**Seed Grant Proposal**

“Why do People Exhibit a Lack of Understanding about Earth’s Climate? Influence of Repeated Feedback”

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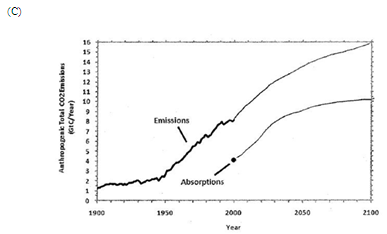
A 2007 U.N. survey found that 54% of Americans advocate “wait-and-see” preferences for policies that mitigate climate change. According to these wait-and-see preferences, they infer that climate mitigation actions can be deferred until there are clear signs of danger (Dutt & Gonzalez, 2012; Sterman, 2008). Recent research has shown that people’s wait-and-see preferences for climate change are likely due to their reliance on a number of cognitive misconceptions about how Earth’s climate system works (Dutt, 2011). One common misconception is the *correlation heuristic*, whereby people incorrectly infer that an accumulation (carbon-dioxide concentration) follows the same path as the inflow (carbon-dioxide emissions). This misconception assumes that stabilizing emissions would rapidly stabilize the concentration, and emissions cuts would quickly reduce the concentration and damages from climate change. This reasoning is incorrect, because reliance on the correlation heuristic significantly underestimates the time delays existent between reductions in carbon-dioxide (CO2) emissions and their effect on the CO­2 concentration (Dutt & Gonzalez, 2012; 2013a; 2013b; Sterman, 2008). Clearly, wait-and-see preferences are likely to make sense in a system with negligible delays, but not in a climate system with considerable time delays. Another common misconception is *mass balance violation*, whereby people incorrectly infer that atmospheric CO2 concentration can be stabilized even when emissions exceed absorptions. Mass balance violation leads to wait-and-see preferences because people think that the current state of the earth’s climate, where emissions are double that of absorptions, would not pose a problem to future stabilization (Dutt & Gonzalez, 2012; Sterman, 2008). Hereafter, we will refer to the correlation heuristic and violation of mass balance as "cognitive misconceptions".

Recent research has started to document the role that repeated feedback about cause-effect relationship (CO2 emissions and CO2 absorptions==>CO2 concentration), provided through computational methods, has on human understanding of dynamic systems, particularly for Earth’s climate system. Researchers have used computer-based simulation tools and decision making games (called microworlds[[1]](#footnote-1)), which have demonstrated a reduction in people’s misconceptions regarding the climate system (Dutt & Gonzalez, 2012; 2013a) and dynamic systems more generally (Dutt & Gonzalez, 2011; Gonzalez & Dutt, 2011; Gonzalez, Vanyukov, & Martin, 2005). However, microworld research for climate education is in its early stages. Research that systematically investigates people’s misconceptions about climate change, and the role that repeated feedback and simulation tools have on reducing these cognitive misconceptions, is critically needed. Such research will help policymakers formulate future education policies for climate education in schools, as well as serve as an effective aid in policymaking for climate change.

The present proposal seeks to make theoretical and practical advancements on the understanding of these cognitive misconceptions and the effectiveness of repeated feedback through microworlds in reducing such misconceptions. Preliminary research has documented some benefits of repeated feedback in computer-based microworlds in reducing people’s misconceptions about Earth’s climate (Dutt & Gonzalez, 2012). In this research, we develop a tool called the Dynamic Climate Change Simulator (DCCS) and use it as an intervention to help participants understand some characteristics of the climate system. DCCS is inspired by generic dynamic stocks-and-flows tasks and it is based on a simplified and adapted climate model (Dutt & Gonzalez, 2011). The DCCS interface (Figure 2) represents a single stock or accumulation of CO2 in the form of a liquid in a tank. Deforestation and fossil fuel CO2 emissions, are represented by a pipe connected to the tank, increase the level of CO2 stock; and, CO2 absorptions, also represented as a pipe on the tank, decrease the level of CO2 stock. In order to test the effectiveness of DCCS, we ask participants to perform in a Climate Stabilization (CS) task after their performance in DCCS. The CS task (Figure 1) is a paper-and-pencil task which has been used widely to document people’s reliance on correlation heuristic and violations of mass balance misconceptions. Although it is expected that DCCS would help reduce people’s misconceptions compared to a no-DCCS intervention; however, very little is currently known on how the reduction is influenced by different characteristics of the dynamic environment, feedback types, and problem complexity. This proposal investigates these factors through a series of laboratory experiments involving the DCCS microworld and the CS task. In these experiments, the CS task is given to participants after they have performed in the DCCS microworld.

