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A decision science approach for integrating social science in climate and energy solutions

Gabrielle Wong-Parodi[1,*], Tamar Krishnamurti[1], Alex Davis[1], Daniel Schwartz[2], and Baruch Fischhoff[1,3]

[1]Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, 15213, USA

[2]Department of Industrial Engineering, University of Chile, Santiago, Chile

[3]Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA, 15213, USA

[*]Department of Engineering and Public Policy, 129 Baker Hall, Carnegie Mellon University, Pittsburgh, PA 15213; Email: gwongpar@cmu.edu; Phone: (510) 316-1631

Abstract

The social and behavioral sciences are critical for informing climate- and energy-related policies. We describe a decision science approach to applying those sciences. It has three stages: *formal analysis* of decisions, characterizing how well-informed actors should view them; *descriptive research*, examining how people actually behave in those circumstances; and *interventions*, informed by the formal analysis and descriptive research, designed to create attractive options and help decision makers choose among them. Each stage requires collaboration with technical experts (e.g., climate scientists, geologists, power systems engineers, regulatory analysts), as well as continuing engagement with decision makers. We illustrate the approach with examples from our own research in three domains related to mitigating climate change or adapting to its effects: preparing for sea level rise, adopting smart grid technologies in homes, and investing in energy efficiency for office buildings. The decision science approach can facilitate creating climate- and energy-related policies that are behaviorally informed, realistic, and respectful of the people whom they seek to aid.

Introduction

Policies for mitigating climate change or reducing the harm that it causes inevitably make assumptions about the behavior of the people who must execute or respond to those policies. Unless those assumptions are realistic, the policies may fail[1]. For example, wind farms have been rejected because planners failed to consider public opposition to changes in their view or the anticipated harm to birds or bats[2]; free weatherization programs have failed because people do not want strangers coming into their homes[3]; rebate programs have experienced rebound effects, whereby residential homeowners use more energy after buying more efficient appliances[4]. Even low-cost, high-benefit technological innovations may not gain acceptance unless consumers can see the benefits and feel able to take advantage of them. For example, many people cannot use information about energy consumption when expressed in unfamiliar units, such as kWh[5-8]. Moreover, without behavioral evidence, one cannot know whether policies have failed because people did not understand them, did not want them, or could not execute them.

We outline a decision science approach to integrating the social and behavioral sciences into climate- and energy-related policy development, in order to realize the potential of natural science and engineering knowledge to address the challenges posed by climate change. Decision science involves *formal analysis* of decisions, characterizing the choices that fully-informed, rational actors would make; *descriptive research*, examining how people actually behave in those circumstances; and, *interventions* designed to bridge the gap between the normative ideal and the descriptive reality[9-11]. Applying this approach requires continuing collaboration with both substantive experts, in order to ensure the accuracy of the analysis and the feasibility of the interventions, and social scientists, in order to create attractive interventions, secure them a fair hearing, and assess their success[12-13]. It also requires continuing interaction with decision

makers, so as to create options that they might find attractive[14-16]. The decision science approach seeks to facilitate informed decision making, so that people understand the risks, benefits and uncertainties well enough to make choices that reflect their values. Here, we illustrate how decision science has been applied in three domains related to mitigating climate change or adapting to its effects, with studies drawn from our own published research (linked to the full reports). Table 1 summarizes results from these studies.

I. Formal analysis

Decision science provides analytical frameworks general enough to accommodate decisions as diverse as those associated with climate and energy. Its first step is formal analysis, characterizing decisions in the structured form of choice options, valued outcomes, and uncertainties regarding the outcomes that each option will produce[11,17,18]. In the U.S., for example, a decision facing electric power generators is how (and how quickly) to reduce CO_2 emissions in the face of EPA's Clean Power Plan[19]; a decision facing homeowners is how to prepare for flooding, given changes to the National Flood Insurance Program[20]. A formal analysis identifies the information that people need in order to make choices consistent with their values. To that end, it must include the relevant options (e.g., affordable actions), valued outcomes (e.g., personal safety, biodiversity), and uncertainties (e.g., will insurance claims be honored?). The evidence relevant to an analysis may come from the natural sciences (e.g., the potency of greenhouse gases), engineering (e.g., the cost and efficacy of control technologies), or the social sciences (e.g., individuals' willingness and ability to pay for emission reductions). The following three examples illustrate such analyses.

