Human “Mis”- perceptions of Climate Change

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Abstract. This research improves our understanding of the Stock-Flow (SF) Failure, found to be a robust problem in the perception of accumulation (Cronin, Gonzalez, & Sterman, 2009). We demonstrate the SF Failure with an interactive simulation in a relevant climate change context (Dynamic Climate Change Simulator (DCCS). In DCCS the climate change problem was simplified to an accumulation (stock), CO_2 concentration; inflows, anthropogenic CO_2 emissions; and outflows, CO_2 absorptions from the atmosphere; using realistic climate models and their predictions. DCCS was used in a laboratory experiment to test participants' ability to control the CO_2 concentration to a goal over 100 to 200 simulated years. Participants confronted one of four scenarios differing in emission decision frequency (every 2 years or 4 years) and rate of CO_2 transfer from the atmosphere (1.2% or 1.6%, of CO_2 concentration). Results show that performance in controlling CO_2 concentration remained poor in all conditions of the task. An investigation of participant control strategies revealed misperceptions of feedback: participants brought CO_2 concentration to the goal fastest for the condition where dynamics were slow and emission decisions were made less frequently, yet their stabilization after reaching the goal remained worst under the same conditions.

INTRODUCTION

Growing evidence indicate human misunderstanding of the basic building blocks of dynamic systems, including stocks, inflows and outflows (Booth Sweeney & Sterman, 2000; Cronin & Gonzalez, 2007; Cronin, Gonzalez, & Sterman, 2009; Sterman & Booth Sweeney, 2002). Many people, often highly educated in mathematics and sciences, fail to understand a basic principle of dynamic systems: that a stock rises (or falls) when the inflow exceeds (or is less than) the outflow (Cronin et al., 2009). This problem, termed Stock-Flow failure (SF Failure), has been shown to be persistent even in simple tasks, with well motivated participants, in familiar contexts and simplified information displays (Cronin et al., 2009).

Climate is a very complex dynamic system that presents important challenges to the perception, interpretation and understanding from the general public (Bostrom, Morgan, Fischoff et al., 1994; Read, Bostrom, Morgan et. al., 1994; Sterman & Booth Sweeney, 2007). For example, Sterman and Booth Sweeney (2002, 2007) have shown that humans often misperceive the dynamics of the Green House Gases concentrations in the atmosphere wherein they tend to use simple but erroneous heuristics, assuming that if one is to increase the gases concentration, emissions should increase as well. Judging that the stock behaves like the flows has been termed the "correlation heuristic" and it has been found to be a robust problem of human thinking in the interpretation of non-linear relationships (Cronin et al., 2009). The faulty participant emission behavior may also be due to the “Misperceptions of Feedback” (MOF) hypothesis (Sterman, 1989) and provides supportive evidence for the “wait and watch” policies currently followed in real world climate policymaking (Sterman, 2008). As per MOF, people tend to neglect the delay in emissions and dynamics due to their cognitive limitations and misperceptions of feedback.

The Stock-Flow Failure has been commonly investigated as a static problem (Cronin & Gonzalez, 2007; Cronin et al., 2009; Sterman, 2002; Sterman & Sweeney, 2002, 2007) in which participants are provided with a graph, indicating the Inflow (that increases the stock) and the Outflow (that decreases the stock) over a time period. People are then asked to make judgments about the level of flows shown in the graph (time point with maximum inflow and time point with maximum outflow) and the level of stock (time point with highest and lowest stock). Different forms of visual information representation have been investigated including line graphs, bar graphs, dot graphs, simpler graphs, textual description of the problem, among others (Cronin & Gonzalez, 2007; Cronin et al., 2009), resulting in no improvement in the judgments of the level of stock. In addition, respondents are often given only one chance to answer the questions with no feedback regarding the accuracy of their responses.

Unlike as done in the past using static, one shot, paper and pencil decision making tasks, we suggest that the Stock-Flow Failure may be best understood using interactive dynamic stock management tasks. In these tasks people attempt to balance the stock by making repeated decisions on the level of inflow and outflow and receiving feedback about their decisions' outcomes. The interactive dynamic stock management tasks would help them build cause-effect relationships resulting in an implicit understanding of the Stock-Flow problem (see Gonzalez, Lerch & Lebiere, 2003 for the Instance Based Learning theory of dynamic decision making).

