the total misperception leading to overextraction of CPR and suboptimal economic performance (Moxnes, 1998). Such consideration implies that CPR managers should try to measure more *and* report faster. However, an organization's financial resources are usually limited, and an increase in investment is not always a viable option. CPR managers, therefore, need to decide if they want to measure more *or* report faster. To support this decision, a disaggregation of the information-perception process is necessary. The goal is to reallocate limited organizational resources to minimize overall misperceptions and maximize the productivity and longevity of CPRs. To achieve this goal, we examine the impact of different organizational resource-allocation schemes on CPR dynamics and its dependent economic capital by disaggregating the perception process into its essential phases.

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Accepted by Andreas Groessler, Received 29 March 2021; Revised 8 April 2021 and 17 April 2021; Accepted 20 April 2021

System Dynamics Review
System Dynamics Review vol 37, No 1 (January/March 2021): 72–92
Published online in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/sdr.1677

While the analysis of information perception is not a novel topic of research, with some of the previous studies focused on firm's strategy (Sterman *et al.*, 2007), public perception of water reuse (Hartley, 2006), management issues in the fishing industry (Crona and Bodin, 2006; Moxnes, 1998), and climate change (Moxnes and Saysel, 2008), very limited research has been done on how information perception influences resource management. Further, the current literature does not provide a clear-cut answer to how information perception can affect the dynamics of common's management. For instance, Tiefenbeck *et al.* (2016) show that real-time information feedback for resource use leads to the elimination of misperception, thus reducing consumption, while Moxnes (2004) argues that information feedback is not sufficient to offset the negative impact of misperceptions.

Measuring and assessing the availability of resources is susceptible to numerous uncertainties from various sources, including human errors, improper machine maintenance, and inaccurate model assumptions (Regan *et al.*, 2002). This process is more complicated for renewable resources such as groundwater or fish as the inflows and outflows to these stocks change dynamically (Moxnes, 1998). Understanding epistemic uncertainty (i.e. systematic error, natural variation, inherent randomness, model uncertainty, and subjective judgment) and linguistic uncertainty (i.e. numerical and nonnumerical vagueness, context dependence, ambiguity, indeterminacy in theoretical terms, and underspecificity) is essential, as some models fail to measure them properly (Regan *et al.*, 2002).

The effect of errors on misperception seems obvious, but even in the absence of estimation errors or uncertainty, the lag between data collection and dissemination in periodic reporting can potentially lead to misperceptions. Understanding the dynamics of these lags is critical as they may contribute to significant changes in resource flow transfers (Keery *et al.*, 2007). Depending on the magnitude of the gap between consecutive measurements and delay in reporting, individuals may fail to identify important changes during that time (Taylor and Alley, 2001). The idea of *duration* impacting an individual's perception of availability may not be overstated, as in some cases, technical reports with data collected in long intervals arrive years after the data is collected. As an example, the New Mexico Office of the State Engineer (NM OSE) provides water-use reports at five-year intervals with an average delay time of 4 years.[i] The measurement or reporting issue is not only a local problem as the cost and time of data collection and dissemination have made national and global agencies unable to promptly release their reports leading to an accumulation of information to be processed (National Research Council, 2004).

[i]NM OSE's technical reports are available at https://www.ose.state.nm.us/Library/tech_reports.php. For the latest NM OSE report, see Magnuson *et al.* (2019).

DOI: 10.1002/sdr

This article contributes to the literature by analyzing how variation in the measurement and reporting phases of information perception may impact a CPR-dependent system's economic performance and the longevity of its resources. We use theoretical dynamic-simulation experiments and predominantly use groundwater as an example of CPR to put the presented arguments and analyses into context. Groundwater is a CPR because it is nonexcludable and subtractable (Ostrom *et al.*, 1994). However, regardless of the examples utilized, the article's outcomes can easily be generalized to the broader concept of commons management. Sterman (1989a) and Moxnes (1998) argue that information perception is a kind of delay that adds to the total misperception errors. While this argument is intuitively reasonable and even tested in some settings, e.g. Rahmandad (2008), its implications for commons' management are not fully understood. The current study will address these issues under different measurement and reporting schemes. In this regard, Section 2 describes the model that we use for our analysis. Section 3 presents and discusses the outcomes of our simulations. And, Section 4 concludes the article.

Model

The model we describe here is developed based on a classic concept of the tragedy of the commons (Hardin, 1968). The main structure of the model is adopted from Anderson (1974). Figure 1 presents the stock and flow structure of the model. A complete listing of parameter values is provided in Appendix A.1 (Table A1).

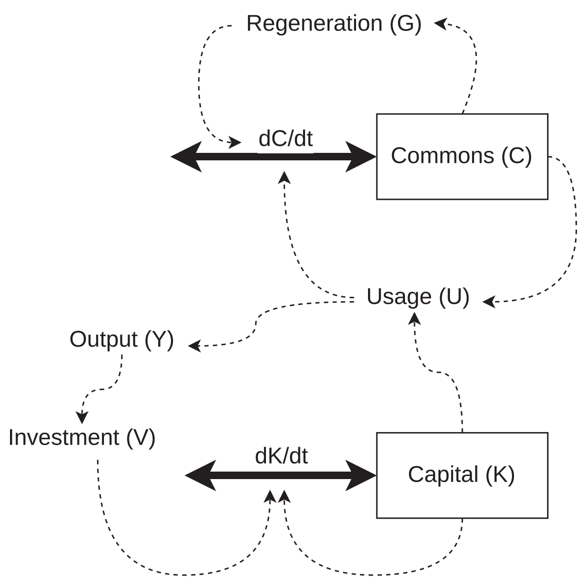
There are two stocks in the model: capital (K) and commons (C). These terms are chosen to be consistent with the original model and the theory of the tragedy of the commons. *Commons*, in particular, stands here for common-pool resources (CPRs). *Capital* is defined as all human (e.g. education and labor productivity) and nonhuman (e.g. infrastructure, equipment, and machinery) factors that contribute to society's economic output (Y).