Preparing for Sea Level Rise

Floods and storms are the most frequent and costly weather-related disasters in United States, causing an estimated $626.9 billion in losses between 1980 and 2011[20,21]. Climate models predict increased coastal flooding due to more frequent and intense high-impact storms[22-23] and rising sea levels[24-25], affecting an increasing number of people living in flood-prone areas[26-27].

Individual actions designed to reduce vulnerability (e.g., home retrofits, flood insurance, evacuation plans) are increasingly promoted as complements to large-scale public defenses (e.g., sea walls, levees)[28-31]. Nonetheless, few people adopt such measures voluntarily[32-33]. Although these low adoptions rates are frustrating to authorities, they might still represent reasonable choices, depending on residents' options, values, and uncertainties.

Determining whether residents should want the options that programs promote requires formal analysis of the decisions facing them. That analysis should consider their feasible options (e.g., retrofitting their home now, leaving it to the next owner), their valued outcomes (e.g., peace of mind, solidarity with neighbors), and the uncertainties regarding which outcomes will follow adoption of each option (e.g., whether government will pay for reconstruction, how climate change will affect storm surge risks). These analyses of individual decisions parallel those in the integrated assessments created for public decisions – which may include predictions of private choices (e.g., settlement patterns on coastal plains)[34].

Adopting Residential Smart Grid Technologies

Smart grid technologies have been promoted as a way to reduce residential energy use, by providing real-time consumption information to system operators (e.g., for managing power quality and guiding spot-market purchases) and to consumers (e.g., for conserving energy based on appliance usage or participating in peak-shaving programs)[35]. According to one estimate,

global smart grid deployment could reduce annual greenhouse gas (GHG) emissions by 0.9-2.2 gigatonnes of CO_2[36]. The U.S. has made major investments in these technologies[37], including the residential meters needed to implement demand-response programs (e.g., by setting higher prices during peak-use hours). If successful, such programs could reduce reserve capacity costs[38], demand for new generation, and system load, thereby making service more reliable, while reducing energy waste and carbon emissions[39].

Whether such programs should, indeed, be attractive to consumers is a matter for analysis, considering consumers' options (e.g., ways to reduce consumption), valued outcomes (e.g., comfort, cost, health, privacy), and uncertainties (e.g., will the privacy of their consumption data be protected? Will savings plans be too complex to follow?). Prior experience provides one basis for assessing those uncertainties. However, its relevance is always conditional on conditioning factors, such as how rigorously the technology has been tested, how committed public utility commissioners are to defending consumers' interests, and how well consumers can follow price signals[40-41]. As a result, expert judgment, interpreting the evidentiary record for specific circumstances, is part of any analysis[42-43].

Investing in Energy Efficiency in Office Buildings

Office buildings account for 16% of commercial sector energy use in the U.S.[44] Although the sector has great potential for cost-effective energy efficiency improvements (e.g., occupancy sensors), adoption rates are low[44-46]. Hoping to speed the diffusion of these improvements, many U.S. cities have established 2030 Districts, committed to reducing energy use by 50% for existing buildings by 2030 (2030district.org).