This study is primarily focused towards determining human perceptions and control on a dynamic system by using a climate like system as an example. It tries to answer the research question on the role humans may choose to play in mitigating global warming and climate change. The Dynamic Climate Change Simulator (DCCS) is an interactive dynamic tool created to help understand the sources of the SF Failure, how people make decisions and how they understand and control simple dynamic systems as suggested by Cronin et al. (2009). DCCS is based on an adapted climate model from the *Dynamic Integrated Climate Economy model-1992* (DICE-92) (Nordhaus, 1992) which is a general macro-economic model to assess the effects and consequences of Earth's climate. In our adaptation, there are two anthropogenic CO_2 emissions into an atmospheric stock. One is the emission due to deforestation and land use and the other is due to the burning of the fossil fuels in automobiles and in industries.

This paper uses DCCS and investigates human perceptions of climate like dynamic system in a laboratory experiment. The experiment intended to determine the effect that a delay in the human emission policy in combination with the speed of climate dynamics (i.e. the variation of rates of CO_2 absorption) would have on the participant's ability to control the CO_2 concentration to safer levels. Both of these factors have been identified as particularly problematic for understanding the climate problem for general public (Sterman & Booth Sweeney, 2007). We present results from this experiment and discuss the implications of DCCS and the behavioral results to the policy interventions and education of climate change for general public.

THE CLIMATE CHANGE MODEL OF DCCS

The model on which the DCCS is based was adapted from DICE-1992 (Nordhaus, 1992) and ideas from Moxnes & Saysel (2004). Figure 1 provides the system dynamics representation of our climate model. The *CO2 in Atmos* represents concentration of CO_2 in the atmosphere (i.e., stock). The CO_2 concentration increases indirectly by human decisions on anthropogenic CO_2 emissions (i.e., inflow) called *User Action CO2 emissions* (thus here User Action CO_2 emissions are made up of 2 kinds of emissions: fossil fuel and deforestation types). The *CO2 emissions into the Atmosphere* are only affected by *User Action CO2 emissions* which in turn increase the stock of *CO2 in Atmos*. The *CO2 absorptions* (i.e., outflow) cause a decrease in the concentrations of the *CO2 in Atmos* stock due to absorptions by terrestrial and ocean ecosystems. As long as the *CO2 emissions into the Atmosphere* or *User Action CO2 emissions* exceed absorption rates, i.e. *CO2 absorptions*, the *CO2 in Atmos* continues to increase. Only when the emissions equal the absorption rates will the *CO2 in Atmos* be stabilized. The arrow from the *CO2 in Atmos* to the *CO2 absorptions* illustrates that the outflow at all times depends on the concentration of *CO2 in Atmos.* For the equation, *CO2 absorptions* are directly proportional to the concentration of CO_2.

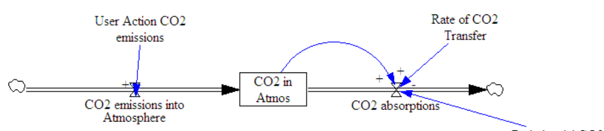

Figure 1. Climate Model.

The *Rate of CO2 Transfer* is a constant multiplier into *CO2 in Atmos* that gives rise to *CO2 absorptions* after the *Pre-industrial CO2* (1970 baseline CO_2 concentration) has been subtracted from the *CO2 in Atmos*. The use of a baseline concentration and year enables us to determine the change in value of *CO2 absorptions* in comparison to a common starting point or datum.

We calibrated the climate model between years 2000 and 2100 with projections given by two extreme *Intergovernmental Panel on Climate Change* (IPCC) emissions scenarios (IPCC, 2001; Nakicenovic, et al, 2000; for details see Dutt & Gonzalez, 2008). Based upon the calibration exercise, we found that *Rate of CO2 Transfer* had values of 0.016 (or 1.6%) per year for the optimistic scenario (called "B1" as per IPCC, 2001) and 0.012 (or 1.2%) per year for the pessimistic one (called "A2" as per IPCC, 2001).