## Statement of Objectives: *To determine the effects of repeated feedback and system complexity on misconceptions about Earth’s climate.*

* 1. Homogenous repeated feedback (**Objective 1a**), where participants play a single problem in DCCS.
  2. Heterogeneous repeated feedback (**Objective 1b**), where participants play different heterogeneous problems in DCCS.
  3. Problem complexity (**Objective 1c**), where participants play a difficult problem in DCCS (problem difficulty is based upon the complexity of the shape of CO2 concentration trajectory over time in the DCCS microworld).
  4. DCCS as a decision aid (**Objective 1d**), where participants could use DCCS to test their hypotheses (a form of feed-forward manipulation for participants).

****Theoretical Background**

Researchers have evaluated people’s wait-and-see preferences for climate change in terms of their reliance on the correlation heuristic and violation of mass balance misconceptions using a one-shot paper-and-pencil climate stabilization (CS) task (Dutt & Gonzalez, 2012; Sterman, 2008; Sterman & Booth Sweeney, 2007) - see Figure 1. In the CS task, participants are asked to sketch CO2 emissions and absorptions that would stabilize the CO2 concentration according to a given scenario by the year 2100 (given in Figure 1A). Participants are given the concentration’s starting value in the year 2000 (Figure 1B), and its historic trends and emissions between the years 1900 and 2000. Participants are asked to sketch the CO2 emissions and absorptions shapes that would correspond to the projected scenario of CO2 concentration between 2001 and 2100. Sterman and Booth Sweeney (2007) report that about 70% of participants at MIT (about 60% of whom had backgrounds in science, technology, engineering, and management (STEM), and a majority of the rest in economics) sketched emissions that were positively correlated with the concentration. Figure 1C, shows an example of a participant that relied on the correlation heuristic, whereby he inferred that the shapes of the CO2 emissions and concentration should look alike. Moreover, 74% of participants violated mass balance in their responses either by failing to keep emissions greater than absorption before the concentration stabilized in the year 2100; or by failing to make emissions equal to absorption when the concentration reached 2100 (Figure 1C). This proposal uses the CS task to evaluate people’s reliance on the correlation heuristic and violation of mass balance misconceptions, and also tests how repeated feedback in a simulation might help reduce these misconceptions.

Figure 1. The climate Stabilization (CS) Task. (A) Participants are given CO­2 concentration stabilization scenario, and (B) they are required to sketch the CO2 emissions and absorptions corresponding to the scenario. (C) A typical response showing reliance on the correlation heuristic (emissions similar in shape to CO2 concentration) and mass balance violation (emissions > absorptions in 2100, i.e., when CO2 concentration stabilizes).

## Repeated Feedback

Sterman (2008) and Sterman and Booth Sweeney (2007) made a qualitative claim that using microworlds and simulations would help provide repeated feedback about the cause-and-effect relationships in a climate change system. Presumably, such repeated feedback would enable people to correct their misconceptions about Earth’s climate and help them understand the dynamics of its climate system. This claim was not corroborated. Other researchers also suggest that experiencing adverse future consequences of climate change (e.g., melting of polar ice caps, drought, and rising sea levels) is likely to improve people’s understandings of Earth’s climate (Weber, 2006). However, the potential of using microworlds to reduce cognitive misconceptions about the climate system has only recently been demonstrated in a few preliminary studies (Dutt, 2011; Dutt & Gonzalez, 2011, 2012, 2013a; Moxnes & Saysel, 2009). For example, Moxnes and Saysel (2009) used a simulated microworld where participants were required to stabilize the CO2 concentration by making emissions decisions every 10 simulated years starting in the year 2010. After every 10 years, participants could see the changes in the concentration as a result of their decisions (the emissions and absorptions were maintained at their preset values for the intermediate 10 year periods). Moxnes and Saysel (2009) demonstrated that better emission decisions were possible through providing participants with repeated feedback about decision actions and outcomes consequences. Feedback in microworlds empowers participants to try new hypotheses and also to understand the cause-and-effect relationships between their decisions about CO2 emissions and absorptions and the resulting CO2 concentration.