A simple formal model of building owners' decisions about investing in energy efficiency would compare the net economic benefit (from energy savings) of each option (e.g.,

efficient lighting) with its costs (purchase, maintenance, disposal, back-up). Options that pass such a cost-benefit test can be subjected to cost-effectiveness analysis, identifying the best buys in energy saving (i.e., those providing the greatest net savings for the least cost) and other investments (e.g., new bathroom sinks). A more complete economic analysis could include the transaction costs of activities such as investigating the options, securing trusted contractors, and completing the associated paperwork (e.g., documenting expenditures, occupancy, ownership). More complete analyses could include additional outcomes such as the expected appeal of better facilities to prospective tenants, disruption to current tenants during renovations, and hassle of working with a program's promoters. More complete still are analyses that consider uncertainty about promised savings, owners' ability to make payments, or occupancy rates. The usefulness of any analysis depends on how fully it includes a decision's critical elements – without which its calculations represent misplaced precision (and its sensitivity analyses represent misplaced imprecision).

II. Descriptive research

Decision science proceeds from formal analysis to descriptive research, characterizing individuals' perceptions in comparable terms. Basic research has identified general ways in which the heuristics that guide lay judgments can produce both insight and bias[47]. Research focused on climate- and energy-related topics has examined how these processes play out in specific domains[48-49]. Our own work (illustrated below) has focused on how people think about specific decisions (rather than, say, on the general framing of climate issues). In that research, we typically elicit either summary judgments, paralleling the inputs for a formal analysis (e.g., the probability of flooding in the next ten years)[16,42], or *mental models* of the processes shaping those

outcomes (e.g., how winds and tides affect storm surges)[50-51]. We typically begin with qualitative research, allowing participants to raise the issues on their minds in their natural language and formulation. We then proceed with structured surveys, assessing the prevalence of key beliefs and values, sometimes supplemented with experiments assessing the influence of specific factors, such as how issues are framed or individuals' political identify is evoked.

Studies that elicit summary judgments draw on research whose roots lie in the dawn of scientific psychology (c. 1875), with tasks assessing the psychological equivalent of physical stimuli (e.g., brightness, heaviness). Researchers found that such "psychophysical" judgments can depend on seemingly subtle aspects of how stimuli are presented, such as where the first two stimuli lie in the overall set and whether whole or fractional numbers are used[52-54]. Studies extending these methods to judgments of risks and benefits highlighted additional concerns, such as the importance of clear, consensual definitions[16,42,43, 55-56]. For example, judgments of "risk" may be misinterpreted, if the term means different things to technical experts (fatalities in an average year) and laypeople (adding a measure of catastrophic potential, for non-average years)[57]. Judgments of the "probability of rain" may be misinterpreted unless laypeople know what forecasters mean by "rain" (the chance of measurable amount, the percentage of the area covered, or the fraction of the day)[58].

Studies of lay mental models have almost as long a history[59-62]. They compare intuitive representations of how a process works to a formal one, with topics as diverse as syllogistic reasoning, the circulatory system, and climate dynamics[63]. In our studies, formal analyses are the standard of comparison. However, unlike studies in other domains, which assume the validity of the formal model, in our research the model can change – if people identify options, values outcomes, or uncertainties that it has missed.

Mental models interviews begin with general questions (e.g., "what comes to mind when you think about wind power?"), so as to avoid presuming that the researchers have identified all relevant elements. In that spirit, interviewees are encouraged to expand on each topic that they address, so as to hear out their views and the language expressing them. The interviews proceed with questions that focus increasingly on topics in the formal analysis. That focus reduces the risk of missing topics because the interview happened to go in other directions, while increasing the risk of suggesting topics that are not naturally part of participants' mental models.

Follow-up surveys can estimate the prevalence of views heard in the interviews. Follow-up experiments can assess the role of specific factors, such as the impact of context (e.g., cues evoking political identity) on expressed beliefs. As with all social and behavioral science research, the development of those instruments requires iterative pretesting, typically with individuals drawn from the target population thinking aloud as they perform a task – with researchers alert to cases where it was not interpreted as intended. Manipulation checks ask respondents in the actual studies to report on how they interpreted questions[55, 64-66].