Capital and commons usage rate (U) are the main drivers of economic output (Y). A Cobb–Douglas function, a transformation to represent the technological relationship between the amounts of production factors (e.g. labor and/or capital) and produced goods and services in an economy (Douglas, 1976), is used to formulate Y (Eq. (1)). In this function, λ is a technology multiplier, while α is the output elasticity of capital,

$$Y_t = \lambda \left(\frac{K_t}{K_0}\right)^{\alpha} \left(\frac{U_t}{U_0}\right)^{1-\alpha} \tag{1}$$

DOI: 10.1002/sdr

Fig 1. Stock and flow structure of the tragedy of the commons model



Not all of the produced value could be reinjected to the economy. Some part of it will be consumed or paid for the production costs. What remains, profit, will be partially invested then. δ represents the fraction of total output invested (V), which will accumulate in the stock of capital (Eq. (2)). The stock of capital (Eq. (3)) also depreciates over time. If the investment is larger than depreciation, capital grows; otherwise, it decays:

$$V_t = \delta Y_t \tag{2}$$

$$K_{t+dt} = K_t + (V_t - \eta K_t)\mathrm{d}t \tag{3}$$

The stock of commons (C), represented by Eq. (4), has a regeneration inflow (G) and a usage outflow (U). Regeneration is a nonlinear function of commons (Eq. (5)) controlled by a normal rate of γ. Commons usage rate (Eq. (6)) is a linear function of capital with β to be an average rate of commons usage per unit of capital. This rate dominates the usage pattern until the stock of commons reaches a critical level determined by θ, which is the maximum rate at which the commons could be extracted. θ could vary for different types of commons. The level of commons could also have a more direct effect on usage rate in some cases such as fisheries. Fish population density is one of the elements that directly influence catch per unit effort (CPUE) which, in turn, may impact total yield, although its significance could depend on specific conditions (Hampton *et al.*, 2005). However, in the case of groundwater depletion, which serves as the main example in this article, there is no clear evidence supporting such direct relationship between

DOI: 10.1002/sdr

storage levels and withdrawals, probably due to the relatively low cost of pumping (Balali and Viaggi, 2015). Thus,

$$C_{t+dt} = C_t + (G_t - U_t)\mathrm{d}t \tag{4}$$

$$G_t = \gamma C_t \frac{C_0 - C_t}{C_0} \tag{5}$$

$$U_t = \min(\beta K_i, \theta C_t) \tag{6}$$

Figure 2 shows the model's capability of reproducing the original results presented in Anderson (1974), where a familiar overshoot and collapse behavior of capital due to the initial abundance of commons is observed. Initially, commons are plentiful, so economic output (Y) invested (V) will increase capital, and more capital will produce more outputs. This positive feedback loop leads to an exponential growth of capital, which simultaneously depletes the commons pool. The depletion occurs as the usage rate (U) surpasses the regeneration rate (G). As commons decline, the growth of output and consequently the capital expansion slow down. When commons decline to a certain level (i.e. low enough to offset the positive impact of additional capital on the production), output starts to decline.

To carefully examine the impact of measurement and reporting errors on commons and capital, we add to the base model a set of regulatory institutions that monitor the commons and their usage rate and control future capital investments to sustain the resource pool. To simulate the decisions of the institutions, we add a component that links the state of the commons (C) and their usage rate (U) to the capital investment (V) (see Figure 3).

We assume that the institutions measure the commons' availability, report the measurements, analyze the reports (e.g. extrapolate and predict trends), and act upon the reports by making decisions for regulating capital investments. The general rule is that declining commons availability leads to tighter control on usage by establishing limits on new capital investments.

The additional linkages create two new negative feedback loops, which may change the system's dynamic behavior. We expect that these feedback loops will improve the commons' sustainability, as reported in Langarudi *et al*. (2019). However, the details of the changes depend on how the "perceived commons availability" is formulated. As mentioned before, perceived commons' availability includes a process that starts with measurement and ends with an effective decision to control investments. In the model, this process goes through calculation of "measured" (M), "reported" (R), "predicted" (P), "decision" (D), and "effective" (E) availabilities. First, the system needs to measure the commons' availability and then report it so the information will become available for the decision-makers. An analysis (e.g. interpolation, extrapolation, forecast) may be needed for the raw

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Fig 2. The base simulation run (S0) of the model reproducing a typical behavior observed in a tragedy-of-the-commons problem [Color figure can be viewed at wileyonlinelibrary.com]