Building on these results, I have developed a very simplified but interactive computer-based microworld of the climate system called the Dynamic Climate Change Simulator (DCCS) (see Figure 2; Dutt, 2011), and I have used it to collect data on how participants control atmospheric CO2 concentration to a goal level under different conditions of feedback delays (Dutt & Gonzalez, 2011, 2012). The two types of manipulated feedback delays employed were the natural delays in CO2 absorptions by oceans and plants, and the frequency with which multiannual emission policies were revised for a simulated climate system. Participants improved their control of the CO2 concentration to a goal level through experiences gained in DCCS, where these experiences might have enabled participants to revise their existing mental models. Similarly, Dutt (2011) put participants from both science (STEM) and non-science (non-STEM) backgrounds in two separate conditions in a laboratory experiment involving DCCS. In one (control) condition, participants sketched the CO2 emission and absorption trajectories they thought to correspond to a given stabilization scenario over 100 years (2001-2100) in the CS task. In a separate (experimental) condition, participants controlled the CO2 concentration as close as possible to a CO2 stabilization trajectory (same as that given in CS task in the control condition) by indirectly manipulating CO2 emissions and absorptions over 100 years. Participants’ performance in DCCS was followed by their performance in the CS task. Results revealed that the DCCS manipulation worked effectively in reducing participants’ correlation heuristic reliance among both STEMs and non-STEMs in the subsequent CS task compared to participants that completed the CS task alone. However, the benefits of DCCS performance were greater for STEMs compared to non-STEMs. One explanation is that previous exposure to mass balance and energy balance concepts in mathematics, science, and engineering enables STEMs to improve their sketches in the CS task because they focus less on the surface features of decision problems, and focus more on the more fundamental underlying structural features of these problems (Chi, Feltovich, & Glaser, 1981; Gonzalez & Wong, 2012).

However, the efficiency of microworlds has still not been fully demonstrated. For example, Dutt (2011) presented the same climate problem to participants in the DCCS as well as the following CS task (shown in Figure 1 and 2). According to Dutt (2011), participants showed reduced misconceptions in CS task after performing in DCCS compared to those that performed in the CS task alone (i.e., without the DCCS intervention). Given that the problem used was the same in both the CS and DCCS tasks, it is likely that participants learnt the problem’s surface features (e.g., cover story, curve shapes, and units) during DCCS training and ignored its structural features (e.g., the underlying dynamics connecting concentration, emissions, and absorptions over time). This speculation about surface versus structure is supported by the procedural reinstatement principle (Healy, Wohldmann, Parker, & Bourne, 2005): that performance is best at transfer when the procedures learned during training are repeated during transfer (as was the case in Dutt’s (2011) study). Moreover, Dutt (2011) presented a climate problem of the same difficulty in both the DCCS microworld and the following CS task. Lastly, participants completed the DCCS microworld prior to attempting the CS task. Therefore, their performance was sequential in nature between these two tasks rather than being parallel, where the DCCS microworld would be provided to participants as a decision aid side-by-side with the CS task. The latter case is more realistic and analogous to the examples of students solving mathematical problems using calculator and computer in schools, and scientists and policymakers using simulation tools while formulating climate policies. The question to ask is whether providing these decision aids simultaneously is likely to help improve people’s environmental decision making?

This proposal builds upon the existing literature and addresses several issues raised above. Specifically, we propose to create heterogeneous problems during DCCS training and transfer participants to similar/different problems in the CS task. The similarity of problems between training and transfer will allow us to test participants’ surface or structural learning. We propose testing the problem similarity in two mutually exclusive ways: 1) according to the diversity in problem’s structure and surface features; and 2) according to the diversity in a problem’s difficulty. According to the heterogeneity of practice hypothesis (Gonzalez & Madhavan, 2011), we expect heterogeneous problems that contain high diversity in surface, structure, and difficulty during DCCS training to likely to produce more effective transfer of knowledge and improved performance in the following CS task. Also, according to the difficulty of training principle (Schneider, Healy, & Bourne, 2002; Young, Healy, Gonzalez, Dutt, & Bourne, 2011), transfer performance in the CS task should be optimal when training is conducted using difficult climate problems in the DCCS microworld. Finally, there is evidence that even in simple descriptive binary-choice decision tasks, when participants are provided with experiential decision aids, they tend to rely on the experience gained in these aids in making descriptive decisions and improve their decision making (Camilleri & Newell, 2011; Jessup, Bishara, & Busemeyer, 2008; Lejarraga & Gonzalez, in press). Therefore, providing an experiential DCCS decision aid side-by-side to the CS task is likely to improve decision making in the CS task compared to a condition without the decision aid.