Dynamic Climate Change Simulator

The DCCS interface (see Figure 2) represents a single *stock* or accumulation of CO_2 in the form of an orange-color liquid in a tank (number 1). Anthropogenic deforestation and fossil fuel CO_2 *emissions*, are represented by a pipe connected to the tank (number 2), that increase the level of CO_2 stock; and CO_2 *absorptions*, also represented as a pipe on the right of the tank (number 3), which decreases the level of CO_2 stock.

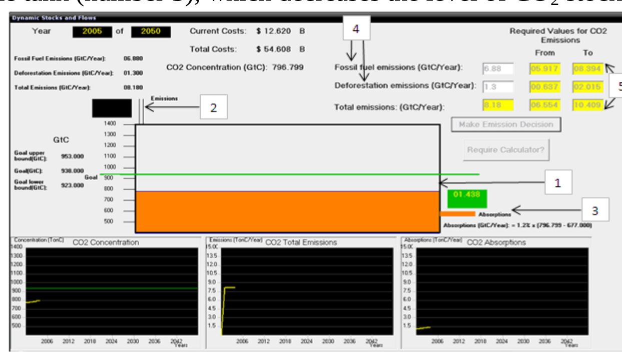

Figure 2. Climate Change Simulator task

The participant's goal in DCCS was to maintain the CO_2 stock within an acceptable range around the goal value of 938 GtC shown with a green horizontal line with a label *Goal*. The participant decided on emissions of two different types: deforestation and burning of fossil fuels (number 4). The participant set the fossil fuel and deforestation emissions in the respective text boxes labeled *Fossil Fuel Emissions (GtC/year)* and *Deforestation Emissions (GtC/year)*, and click the *Make Emission Decision* button. To avoid extreme exploration of participants' emission decisions, we restricted the fossil fuel and deforestation emissions values to between *From* and *To* ranges calculated after each emission decision time step executed by the participant (number 5; for details on calculations see Dutt & Gonzalez, 2008). When a participant makes a decision DCCS moves autonomously by a number of time steps to a future year. For other details on DCCS please see Dutt & Gonzalez (2008). In the next section, we describe the laboratory experiment conducted using DCCS.

EXPERIMENT

In this experiment, using DCCS, we manipulated the frequency of human emission decisions and the dynamics of the absorption rate in the system. The variation in speed of dynamics of the climate system enabled us to capture the uncertainty and variability that might be present in future years in the *Rate of CO2 Transfer* parameter. The manipulation of frequency of emission decisions is motivated from the fact that in the past human beings have shown a poor understanding of feedback delays in dynamic systems (Brehmer, 1989; Diehl & Sterman, 1995; Dörner, 1980). As explained earlier, two rates of transfer result from these two scenarios: 1.6% (optimistic scenario, rapid dynamics) and 1.2% (pessimistic scenario, slow dynamics). When emission decisions are less frequent, there is a larger time gap between two consecutive decisions, and thus combined with slow climate dynamics (1.2% rate of CO_2 transfer) are expected to result in poor climate control. On the other hand, high frequency of emission decisions combined with rapid dynamics (i.e. 1.6% rate of CO_2 transfer) is expected to result in best control of the system. That is, we expected total CO_2 emissions to be a function of the frequency of decisions as well as the speed of the system dynamics. Also, we expected that a system with higher feedback delays would produce poorer performance in terms ability to control CO_2 to goal over time. This would be reflected in lesser number of participants reaching and stabilizing CO_2 at the goal and taking more time to reach and stabilizing CO_2 at the goal under conditions of more feedback delay (Forrester, 1961; Sterman, 1989). These effects would be primarily attributed to a participant's inability to take into account the feedback delays and non-linearity of the dynamic task.