Preparing for Sea Level Rise

Our descriptive research began with structured interviews, asking participants to think aloud while using the Surging Seas decision aid (http://sealevel.climatecentral.org/) (Figure 1). Those interviews allowed us to capture many aspects of their thinking, such as their intuitive conceptualization of the probability and impact of flooding events. However, they left us uncertain about how people thought about one key factor in the formal analysis of decisions involving coastal flooding exacerbated by sea-level rise: the time horizon. Their natural perspective could depend on both pragmatic concerns (e.g., how long they expect to live in an area) and subjective feelings of psychological distance[67-68]. For example, one study found greater

concern about climate change when people had shorter time horizons (and less psychological distance)[70]. On the other hand, with shorter time horizons, there is also less chance of bad things happening, which could reduce willingness to translate concern into action.

In order to investigate how such processes play out in one specific context, we randomly assigned people to one of three time frames [2020/2050/2100], when making judgments using the Surging Seas decision aid (e.g., "Keeping what [I] learned about coastal floods in [County] in mind…I would still move with my family to [County] (if I was planning on doing that already);" "Now, please set the highest expected flood height that you and your family would be willing to live with, at some point between today and [2020/2050/2100], before deciding to move to [County]. What height did you pick?"). We found similar responses to all three time horizons[68]. One possible explanation of that seeming insensitivity to time horizon is that immersion in the decision aid overwhelmed any effects of the time period manipulation. A second possible explanation is that changing the time period had canceling effects, with longer periods both showing greater risks and increasing participants' psychological distance from them.

In another experiment, we examined the effect of evoking respondents' political identity on their judgments[71]. The politically polarized debate over climate change[72-73] has raised the prospect of personal values acting as "perceptual screens," so that people interpret (and perhaps misinterpret) messages in ways that reinforce their existing views and allegiances[74-76] – as special cases of general psychological processes, such as confirmation bias[77] and motivated reasoning[47,78-81]. Our study manipulated political identify on climate change in the context of decisions about buying a home in an area subject to sea level rise. In order to make the task more realistic (while still hypothetical), participants used the real estate search website Zillow® together with the Surging Seas decision aid. We found that, once immersed in that decision,

participants with different political views responded similarly, except when a strong appeal to their political identity was embedded in the task. However, even that difference vanished when participants stated their position on climate change beforehand, seemingly allowing them to focus on the practical decision, once their identity was acknowledged. Political positions have, however, been found to affect behavior on less involving tasks[81-83].

Adopting Residential Smart Grid Technologies

Some customers' responses to smart grid technologies reflect issues seemingly missing from the formal models of those technologies' advocates, such as concern over privacy, health effects, and unfair electricity bills[84-85]. In order to create a comprehensive picture of those concerns, we conducted mental models interviews, followed by a survey examining the prevalence of decision-relevant beliefs expressed in those interviews, using the language revealed there[86]. Principal components analysis found that customers' concerns loaded on three factors: (1) *fear of being controlled*, including concerns about privacy and utility company control over electricity use (e.g., switching off air conditioning during peak demand); (2) *tangible benefits*, including expectations for financial savings and reduced blackout risk; and (3) *accountability* of the utility company, including perceived opportunities to check the accuracy of electricity bills and receive appliance-specific usage information. Logistic regression models found more positive attitudes toward smart meters among people who saw them as bringing tangible benefits and among those who had less fear of being controlled. Those attitudes were, however, unrelated to accountability, perhaps a fortunate result for smart meter advocates, as the interviews found that consumers expected much better feedback than the meters can provide.