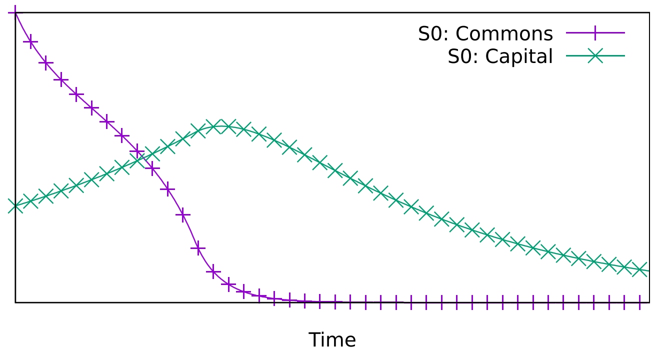
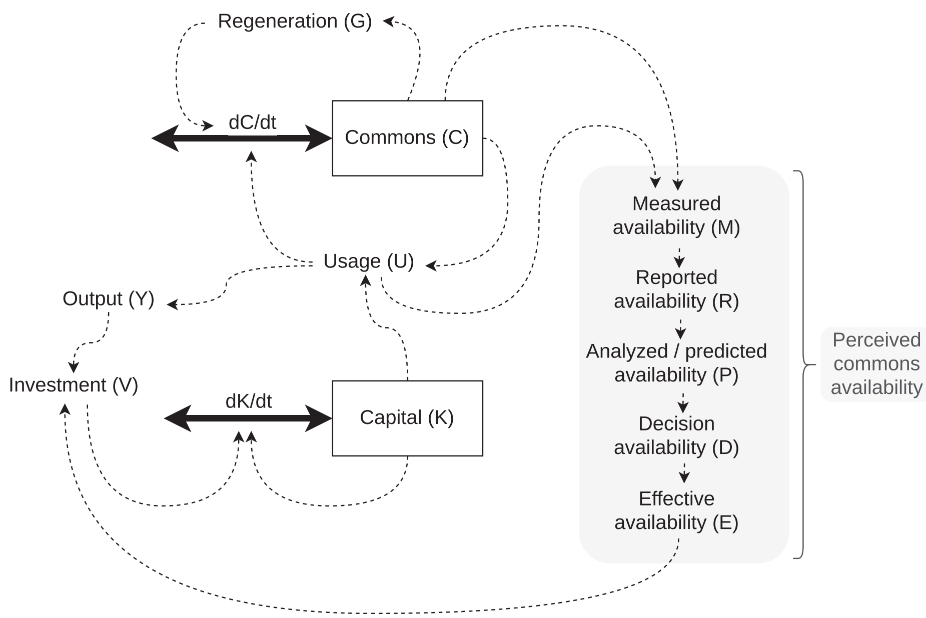


Fig 3. A dynamic perception of commons availability added to the base tragedy-of-the-commons model to control capital investments



information to be useful for decision-making. Once the analysis is complete, decisions can be made. However, the decisions may take some time and processes (e.g. bureaucracy in local governments or preparation for new investment schemes) to effectively influence the investments.

Results

The compound effect of the perception process is expected to lead to misperception and cause suboptimal behavior (Moxnes, 1998). However, to

DOI: 10.1002/sdr

better understand the impact of information perception on commons' dynamics, we incrementally introduce the perception process. At each step, we compare the results with previous simulations and observe the model's behavior. In particular, we look at two performance measures: commons and capital. We expect with each addition that the commons deplete faster and the capital overshoots more severely except for the case of "predicted availability" which is expected to improve the system's behavior. The following subsections elaborate on these expectations and the results of the experiments.

Instantaneous effect of availability on investment

The minimum structure we need in the model to simulate the impact of availability on capital investment includes "measured" and "decision" availabilities. In this case, we measure the availability and then transform it to a multiplier that will enter the investment function. In this process, there will be no errors or delays in the measurements and decisions. This assumption, although unrealistic, will help us understand the dynamics of the system. Later, we will incrementally add more variables to test more realistic cases.

Measured availability (M) is an index representing the current commons' state relative to its demand. M is a normalized ratio of commons (C) to commons usage rate (U) as shown by Eq. (7). Initially, M is 1. If C declines, U increases, or both, *ceteris paribus*, availability declines, and vice versa,

$$M_t = \frac{C_t}{U_t} \div \frac{C_0}{U_0} \tag{7}$$

At this stage, we assume that there is no reporting delay. We also assume that the measured availability is used in decision-making without any additional processing or analysis. Therefore, "measured" (M), "reported" (R), and "predicted" (P) availabilities are all equal. We will release these assumptions and analyze their impact on the system's behavior later in the article.

To simulate the impact of M on investment (V), we assume a positive relationship between M and decision availability (D). D is defined as a transformation that translates the availability to a multiplier that will enter the investment function through "effective" availability (E). E is a function that applies an exponential averaging to D. For now, we assume no delay for the decision availability to become effective; thus $E_t = D_t$. To include the impact of decision availability on investment, we rewrite Eq. (2) as follows:

$$V_t = \delta Y_t E_t \tag{8}$$

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The transformation we assume for D should have a specific set of attributes. We should make sure that $0 \leq D \leq 1$, $D^{'} > 0$, $D^{''} \leq 0$. Further, D should be monotonic.

Negative values of D would imply the intentional destruction of capital, which could lead to negative values of capital in some cases. Although this could happen in certain hypothetical circumstances, it is beyond the scope of our analysis. If D goes above 1, the system will invest over its normal physical and economic capacity. This unlikely assumption may risk the model to fail some extreme condition tests.[ii] The plausibility of this assumption also depends on how we interpret the initial setting of the model. If the system is initially producing at its maximum capacity, then $D > 1$ becomes meaningless as capital will be the bottleneck for growth. That is, more-than-normal commons availability will not be able to substitute for the lack of capital.

The slope of D should be positive, meaning that greater availability should lead to greater investment and vice versa. The monotonicity of the function also ensures that this rule does not change at different levels of availability.

Finally, D is not a convex function as we assume decision-makers underreact rather than overreact to availability. If availability declines by 1 percent, decision-makers do not limit the investment by more than 1 percent.[iii]

To incorporate these attributes in the function of decision availability, we write Eq. (9) as follows:

$$D_t = 1 - \frac{1 - P_t}{(P_t + 1)^{\zeta}} \tag{9}$$

In this equation, ζ controls the concaveness of the function.[iv] The larger values of ζ replicate lower aggressiveness (or higher tolerance) in decision-making in response to availability, as shown in Figure 4. That is, the investment will not be affected easily as availability declines. However, as availability plummets to critical levels, the investment will decline increasingly. In an extreme case ($\zeta = 100$), decision-makers do not react until the resources are depleted completely. In a situation where decision-makers are perfectly agile ($\zeta = 0$), adjusting the investments is proportionate to availability changes. In this case, we have a linear function with constant proportionality of 1 (i.e. an identity function).