Methods

Experimental design. Participants were randomly assigned to one of four scenarios: rapid-high, where rate of CO_2 transfer is 1.6% per year with CO_2 emission decisions made every 2 simulated years; rapid-low, where rate of CO_2 transfer is 1.6% per year with CO_2 emission decisions made every 4 simulated years; slow-high, where rate of CO_2 transfer is 1.2% per year with CO_2 emission decisions made every 2 simulated years; and slow-low, where rate of CO_2 transfer is 1.2% per year with CO_2 emission decisions made every 4 simulated years. The goal under all four conditions was to maintain the level of CO_2 within +/- 15 GtC from the 938 GtC goal (i.e. 923 GtC to 953 GtC and taken from IPCC, 2001). We ran the rapid dynamics condition for 100 simulated years and the slow dynamics condition for 200 years to equalize the number of decisions made in all four conditions to 50 decisions. The *From* and *To* ranges of fossil fuel emissions were set at -14% to +22% of the value of current fossil fuel emissions. Also, for deforestation emissions, the *From* and *To* ranges were set as -51% to +55% of the value of current deforestation emissions. We used absolute discrepancy, fossil fuel, deforestation and total participant emissions as dependent variables to discuss participant decision making strategies.

Participants. Fifty three graduate and undergraduate students from diverse fields of study participated in this experiment, 26 were females and 27 were males. Ages ranged from 18 years to 54 years (Mean= 26 years, SD= 8 years). As high as 70% of the participants self-reported to have degrees in science, technology, engineering and management (STEM). Fourteen participants were randomly assigned to the slow-low condition and thirteen participants were assigned to each of the slow-high, rapid-high and rapid-low conditions. All participants received a base pay of $5. The participants could earn an additional maximum bonus of $3, based on their performance in the DCCS (For details, see Dutt & Gonzalez, 2008).

Procedure. Participants were given instructions and full information before starting the DCCS task. Participants were encouraged to ask questions. Finally, participants were reminded on the requirements of the control task where every detail was kept transparent to the participant including the delay in their emission decisions and that in the system's dynamics. Once all participants acknowledged that they understood the system and task requirements they were allowed to interact with the DCCS task.

Results

Effects of frequency of emissions decisions and dynamics of absorption rate. Mann-Whitney test reported that the discrepancy in the low condition (*Median* = 61.77 GtC) was significantly higher than the discrepancy in the high condition (*Median* = 45.57 GtC) with $U = 267.00$, $Z = -3.00$, $p < .01$, $r = -.21$. Thus, the frequency of emission decisions did have a significant effect on the absolute value of discrepancy. Also, Mann-Whitney test reported that the discrepancy in the slow condition (*Median* = 61.67 GtC) was significantly higher than the discrepancy in the rapid condition (*Median* = 37.42 GtC) with $U = 182.00$, $Z = -3.00$, $p < .01$, $r = -.41$. Thus, the absorption rate had a significant effect on the absolute value of discrepancy. Figure 3 shows the average absolute discrepancy per condition. The red line in Figure 3 is the "optimal"s discrepancy at 15 GtC and in all conditions the discrepancy is greater than the optimal value i.e. outside the permissible goal range.

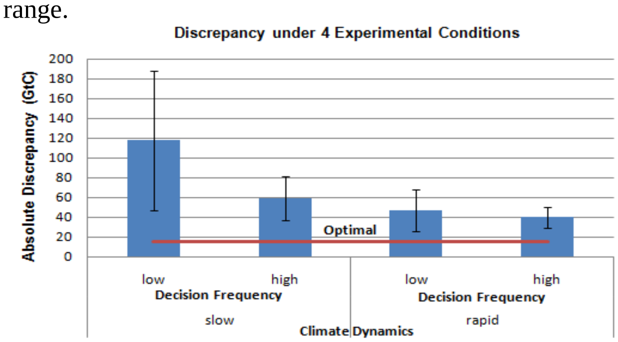

Figure 3. Absolute Discrepancy (GtC) under four experimental conditions. Red line is at 15 GtC and shows the permissible goal range (participants kept discrepancy outside the goal range in all conditions). Error bars show 90% confidence interval around the point estimate.

Proportion of who reach the goal but can and cannot stabilize at the goal. To do this analysis, we calculated the number of participants that did not reach the goal range and did not stabilize at the goal range for 8 consecutive decision points, did reach the goal but did not stabilize at the goal range for 8 consecutive decision points, and did reach the goal and did stabilize at the goal range for 8 consecutive decision points under four different experiment conditions. To get the proportions, the number of participants under three different goal reaching and stabilizing categories for four experimental conditions was divided by the total number of participants. These proportions have been shown in figure 4 for all four experimental conditions under the three different categories of goal reaching and stabilization. There is clear pattern evident in figure 4. As the feedback delay on account of climate dynamics and frequency of emission decisions decreases i.e. we move from slow-low to rapid-high conditions, there is an increase in proportion of people who could both stabilize and reach the goal range and at the same time a decrease in proportion of people who either don't reach the goal range or reach the goal range but do not stabilize the CO_2 at the goal range for eight consecutive decision points.