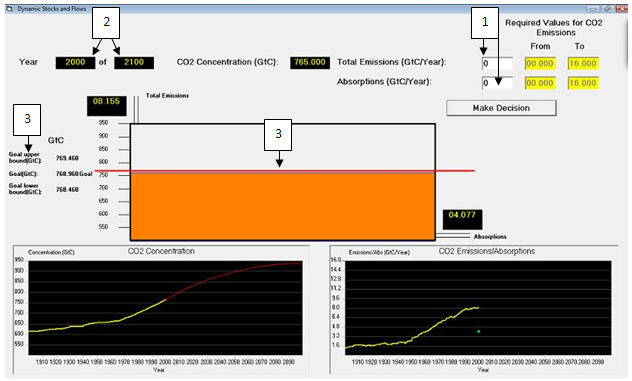


Figure 2. The Dynamic Climate Change Simulator (DCCS) microworld. The microworld is a dynamic replica of the CS task. (1) Participants set yearly CO2 emissions and absorptions and press Make Decision button. (2) The system now moves forward a certain number of years. (3) Participants need to maintain their CO2 concentration at the red goal line in the tank (which represents the atmosphere) and follow the CO2 concentration trajectory shown in the bottom left panel.

## Technical Approach

Four laboratory experiments are proposed that will help clarify the effects of repeated feedback about the climate system. In all the proposed experiments modified versions of a dynamic simulation, DCCS, will be used. All experiments will involve training and transfer phases with human participants (more details are presented below). During the training phase, we will use different manipulations of learning and feedback in DCCS and we will use the CS task during the transfer phase (**Objective 1a, 1b, 1c, and 1d**). In Experiment 1, we will test the benefit of DCCS when problems faced by participants between the training and transfer are different. In Experiment 2, we will test how heterogeneity based upon surface features (e.g., problem’s cover story and units) compares to heterogeneity based upon structural features (e.g., problem’s underlying dynamics) in its ability to improve understanding at transfer. According to the heterogeneity of practice hypothesis (Gonzalez & Madhavan, 2011), we expect heterogeneous problems with high surface or structural diversity during DCCS training to likely to produce more effective transfer of knowledge and improved performance in the CS task. In Experiment 3, we will focus on the difficulty of problems encountered. For example, school children are trained on simple/difficult problems in class to prepare them for different problems in their exam. According to the difficulty of training principle (Schneider et al., 2002; Young et al., 2011), transfer performance in the CS task should improve when training is conducted using difficult climate problems in DCCS compared to simple problems. Finally, in Experiment 4, we aim to evaluate the effectiveness of decision aids in reducing people’s misconceptions when they have at their disposal an aid that simulate future CO2 concentration outcomes by assuming different CO2 emission policies. The research design, rationale, methods, statistical analyses, and interpretation of results of each experimental set will be described in full detail in the proposal.

# Experiments

We propose a series of laboratory experiments that will help clarify the effects of repeated feedback, on people’s cognitive misconceptions about the climate system. We propose four sets of experiments. One example of each set is described in detail below. In all the proposed experiments, we will use modified versions of a dynamic simulation, DCCS. All experiments will involve training and transfer phases. During the training phase, we will use different manipulations of learning and feedback in DCCS and we will use the CS task during the transfer phase (**Objective 1a, 1b, 1c, and 1d**). The research design, rationale, methods, statistical analyses, and interpretation of results of each experimental set are described in detail below.

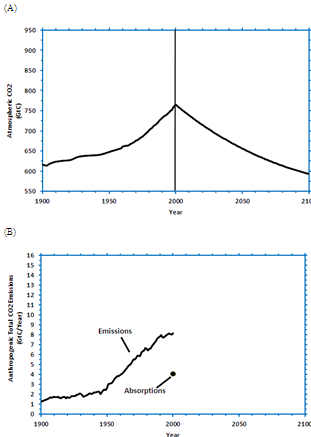
*Participants*. Approximately 650 adults between the ages 18 to 40 will be recruited from Mandi and surrounding areas for four behavioral studies. We plan to have sizeable participant populations distributed in different conditions of the four experiments (reported below) to yield a medium to large effect size in our results. A power calculation revealed that for an Alpha = 0.05 and a Power = 0.80, it would need N=50 samples in each condition for a medium effect size of 0.50 (one-tailed test). Each of the four experiments will be run at Indian Institute of Technology, Mandi, India. Experimental sessions are expected to be about 60 to 90 minutes long per participant, and participants will be paid Rs. 100 to Rs. 150 for their effort (Rs. 100 for a 60 minutes session and Rs. 150 for a 90 minutes session).