We run the model with two different scenarios for ζ. The first scenario (S1) assumes $\zeta = 2$. The second scenario (S2) assumes $\zeta = 0$. In Figure 5, the

[ii]For example, if $D = 20$ and $\delta = 10\%$, society will invest twice as large as their total output, which is not realistic.
[iii]The model can easily accommodate a scenario in which decision-makers overreact to availability (i.e., $D^{''} > 0$).
[iv]To test a convex form for "decision availability" (D), interested readers can set the parameter to stay within the range $-1 \leq \zeta < 0$.

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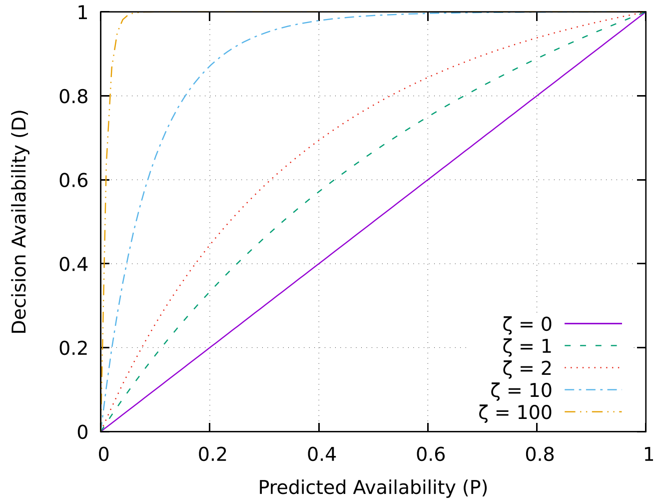

Fig 4. Potential scenarios of decision availability (D) as a function of predicted availability (P) [Color figure can be viewed at wileyonlinelibrary.com]

model outputs under S1 and S2 scenarios are compared to the base simulation (S0), where we had no feedback between availability and investment.

As we expected, the inclusion of the feedback between availability and investment improves the commons. However, it is not sufficient to avoid the tragedy if the regulatory institutions are not perfectly agile to respond to availability. In S1, capital performs worse than the base case as fewer resources are extracted. In S2, the capital still performs worse in the short-run, but its long-run stability is an important advantage. The tragedy will be avoided in this case because decision-makers react to the availability in a timely fashion. Therefore, a proportionate, identity reaction to declining commons availability is an effective decision rule to avoid the tragedy.

Is measurement frequency important?

So far, we have introduced the commons availability perception processes by including only two (M and D) out of five variables involved (see Figure 3), implying that there has been no systematic bias involved in the management's perception of availability. Further, there has been no delay between the arrival of the information and the making and enacting of investment control decisions. In other words, the regulatory institutions have complete information about the availability of resources and act upon it immediately.

We test different conditions utilizing a lower measurement frequency representing systems that do not enjoy a live monitoring (measurement) system. In the previous model, measurements were being reported live (at every time step) as $R_t = M_t$. Here, we redefine reported availability (R) as a "sample and

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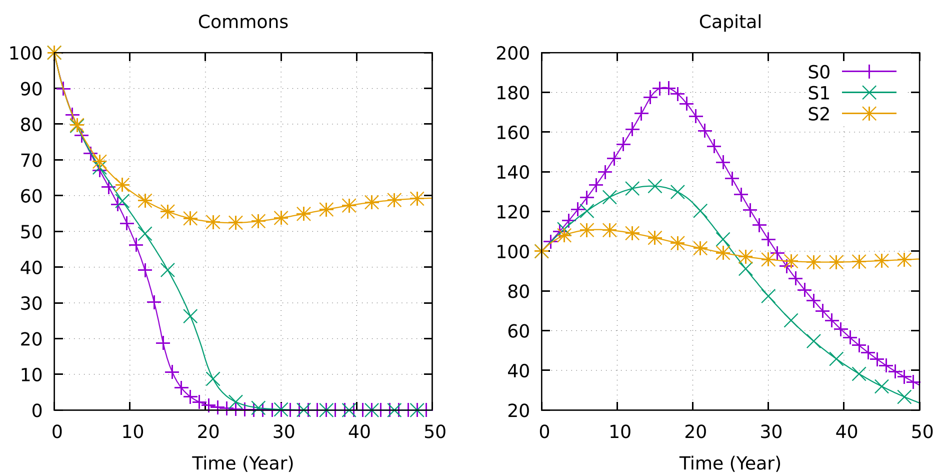

Fig 5. The model outputs under S1 ($\zeta = 2$) and S2 ($\zeta = 0$) compared to the base simulation, S0 (no feedback between availability and investment) [Color figure can be viewed at wileyonlinelibrary.com]

hold" explained by Eq. (10) where ρ is the reporting delay and ω is the measurement interval. The condition in the first statement of Eq. (10) ($t \bmod \omega = 0$) means that "t is dividable by omega." Since this scenario represents a sample and hold process, it is basically a type of delay with infrequent updates of the measured value. For now, we assume $\rho = 0$, i.e. the measurements occur infrequently but they are reported immediately. Thus,

$$R_t = \begin{cases} M_{\max\left(0, t-\frac{\rho}{dt}\right)}, \dfrac{\rho}{\mathrm{d}t} \in \mathbb{Z} & \text{if } t \bmod \omega = 0 \\ R_{t-dt} & \text{otherwise} \end{cases} \tag{10}$$

In previous simulations, ω was 0, thus $R_t = M_t$. If we run the model with a larger ω, we expect to see a less stable behavior than previous cases. The instability is due to the systematic error in the regulatory institution's perception of reality. The measurement interval leads to an overestimation of availability when availability is monotonically declining. It leads to an underestimation when availability is monotonically increasing. Since this perception gap is within a major negative feedback loop, an oscillatory behavior is expected (Kampmann and Oliva, 2008). Figure 6 shows the simulation results when S1 and S2 are both run with $\omega = 5$. A five-year interval is selected as it matches our example case (Magnuson *et al.*, 2019) and many other real-world cases (e.g. population censuses).