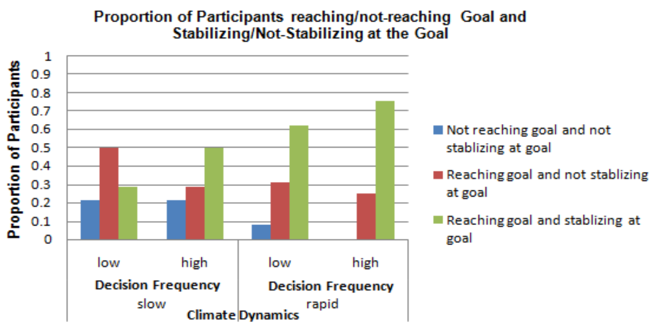

Figure 4. Proportion of participants reaching/not-reaching goal range and stabilizing/not-stabilizing at the goal for eight consecutive time periods after reaching the goal across 4 different experimental conditions.

Decision point at which participants reach and stabilize CO_2 concentration at the goal. For the purpose of this analysis we defined reaching the goal first time to mean the decision point at which participants first attain the goal range. For the purpose of stabilizing CO_2 at the goal we are interested in the earliest decision point (out of 50 decision points) after which the participant is able to keep CO_2 concentration in the goal range for the next eight consecutive decision points (results are similar on changing the definition to include seven, six, five, four, three and two consecutive decision points; as we increase the number of consecutive decision point criterion beyond eight the most difficult condition looses a number of participants making data analysis infeasible).

Figure 5 shows the earliest decision point for reaching the goal range under the four different experimental conditions and figure 6 shows the results of earliest decision point among 50 decision points at which participants reach the goal range and stabilize CO_2 concentration for three definitions of stabilization (those based upon 2, 4 and 8 consecutive decision points) across four different conditions. Making a definition of stabilization higher than 8 consecutive decision points produced no participant in the slow-low condition so that was assumed to be a reasonable upper bound. The results revealed that the effect of dynamics of absorption rate did not significantly affect the earliest decision point for reaching the goal nor did it affect the earliest decision point at which participants reached and stabilized CO_2 at the goal range for three different definitions of stabilization. Also, there was no effect of frequency of emissions decisions on the decision point for reaching and stabilizing at the goal range.

On average, participants reach the goal range faster in the condition with maximum feedback delay i.e. slow-low condition and reach the goal slowest for the condition of least feedback delay i.e. the rapid high condition. The other two intermediate conditions on average make participants reach the between the two extremes. Also, the average earliest decision point across different definitions of stabilization occurs at a higher value when condition involves greater feedback delay (slow-low) than when it has the least feedback delay (rapid-high). Other conditions have their stabilization decision point between the slow-low and rapid-high conditions. Both these results as seen in figure 5 and figure 6 are consistent with the earlier observation that participants keep their fossil fuel and deforestation emissions closer to the TO value for conditions in which there is more feedback delay (slow-low). Keeping emissions closer to the TO value makes participants reach the goal faster (as seen in figure 5 for slow-low condition compared to rapid-high condition) but in turn makes them unable to stabile the CO_2 concentration once they are in the goal range as it becomes too late to do so. On account of misperceptions of feedback, the results show that participants reach the goal but cannot stabilize the CO_2 concentration at the goal quick enough in the conditions which have more feedback delay.