## Experimental Set 1: Homogenous Repeated Feedback

Dutt (2011) gave participants training on a problem in the DCCS microworld and immediately transferred them to attempt the same problem in the CS task. When the transfer performance was compared with performance of participants in the CS task without the DCCS training, Dutt (2011) found a decrease in correlation heuristic reliance and mass balance violation. However, the decrease in misconceptions could be due to the similarity between problems in training (in DCCS) and transfer (in the CS task). What would be the benefit of DCCS when problems between training and transfer are different? And how does the performance in a different problem in the CS task compare to participants who only perform in the CS task and do not get any DCCS training? The answer to this question could significantly help in formulating effective education policies for climate education as it would indicate how we solve simple climate problems relate to misconceptions. The present study was designed to answer these fundamental questions.

*Methods*. Participants will be randomly assigned to one of four between-subjects conditions (with N=50 in each condition): CS-Same, CS-Different, DCCS-CS-Same, and DCCS-CS-Different. In both the DCCS-CS-Same and DCCS-CS-Different conditions, participants will play 3 rounds of DCCS repeatedly and will then be transferred to the CS task immediately. In the CS-Same and CS-Different conditions, participants will play an unrelated task for the average time it takes to complete the 3 rounds in the DCCS task and will then be transferred to the CS task immediately (the unrelated task is provided to equalize the time spent in all four conditions). All experimental sessions are supposed to last 90 minutes. The climate problem given in the CS task of the DCCS-CS-Same condition and the CS-Same condition will be exactly same. The problem given in the DCCS-CS-Different condition and CS-Different condition will be exactly same. In the DCCS-CS-Same and CS-Same conditions, participants will be given the exact same climate problem during different rounds of the DCCS microworld and in the following CS task, and this problem will be the same as in Figures 1 and 2 (i.e., the CO2 concentration increases from 765GtC in 2000 to stabilize at 936GtC by 2100). Similarly, in the DCCS-CS-Different condition, the problem given during the DCCS training will be again the same as that described in Figures 1 and 2; however, the problem given in the CS task will be the one shown in Figure 3, where the CO2 concentration now decreases from 765GtC in 2000 to stabilize at 594GtC by 2100. Figure 3’s problem will also be given to participants as part of the CS task in the CS-Different condition.

Figure 3. The climate Stabilization (CS) Task. (A) Participants are given CO­2 concentration stabilization scenario, where CO2 concentration decreases from year 2001 and stabilizes by year 2100. (B) Participants are required to sketch the CO2 emissions and absorptions corresponding to the stabilization scenario.



In each of the three rounds in DCCS microworld, participants will be asked to keep their CO2 concentration as close as possible to the given CO2 concentration stabilization trajectory over time. In each round, participants will set CO2 emissions and absorptions for a 5 year period by entering the values at the start of the period. Then, participants will click the “Make Decision” button in DCCS (see Figure 2) and DCCS will automatically simulate these CO2 emissions and absorptions by treating them as constants for the next 5 years. At the end of the 5 year period, participants will again set emissions and absorptions for the next 5 year period and DCCS will simulate these values once again for the next 5 years. After participants have completed 100 years in DCCS, the current round will end and participants will start a new round. In the new round, DCCS will restart to the year 2000. At the end of all three rounds, participants will be transferred to the CS task. In the CS task, participants will be asked to sketch the CO2 emissions and absorptions that they think would correspond to the CO2 concentration stabilization trajectory over a 100 year period (from 2001 to 2100). Participants will be compensated based upon the time they spent in the lab (~ Rs. 150 per participant for a 1.5 hour long study).

*Statistical analyses*. Participants’ responses in the CS task in different conditions will be coded as relying on correlation heuristic and/or violating mass balance. If the correlation coefficient between participants’ sketched CO2 emissions and CO2 concentration trajectory is greater than 0.8, their response will be classified as relying on correlation heuristic. Furthermore, if participants do not equalize CO2 emissions and absorptions in 2100 (when the CO2 concentration stabilizes) and do not keep CO2 emissions greater than (less than) CO2 absorptions before 2100 in Figure 2 (Figure 3), their response will be classified as violating mass balance. We will compare the proportion of correlation heuristic reliance and mass balance violation responses between the CS-Same and DCCS-CS-Same conditions and between CS-Different and DCCS-CS-Different.

*Interpretation of results*. We expect repeated feedback in the DCCS microworld to reduce participants’ misconceptions. Any significant differences between CS-Same and DCCS-CS-Same conditions and between CS-Different and DCCS-CS-Different conditions will indicate effectiveness of training in the DCCS microworld. A difference between CS-Different and DCCS-CS-Different conditions will indicate the effectiveness of DCCS with dissimilar climate problems between training and transfer. Such a finding would provide insights into whether participants learn the structure of the problem rather than its surface features during training (**Objective 1a**).