If the base case is a tragedy (the regulatory system reacts slowly to commons availability changes, i.e. S1 in Figure 6), the extended measurement interval (S3 in Figure 6) will worsen the situation by depleting the commons more rapidly. The capital experiences a higher peak, despite ending up at a lower final state.

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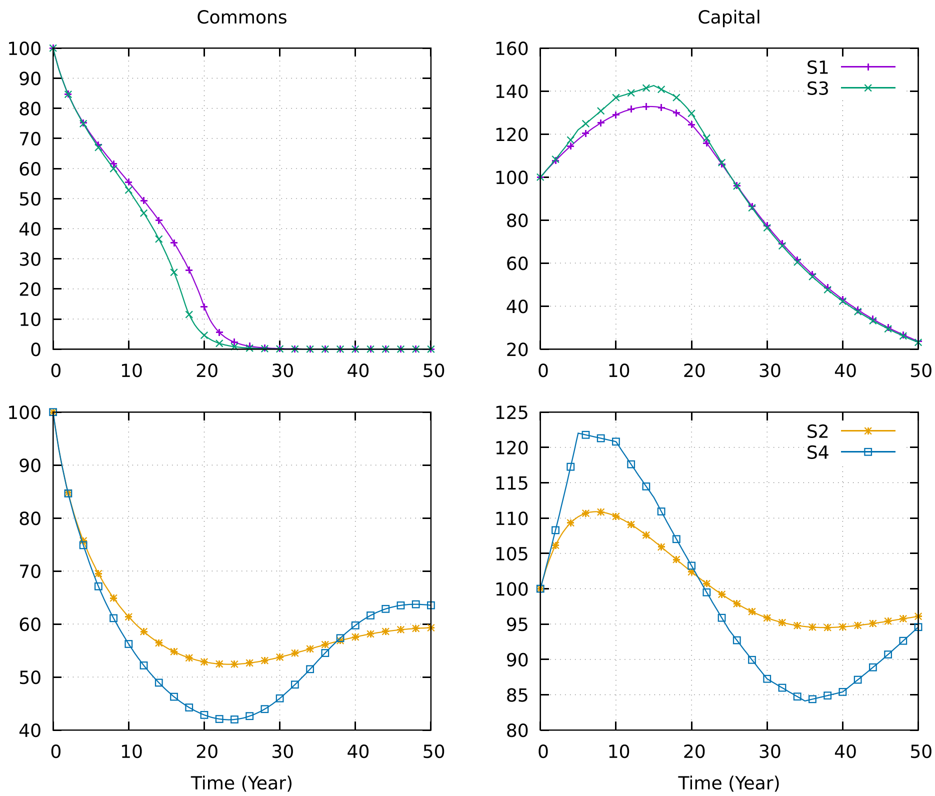

Fig 6. The model outputs under S3 (S1 + $\omega = 5$) vs. S1 (tolerant regulation) and S4 (S2 + $\omega = 5$) vs. S2 (responsive regulation) [Color figure can be viewed at wileyonlinelibrary.com]

If the base case is a tragedy resolution (the regulatory system reacts quickly to commons availability changes, i.e. S2 in Figure 6), the extended interval (S4 in Figure 6) will lead to a better final commons, but it worsens it in the midterm by increasing the system's instability. If we extend the simulation time, we will see that the system will reach a similar steady state in both cases. In other words, the main difference between the cases is their stability measures.

As discussed above, the system underperforms because of the systematic error in information perception. This problem is illustrated in Figure 7, where we measure availability (diamonds) in ω intervals. For periods before any new measurement, we use the most recent measurement for prediction (square). At a certain point in time, t, we assume that the actual value we want to predict is x. At that point, the most recent measurement we have is y. Then, the gap between y and x (i.e. ϵ) will be our measurement error. Therefore, in the example illustration, the total error will be the integral of all the areas between the orange dotted lines and the solid line. The higher the measurement interval (ω), the larger the total error.

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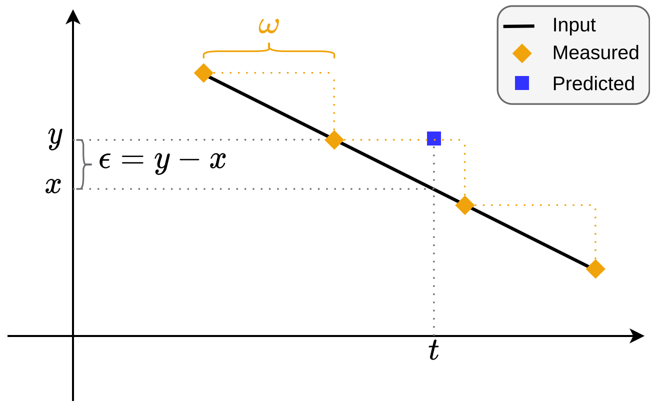

Fig 7. An illustration of the relationship between measurement interval (ω) and perception error (ϵ) [Color figure can be viewed at wileyonlinelibrary.com]

Measurement agility vs. reporting agility

How will the results change if we add a reporting delay to the model? This change will make the model more realistic as we have observed an average reporting delay of 4 years in our real-world example (Magnuson *et al*., 2019). We start with our last scenario (S4), where we had a responsive regulatory institution ($\zeta = 0$) and add a four-year delay to its reporting process. This is achieved by setting $\rho = 4$ in Eq. (10). Simulation results are shown in Figure 8.