Investing in Energy Efficiency in Office Buildings

Motivated by the puzzlingly low rates of investment in energy efficiency technologies for offices, Davis *et al*. (in review) conducted mental models interviews and a follow-up survey with owners of class B and C (i.e., non-premier) office buildings[87]. Both the interviews and the survey were structured around a formal model of the owners' energy efficiency decisions that included both economic and non-economic concerns. Respondents' perspectives were elicited with sufficient detail to evaluate the attractiveness of both currently available options and potentially better ones. When provided estimates of the expected costs and benefits of energy efficient lighting systems, survey respondents demonstrated a surprising willingness to invest (given the lack of actual adoption). However, when asked about financing programs to help pay for those investments, many owners expressed a principled objection to incurring debt, with some even rejecting loans at zero percent interest. For those individuals, the net present value calculation of a simple economic model is irrelevant. Rather, they need an analysis that evaluates energy-efficient options without assuming a positive discount rate. Many respondents expressed skepticism about the claims made for energy savings and about the motives of the people making them – all concerns missing from promoters' analyses of owners' decisions.

III. Interventions

Disparities between formal models and descriptive realities offer opportunities for interventions designed to improve the models (so that they capture decision makers' concerns), the options (so that they address users' needs), or the communications with decision makers (so that the options are understood and those offering them are trusted). Basic research should inform the program design process, suggesting directions, followed by vigorous pre-testing of successive designs, and rigorous evaluation of the one that is eventually deployed. Sound design

has many facets (e.g., tone, wording, aesthetics, organization), and hence can draw on inputs from many research areas[88-89]. Evaluation similarly draws on the research areas needed to measure a program's success in achieving goals such as how well people understand program, how attractive the find it, and how well they can implement their choices.

Preparing for Sea Level Rise

In our evaluation of Climate Central's Surging Seas Risk Finder decision aid (Figure 1)[68,71], we sought to draw on these diverse research literatures, guided by empirical assessment of the aid's success in meeting three evaluative criteria: users' (1) *knowledge*, measured by their ability to recall decision-relevant facts; (2) *preferences*, measured by the consistency of their judgments with alternative displays (e.g., with different time horizons); and (3) *active mastery,* measured by their ability to make sound inferences based on the presented material. Changes prompted by that testing included introducing bright colors to highlight important features, reorienting a bar showing water level from horizontal to vertical (in order to match intuitive notions of depth), and making the welcome screen more welcoming by reducing clutter (e.g., moving detailed information to secondary screens accessed by advanced tabs). Surging Seas was, we believe, the only website on the initial rollout of www.data.gov/climate to have undergone such user testing.

Adopting Residential Smart Grid Technologies

Smart grid-enabled technologies can provide real-time feedback to customers about their energy consumption, through devices such as in-home displays (IHDs). Promoters of the technology postulate that such feedback will improve consumers' mental models of their home energy use[90-92], so that they use existing appliances more effectively, and allow introducing more

attractive products (e.g., home automation systems) or programs (e.g., dynamic pricing)[93]. Many studies have examined how well that potential has been achieved.

In a systematic review, Davis *et al.* (2013), evaluated the methodological soundness of all accessible studies examining the impacts of programs offering IHDs or demand pricing. Their evaluation asked whether those studies had methodological flaws identified by medical researchers as biasing the conclusions of clinical trials[94-95]. As seen in Figure 2, the risk of such biases often could not be estimated because critical details were missing in the research summaries – often found in the gray literature of technical reports issued without independent peer review. When risk of bias could be assessed, it was often high because participants in these experiments were volunteers, selected their treatment group, or dropped out at high rates overall or disproportionate rates across treatment groups. After applying a correction factor estimated from medical clinical trials, there was only weak evidence that IHDs helped homeowners reduce their energy use and no evidence of reducing peak energy use or enhancing the effectiveness of dynamic pricing programs.

As an input to designing more effective IHDs, we had consumers create their own displays by selecting the information features that they wanted, from among ones offered on commercially available IHDs[96]. Most participants wanted only a few key features, most commonly information on their overall bill and electricity usage of specific appliances[97]. Participants reported strong dislike of features such as comparisons with their neighbors' usage, a popular intervention[98]. A follow-up study[96], with a display that included the desired features (Figure 3), found, however, that people often could not use the information provided by these desired features. For example, although people preferred receiving appliance-specific feedback

in dollar units, they actually learned more about how to rank the relative consumption of various appliances from simply being told how much electricity those appliances used.