## Experimental Set 2: Heterogeneous Repeated Feedback

It is still not a common knowledge on how heterogeneity based upon surface features (e.g., problem’s cover story and units) compares to heterogeneity based upon structural features (e.g., problem’s underlying dynamics) in its ability to improve performance at transfer. Furthermore, it is not known how similarity/differences between problems during training and transfer, or the problem's heterogeneity based upon structure/surface features effects performance at transfer. Here, I will test heterogeneous problems which are diverse in surface and structure. According to the heterogeneity of practice hypothesis (Gonzalez & Madhavan, 2011), one expects heterogeneous problems with high surface or structural diversity during DCCS training to likely to produce more effective transfer of knowledge and improved performance in the CS task.

*Methods.* Participants will be randomly assigned to one of four between-subjects conditions (with N=50 in each condition): CS-Surface, CS-Structure, DCCS-CS-Surface, and DCCS-CS-Structure. In both DCCS-CS-Surface and DCCS-CS-Structure conditions, participants will play 3 rounds of DCCS repeatedly with heterogeneous problems that are either based upon surface features or structural features and will then be transferred to the CS task immediately.

In the CS-Surface and CS-Structure conditions, participants will play an unrelated task for the average time it takes to complete the 3 rounds in the DCCS task and then be transferred to the CS task immediately. In the DCCS-CS-Surface condition, participants will first tackle Figure 1’s problem in each of the three rounds repeatedly in DCCS, however, the problem presented in each round will now differ randomly in the cover story and units used (i.e., in surface features). We will use a glucose cover story (inflow=glucose intake, outflow=glucose metabolized, and accumulation=glucose concentration in blood over 100 time periods), a water cover story (inflow=water input, outflow=water output, and accumulation=water in a tank over 100 time periods), and a temperature cover story (inflow=heating, outflow=cooling and accumulation=temperature in a room over 100 time periods). In each of these three (cover story) problems, participants will control the accumulation level to an accumulation stabilization trajectory in DCCS by making inflow and outflow decisions every 5 time periods repeatedly. After finishing three rounds in DCCS, participants will be transferred to the CS task where they will attempt two problems that will be presented in a random order. Both these problems will correspond to Figure 1’s problem, where one of the problems will be presented with the climate cover story (i.e., just like Figure 1’s problem and be different from problems presented during DCCS training), while the other problem will be presented with the temperature cover story (i.e., similar to one of the problems during the DCCS training). In both problems, participants will need to sketch the shape of inflow and outflow that corresponds to the accumulation stabilization scenario. The CS-Surface condition will also contain the same two problems as part of the CS task; however, the condition will not include training in DCCS microworld.

Figure 4. The two problems presented (out of the three total) in the DCCS-CS-Structure condition in the DCCS microworld. (A). The stabilization occur in 2085. (B). The stabilization occurs in 2070.

In the DCCS-CS-Structure condition, participants will first perform in three different climate problems presented randomly in each round in DCCS. Each problem will provide a different CO2 stabilization trajectory, where CO2 concentration increases from 765GtC in 2000 to stabilize at 936GtC by 2100 or earlier. In one of these three problems, the stabilization will occur in year 2100 (Figure 1’s problem). In the other two problems, the stabilization at 936GtC will occur much earlier in years 2070 and 2085, respectively, and the 936GtC value will be maintained till the end year 2100 (see Figure 4). In each DCCS problem, participants will be asked to control the CO2 concentration to the stabilization trajectory over a 100 year period by making emission and absorption decisions every 5 years, repeatedly. Once participants complete the three rounds in DCCS, they will be transferred to the CS task immediately where participants will attempt two problems presented in a random order. One of these two problems will be Figure 1’s climate problem (i.e., similar to one of the problems in the DCCS training), and the other problem will be Figure 3’s climate problem (i.e., different from all problems in the DCCS training). In both CS problems, participants will need to sketch the shape of CO2 emissions and absorptions that correspond to the CO2 concentration stabilization scenario. The CS-Structure condition will contain the same two problems in the CS task and will not include training in DCCS microworld. Participants will be compensated based upon a 1.5 hour-long study in the lab (~ Rs. 150 per participant).

*Statistical Analysis.* Multiple behavioral analyses will be conducted.Proportion of responses demonstrating correlation heuristic reliance and mass balance violations will be compared between the DCCS-CS-Surface and CS-Surface conditions, and between the DCCS-CS-Structure and CS-Structure conditions.