Together, low measurement frequency and high reporting delay are sufficient to countervail the positive effects of a perfectly responsive regulatory institution and turn a relatively successful case to a tragedy of commons. In S5, the commons deplete because the data for availability arrives late and with errors. So, the overextraction continues for too long. During this period, the commons pass a (e.g. geological) threshold beyond which the system will have only little chance to recover. As such, the commons decline to a critically low level that is irreversible. In the absence of such a threshold, the system would oscillate around the same equilibrium state but with greater amplitude.

It is particularly interesting that under certain circumstances, even if we get our “decision rules” (Eq. (9) in this case) right, intrinsic and inevitable delays and systematic gaps in our perception of reality could lead to a case of tragedy. The additional gap in perception caused by the reporting delay is illustrated in Figure 9. We can see that the additional delay has pushed the predicted value horizontally. Depending on the input curve slope, this horizontal shift will increase the total error (ϵ). Note that when the input has a negative slope, the error would be positive, meaning that we are overestimating the input. The opposite will happen if the input has a positive slope.

Now we can ask what the difference is between measurement and reporting agilities. Is there any trade-off between them? We hypothesize that

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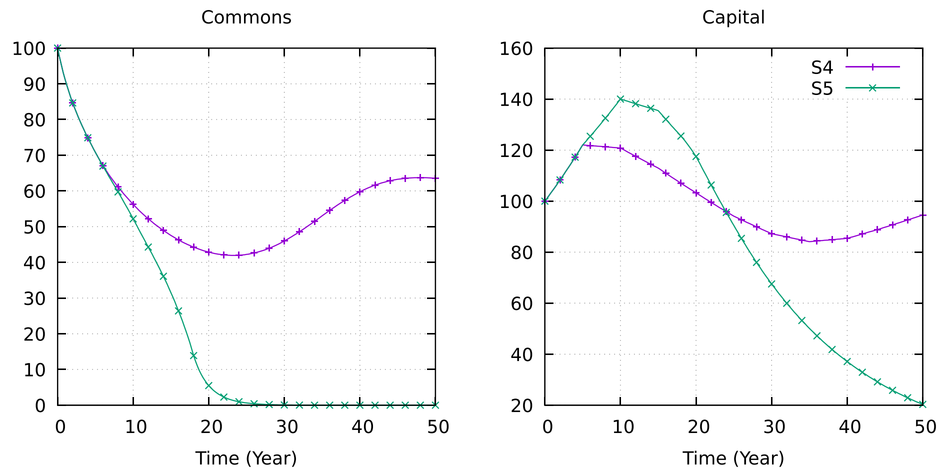

Fig 8. The model outputs under S5 ($\rho = 4$) vs. S4 ($\rho = 0$); both scenarios include a responsive institution ($\zeta = 0$) and a 5-year measurement interval ($\omega = 5$) [Color figure can be viewed at wileyonlinelibrary.com]

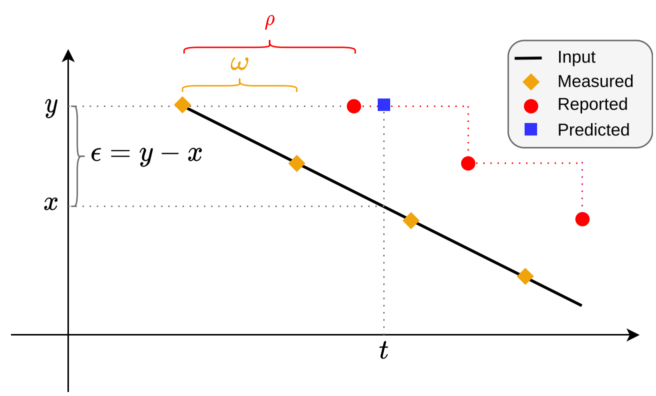

Fig 9. An illustration of the relationship between reporting delay (ρ) and perception error (ϵ) [Color figure can be viewed at wileyonlinelibrary.com]

these two concepts have more or less the same effect on the system's dynamics. We can probably interpret both of these effects as time delays in the perception of information. Therefore, the total delay we have introduced so far should be around $\omega + \rho = 9$. To test this hypothesis, we compare our last scenario (S5) with two other cases that are exactly similar to S5 except for the values of measurement frequency (ω) and reporting delay (ρ):

- S6 $\equiv \omega = 8, \rho = 1$ i.e. measurements occur less often but reported faster
- S7 $\equiv \omega = 1, \rho = 8$ i.e. measurements occur more often but reported slower

Both of these scenarios have a total $\omega + \rho = 9$. Therefore, we expect these scenarios to produce an output similar to each other and to S5. Results (Figure 10), however, reject our hypothesis. Compared to other cases, S6 conserves more resources in the midterm, although overall behavior is

DOI: 10.1002/sdr

similar. In a case of tragedy, we can say that investment in reporting agility saves more resources than investment in measurement agility. This investment strategy leads to a lower peak in the capital, though.