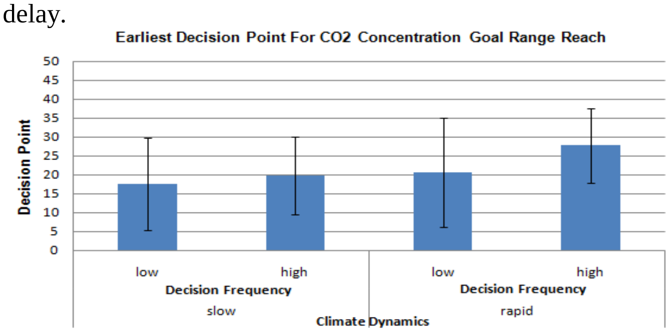

Figure 5. Earliest decision point at which participants CO_2 concentration reaches the goal range across four different experiment conditions. Error bars show 90% confidence interval.

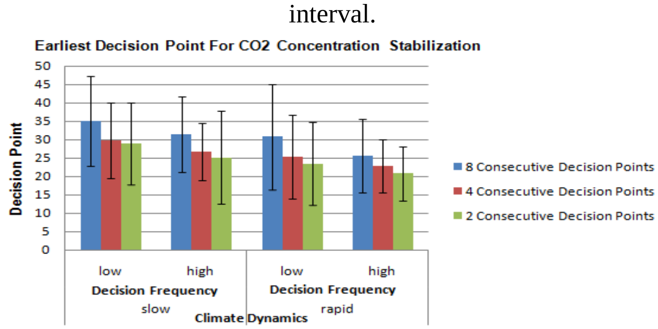

Figure 6. Earliest decision point at which participants achieve stabilization of CO_2 concentration between goal range across four different experiment conditions for three different definitions of stabilization (for 2, 4 and 8 years). Error bars show 90% confidence interval.

DISCUSSION AND CONCLUSIONS

Many of the complex dynamic effects found in the real world can be better understood with simple tasks (Cronin et al., 2009) and here we present a demonstration of such a process in DCCS.

Results show that even for a batch of participants where 70% belonged to science, technology, engineering and management, participants were generally poor at controlling the CO_2 concentration in all four conditions and showed evidence of higher discrepancy for slower dynamics and less frequent emission decisions. In addition, discrepancy was away from optimal under all four conditions. Participant emissions decision strategies show support of use of longer times to stabilize CO_2 concentration to goal level in the presence of conditions of slower dynamics and less frequent emission decisions although reaching the goal faster under the same conditions. Less frequent emissions and slower dynamics decisions produce degraded performance, perhaps due to the higher feedback delays involved.

The primary reason for the poor participant performance is attributed to the MOF hypothesis (Sterman, 1989). From the results it can be inferred that people took an "open loop" view of an actual closed loop system, failed to account for feedback delays between actions and responses, did not comprehend the system dynamics and ignored the non linearity present in the system. This also led participants to take more number of decision points under conditions of feedback delay as depicted in our results. Also, the same open loop approach caused lesser proportions of participants to reach and stabilize CO_2 concentration at the goal range under conditions of feedback delay.

In the slow and low dynamic conditions where people experience a feedback delay of four years between two consecutive decision points and the system dynamics is 1.2% of CO_2 concentration, they tend to neglect this delay in emissions and dynamics probably due to their cognitive incapacities and misperceptions of feedback as inferred from the results. On the other hand, for the rapid and high dynamic conditions, the frequency of emission decisions is double and dynamics is rapid (1.6% of CO_2 concentration) resulting in lesser feedback delay and better human performance.

This participant emission behavior where they take more time to reduce discrepancy provides supportive evidence for the "wait and watch" policies currently followed in real world climate policymaking (Sterman & Booth Sweeney, 2002). People in today's world want to continue to maintain emissions at high levels rather than take actions which are geared towards reducing them (Sterman & Booth Sweeney, 2007). It appears that at the current pace, people will continue to hold emissions at higher values until the concentrations of GHGs start overshooting the desirable goal amounts. They will only realize the misperceptions of their actions when it is already too late to correct their actions, due to the delays present in the system (Sterman & Booth Sweeney, 2002). The realization of misperceptions on actions and tendency to act when it is too late is seen in our results where participants are able to bring the CO_2 concentration at a rapid pace (i.e. in less number of decision points) to the goal under conditions of maximum feedback delay, yet when they are at the goal they are unable to stabilize the CO_2 at the goal range for a longer period of time. A way to cure this problem is the creation of educational tools like DCCS and generation of practice and learning programs. This is a subject of future and continuing research.

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