*Interpretation of results*. The comparisons of the two problems in the CS tasks of the DCCS-CS-Surface and CS-Surface conditions and in the DCCS-CS-Structure and CS-Structure conditions will allow us to measure the effectiveness of the surface/structural heterogeneity. Furthermore, how these homogeneous conditions help/hinder transfer to similar/different transfer problems in the CS task compared to the problems done during the training rounds in DCCS (**Objective 1b**). We expect a reduction in misconceptions in conditions involving DCCS compared to conditions without it. Also, on account of the procedural reinstatement principle (Healy et al., 2005), we expect better performance in both structure and surface conditions when the conditions learned during DCCS training are similar to those encountered in the CS task.

## Experimental Set 3: Problem Difficulty

Another way in which training conditions might differ is by the difficulty of problems encountered. For example, school children are trained on simple/difficult problems in class to prepare them for different problems in their exam. According to the difficulty of training principle (Schneider et al., 2002; Young et al., 2011), transfer performance in the CS task should improve when training is conducted using difficult climate problems in DCCS compared to simple problems. Based upon the general effectiveness of training in DCCS (Dutt, 2011), we expect the transfer performance will improve in both simple and difficult training conditions compared to conditions that do not involve DCCS training.

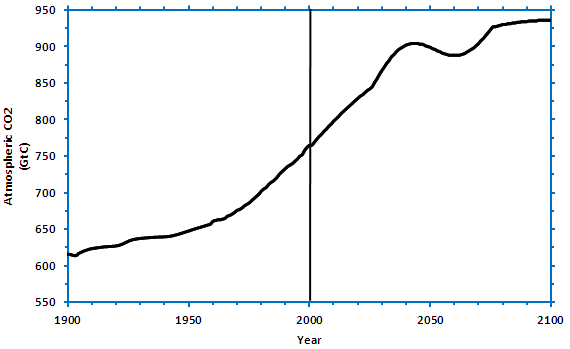


Figure 5. The CO2 concentration stabilization trajectory to be used as the difficult problem in Experiment 3.

*Methods*. Participants will be randomly assigned to one of three between-subjects conditions (with N=50 in each): DCCS-CS-Easy, DCCS-CS-Difficult, and CS. In both the DCCS-CS-Easy and DCCS-CS-Difficult conditions, participants will play three rounds of DCCS with a single easy or difficult problem repeated, and will then immediately transfer to the CS task, where they attempt a different problem. DCCS in different rounds of the DCCS-CS-Easy condition will use Figure 1’s problem. However, the DCCS performance in different rounds of DCCS-CS-Difficult condition will make use of the problem described in Figure 5. The shape of CO2 concentration scenario in Figure 5’s problem is more complex compared to Figure 1’s problem (although the CO2 concentration in both problems has about the same value and trajectory of movement over time).

In the DCCS-CS-Easy and DCCS-CS-Difficult conditions, participants will control the CO2 concentration to the stabilization trajectory in each of the three rounds in DCCS by making inflow and outflow decisions every 5 time periods repeatedly. At the end of each round, DCCS will be reset to the year 2000 for the next round till all three rounds are completed. After participants finish, they will be transferred to a different problem in the CS task. In the CS condition, however, participants will play an unrelated task for the average time it takes to complete all three rounds in the DCCS task (in the conditions involving DCCS) and then be transferred to the CS task immediately.

Under all conditions, participants will attempt the problem shown in Figure 3 in the CS task, where they will sketch the shape of CO2 emissions and absorptions that correspond to the decreasing CO2 concentration stabilization trajectory between 2001 and 2100. Participants will be compensated based upon the time they spent in the lab (~ Rs. 150 per participant for a 1.5 hour-long study).

*Data Analysis*. Participants’ cognitive misconceptions will be evaluated in the CS task in all conditions. A comparison will be made between the CS task's three conditions: CS-DCCS-Easy, CS-DCCS-Difficult, and CS.

*Interpretation of results*. A comparison of the CS task's performance between the CS and DCCS-CS-Easy conditions, and between the CS and CS-DCCS-Difficult conditions would show the effectiveness of training in DCCS. Moreover, a comparison of CS performance between the DCCS-CS-Easy and DCCS-CS-Difficult conditions will reveal the advantage of the training on a difficult climate problem in the DCCS microworld (**Objective 1c**). We anticipate that the results of these comparisons will show the best performance (least proportion of misconceptions) in the DCCS-CS-Difficult condition and the worst performance (most proportion of misconceptions) in the CS condition.