It is easy to replicate the results for a tragedy resolution case (where resources do not deplete completely and eventually reach a balance). It can be shown that S6 provides more stability than S5, while S7 creates more instability in the system. How does greater measurement agility in return for lower reporting agility (S7) destabilize the system? Figure 11 could shed some light on this problem. Here, we have an illustrative comparison between agile reporting but sluggish measurement (e.g. S6) and agile measurement but sluggish reporting (e.g. S7). Although $\omega+\rho = \omega^{'}+\rho^{'}$, we can see that the reported values in the agile reporting case (diamonds) lay closer to the input curve than do the reported values in the agile measurement case (circles). This condition implies that the agile reporting case has a smaller total error than the other case, i.e. $\epsilon^{'} < \epsilon$.

Note that this generalization is valid only for cases that are declining monotonically. In a case with a monotonically increasing trend, the opposite will be true. That is, an agile measurement case will produce less total perception error than an agile reporting case. If the input is nonmonotonic with significant irregularities and without any discernible trend, it is difficult to predict which agility works best to minimize the perception error.

Effective decision-making

It takes time for perceived and analyzed commons' availability to transform into practical decisions and eventually affect capital investments. We call this eventual effect on investment; "effective availability" (E). In system dynamics modeling, this process is usually formulated using an exponential smoothing function (Langarudi and Bar-On, 2018). Following the same tradition, we write Eq. (11)[v] to explain E as a first-order information delay of D,

$$E_{t+\mathrm{d}t} = E_t + \frac{D_t - E_t}{\psi}\mathrm{d}t \tag{11}$$

where, ψ is the average delay time for decision availability (D) to change capital investments effectively.

The delay incorporated in the formulation of E will prolong the entire process of information perception and exacerbate the system's instability. We tested the model with $\psi = 1$ (and higher values), and the simulation results (not shown here graphically) confirmed our expectations. This observation is not surprising as the delay strengthens the major negative feedback loop that

[v]So far, we have been assuming that $E_t = D_t$, i.e. decision availability, took no time to change capital investments effectively.

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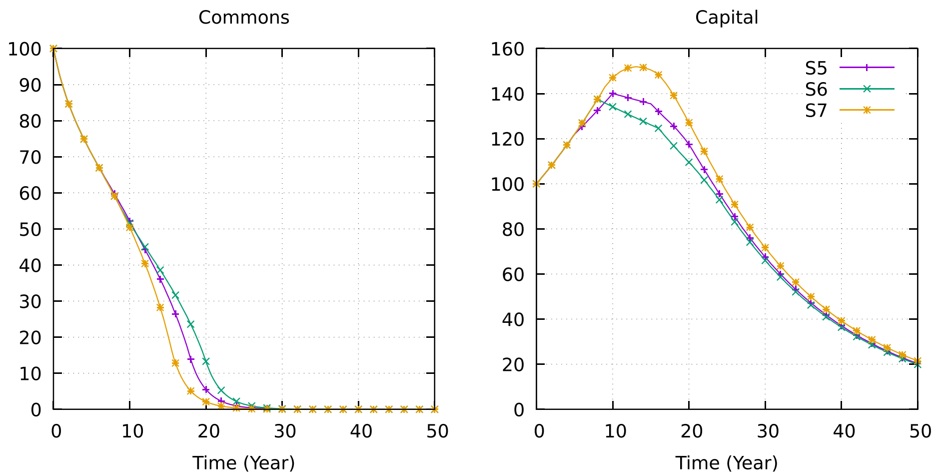

Fig 10. The model outputs under S5 ($\omega = 5$, $\rho = 4$) vs. S6 ($\omega = 8$, $\rho = 1$) and S7 ($\omega = 1$, $\rho = 8$) [Color figure can be viewed at wileyonlinelibrary.com]

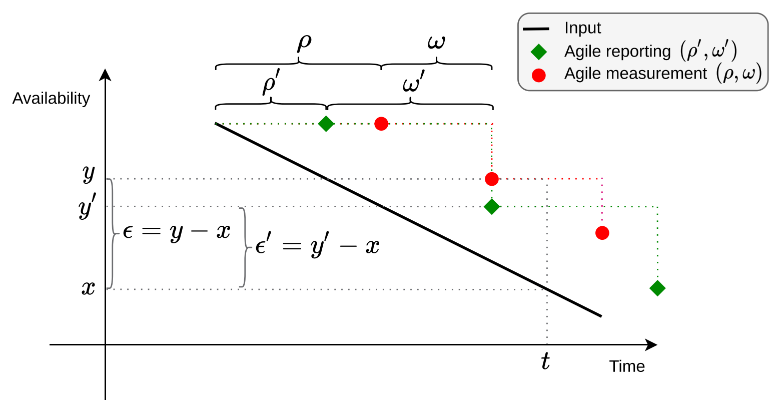

Fig 11. An illustrative comparison between an agile reporting but sluggish measurement (diamonds) and a sluggish reporting but agile measurement (circles) [Color figure can be viewed at wileyonlinelibrary.com]

connects commons to the investment. As we discussed earlier, and exemplified in a socioenvironmental context (Page *et al.*, 2019), such a negative feedback loop could destabilize the system.

The model's regulatory institutions do not apply any analytical processes to the reported availability. They decide based upon the most recent data point until the next data point arrives through reporting, i.e. $P_t = R_t$. With this assumption, we saw that the reporting agility might be more important than the measurement agility for our conservation efforts when resources are declining. This implication still holds if decision-makers interpolate over the historical data and use the estimated trend to extrapolate instead of using the last available data point (see Appendix A.2 for technical details).

DOI: 10.1002/sdr

Conclusion

In this article, we developed a system dynamics model to analyze the impact of information perception on the use of common-pool resources (CPRs) and the economic development that relies on it. We deployed Anderson's tragedy of the commons model (Anderson, 1974) as the basis of our analysis. We then added a component to the model that measures "perceived commons availability" in a certain time interval based on the commons stock and its usage rate. This measured availability would be reported with a delay and used for the decision on capital investment. If availability declines, the investment will slow down in order to preserve commons.

Simulation experiments on the model revealed that even with a perfectly responsive management system in which the regulator responds to commons availability proportionately (i.e. 1 percent decline in availability translates into 1 percent decline in capital investment), measurement intervals and reporting delays could create a systematic bias leading to a tragedy of the commons. It is believed, e.g. by Sterman (1989a) and Moxnes (1998), and we showed here, that the information perception function is an aggregate delay process and adds to the total misperceptions leading to overextraction of resources and suboptimal economic performance. This result is consistent with the findings of Tiefenbeck *et al.* (2016) that suggest investments in reducing information perception lags could improve resource conservation.

Nonetheless, our study goes beyond the aggregate representation of the information-perception process by breaking it down to its essential components in an almost similar way that Kahneman *et al.* (1997) disaggregate the utility perception process. The added "perceived commons availability" component in the model assumes a set of regulatory institutions that measure availability, report it, analyze (e.g. predict) it, make decisions upon it, and eventually implement the decisions to effectively control investments. This breakout helps us go deeper into the misperception question and improve the system's performance given constant, limited organizational resources. Each phase within the information perception process consumes a certain amount of organizational resources such as labor, equipment, and time. A reallocation of resources between these phases is a management lever to improve the system. In particular, we tested the hypothesis that such a reallocation between measurement and reporting efforts can change CPR management scenarios' outcomes.

The results suggest that reporting agility has greater leverage than measurement agility in a system with a *declining* CPR. That is, investment in speeding up the reporting process pays off more than investment in more frequent measurements if CPRs are depleting. The opposite occurs in a system with an *increasing* CPR. That is, measurement agility becomes more important than reporting agility if CPRs are improving over time. In systems

DOI: 10.1002/sdr

with oscillatory behavior, the regulators should implement a flexible CPR management system to switch priorities between measurement and reporting agilities.

The results are tested against uncertainty in inputs and assumptions; details are not reported here. It can be shown that randomness in inputs will not change the implications of our analysis as long as it is not large enough to obscure the general trends, as reported by Langarudi and Silva (2017).

This article reveals the importance of breaking down the information perception process to its essential elements and investigating them in detail. This idea contrasts with the common practice in dynamic simulation modeling, especially system dynamics, where information perception is usually formulated as an exponential averaging (smoothing) function (Morrison and Oliva, 2017). Langarudi and Bar-On (2018) show that a higher resolution is critical for modeling decisions that rely on *utility* perception but do not deem such a resolution as critical for modeling decisions that rely on *information* perception. There is still a long way to identify and test the impact of each of the information perception elements in different managerial settings. In particular, the effect of forecasting, as an alternative process to *predicted availability* (*P*), could be tested on the model as briefly discussed in Appendix A.2. Another future line of research could incorporate the findings from neuroscience in economic models (Brocas, 2012) to highlight the influence of heterogeneity in decision-making by regulators.

Acknowledgement

Funding for this research was provided by the National Science Foundation INFEWS/T1 Program under Award No. 1739835, the U.S. Bureau of Reclamation / New Mexico State University Cooperative Agreement R16AC00002, the State of New Mexico Legislature NMWRRI2018, and the Agricultural Experiment Station, New Mexico State University.

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DOI: 10.1002/sdr

APPENDIX

Model parameters

Table A1. The model parameter values and description

Parameter	Value	Description {Unit}
α	0.5	Output elasticity of capital {1}
β	0.1	Capital's commons usage rate {unit/yr./\$}
γ	0.4	Normal regeneration rate {1/yr.}
θ	0.8	Maximum commons extraction rate {1/yr.}
λ	100	Technology multiplier {\$/yr.}
δ	0.1	Investment rate {1}
η	0.06	Depreciation rate {1/yr.}
ζ	2	Concaveness of the decision availability function {1}
τ	10	Expected commons coverage time {yr.}
ω	5	Measurement interval {yr.}
ρ	4	Reporting delay {yr.}
ψ	1	Information delay time for effective availability {yr.}
κ	10	Averaging time used in the forecast function {yr.}
φ	10	Forecast horizon {yr.}
C_0	100	Initial commons {unit}
K_0	100	Initial capital {\$}
Q_0	1	Initial reported commons availability {1}
E_0	1	Initial effective commons availability {1}

Forecasting component

If decision-makers interpolate over the historical data and use the estimated trend to extrapolate instead of using the last available data point, they can reduce total misperception error and improve the system's behavior, especially if the system behaves monotonically. To test this hypothesis, we can add a forecasting mechanism to the model, e.g. by averaging historical values (Eq. (12)) and then using this average value (Q) to calculate historical trend of inputs (R) and estimate "predicted availability" (Eq. (13)):

$$Q_{t+dt} = Q_t + \frac{R_t - Q_t}{\kappa} \mathrm{d}t \tag{12}$$

$$P_t = \max\left(0, R_t\left(1 + \varphi \frac{R_t - Q_t}{\kappa Q_t}\right)\right) \tag{13}$$

Here, κ is the length of history we consider in calculating historical trends, and φ is our forecasting horizon.

DOI: 10.1002/sdr

It can be shown that the added forecasting mechanism will speed up the process of adjustment and improve performance. In a system with increasing commons, forecasting could worsen the situation as it will lead to over-optimism, overinvestment, and, consequently, overextraction of commons, leading to an overshoot of capital and collapse of the commons. We can also show that an extended forecasting horizon (φ) stabilizes the performance measures, commons and capital, in the long run while changing κ does not affect the outcomes.

DOI: 10.1002/sdr