## Experimental Set 4: Side-by-side Decision Aids While Solving Problems

There are numerous situations during schooling when students might make use of decision aids (e.g., computers and calculators) to assist them in solving complex mathematical problems. Similarly, climate scientists and climate policymakers are likely to use decision aids like simulation tools while formulating future GHG emission policies. Here a scientist or policymaker wants to evaluate the effects of a future emission policy on the CO2 concentration/global temperature through the use of decision aids. The aim of this experiment is to evaluate the effectiveness of decision aids in reducing people’s misconceptions when they have at their disposal an aid that simulate future CO2 concentration outcomes by assuming different CO2 emission policies. Determining the effectiveness of decision aids will enable policymakers to shape future education policies that propose the use of such aids both in school education and formulating climate policies.

*Methods*. Participants will be randomly assigned to one of two between-subjects conditions (with N=50 in each condition): Aid and No-Aid. In both conditions, participants will attempt two problems in the CS task that are presented to them in a random order. One of these problems will be the one shown in Figure 1, and the other will be the one shown in Figure 3. In the Aid condition, participants will be provided with a slightly modified DCCS microworld side-by-side the CS task. In the No-Aid condition, participants will be asked to attempt the two CS problems without DCCS. In the Aid condition, participants can use DCCS anytime to enter 10-yearly emission and absorption values over a period of 100 years (i.e., a total of 10 values for each of the emissions and absorptions) and simulate the resulting CO2 concentration (the DCCS microworld will simulate the entered values rapidly in about 1-2 seconds of time delay). Participants can then reset DCCS to the year 2000 and simulate different emission and absorption values. Participants could try DCCS as many times as they want to before sketching their CO2 emissions and absorptions in the CS task. Participants will be compensated based upon the time they spent in the lab (~ Rs. 100 per participant for an hour long study).

*Data Analysis*. Participants’ cognitive misconceptions will be evaluated for both problems in the CS task across both the Aid and No-Aid conditions. Also, we will record the number of times participants use the DCCS decision aid in the Aid condition and the trajectory of their entered CO2 emissions, absorptions, and simulated CO­2 concentration curves in each use of the DCCS microworld.

*Interpretation of results*. A comparison of CS task performance (misconceptions) in both problems across will show the effectiveness of providing the DCCS microworld as a simultaneous decision aid. We expect improved performance in the Aid condition compared to the No-Aid condition (**Objective 1d**). In addition, participants who use the decision aid more often should show a smaller proportion of misconceptions. Furthermore, participants’ simulated CO2 trajectory in each DCCS simulation is likely to bring them closer to the CO2 stabilization trajectory provided in problem in the CS task.

# Intellectual Merit and Broader Impact of the proposed Research

Currently, public support for policies that mitigate climate change is weak. One possible reason may be cognitive misconceptions about the dynamics of Earth’s climate. The proposed work will demonstrate the benefits of using computer-based simulation tools to reduce such misconceptions. The research proposed has important implications for developing effective climate education programs that make use of microworlds. The resulting interventions would likely improve people’s understanding about Earth’s climate and help them to make better and informed environmental decisions. Our results will provide concrete predictions as to how learning and decision aids may promote or impede misconceptions. In summary, the project will provide concrete scientific findings on human misconceptions, how they improve as a result of repeated feedback in microworlds.

# Schedule and Management Plan

As per the activities listed in the diagram above, the proposed project is scheduled to start on August 1st, 2014 and end on 23rd June, 2017.

**Budget**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Item** | **BUDGET** | | | **(in Rupees)** |
|  | 1st Year | 2nd Year | 3rd Year | Total |
| Travel (India and Overseas) | 70,000 | 70,000 | 70,000 | 2,10,000 |
| Computer Cost (6 total) | 40,000 x 6 |  |  | 2,40,000 |
| Furniture (False partition, Table, Chair) | 70,000 |  |  | 70,000 |
| Payments in Experiments | 65,000 | 35,000 | 10,000 | 1,10,000 |
| Total |  |  |  | 6,30,000 |

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1. Climate simulation tools (or microworlds) are climate games that allow laypeople and policymakers to observe changes in CO­2 concentration/atmospheric temperature as a result of setting different CO2 emission policies and prevailing absorption rates. These microworlds allow researchers to compress geographical space (depict changes globally) and compress time (depict changes over 100-200 years) on a computer screen. The use of microworlds for understanding and explaining climate change is becoming popular (See these websites for some examples: http://www.hss.cmu.edu/departments/sds/ddmlab/researchn.htm#dccs, http://climateinterative.org; http://scripts.mit.edu/~jsterman/climate/master/; http://www.astr.ucl.ac.be/users/matthews/jcm/; and http://www.google.com/landing/cop15/) [↑](#footnote-ref-1)