Investing in Energy Efficiency in Office Buildings

Each result from study of owners of class B and C commercial office buildings suggests a direction for designing interventions. For example, owners' skepticism about the motives and claims of the promoters of energy efficiency interventions suggests enlisting trusted contractors as change agents, enabling them to provide information and implement improvements, as part of their ongoing work on a building's energy systems. The owners' unwillingness to take on debt, even with subsidized interest rates, suggests emphasizing programs that address their uncertainty about their ability to make payments, such as occupancy sensors, with modest capital costs and relatively predictable energy savings. We hope to test such programs in future research.

For field trials of any intervention, one methodological concern is the Hawthorne effect (named after a Western Electric factory where it was first described in the 1920s), whereby knowledge of being in a study affects participants' behavior, independent of any effects of the intervention. As a result, a Hawthorne condition is a natural part of any field trial. Schwartz *et al.* (2013) estimated the size of such an effect in an experiment that sent a postcard to randomly selected residential customers, saying that they had been enrolled in a one-month study of their "electricity consumption," followed by weekly reminders[99]. Over the month, participants reduced their consumption by 2.7%, an effect comparable to actual interventions. A second methodological concern with field trial data is performing so many statistical analyses that spurious relationships emerge by chance[100]. We controlled for this possibility by specifying the analyses in advance and checking their robustness by evaluating different model specifications (e.g., using a two-year or four-year baseline for estimating consumption without the postcards).

Discussion and Conclusion

Facilitating informed decisions about climate- and energy-related policies requires understanding the facts of those choices (e.g., the relevant climate science and technological realities), their structure (i.e., the relevant options, valued outcomes, and uncertainties), and the individuals who bear the consequences. Decision science offers a systematic approach to recruiting and integrating the relevant evidence. It involves an iterative process involving subject matter experts, to identify potentially relevant issues; social scientists, to characterize decisions makers' perspectives and options; and decision makers, to hear and inform them. Social and behavioral science research informs each step of this process, addressing questions such as how to elicit experts' knowledge, describe decision makers' preferences and constraints, convey those preferences to experts hoping to create attractive options, and communicate the costs, benefits, and uncertainties of those options to decision makers.

The decision approach is most effective when it (a) draws most broadly on basic social and behavioral science research, rather than restricting itself to a sub-discipline or theory; (b) uses methods appropriate to the task; and (c) is involved early in the design process, so that it can shape options in their formative stages[16]. To those ends, the studies summarized here applied research from cognitive psychology (e.g., confirmation bias), personality psychology (political identity), and social psychology (group norms). They included formal analyses, systematic reviews, mental models interviews, structured surveys, experiments, and user testing of websites. They came at the beginning of design processes, during critical reassessments, and after failures.

The formal analyses that structure decision science applications facilitate such inclusiveness by their theoretical neutrality and their ability to accommodate knowledge from the social, behavioral, natural, and engineering sciences. The decision science approach can improve

not only communication among the sciences, but also between them and the public they hope to serve. It can increase the chances of programs being attractive and being understood as such – thereby increasing the public's faith in its experts. It can also help experts to diagnose the sources of failures – thereby increasing the experts' faith in their public, which will not be seen as rejecting programs for inexplicable reasons. Thus, by helping experts and decision makers to understand one another, decision science might improve the quality of the options and the decisions, as well as respect between the parties.

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Corresponding Author

Gabrielle Wong-Parodi is the designated corresponding author. Department of Engineering and Public Policy, 129 Baker Hall, Carnegie Mellon University, Pittsburgh, PA 15213; Email: gwongpar@cmu.edu; Phone: (510) 316-1631

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All authors contributed to the writing of the paper and the research reported in it.

Additional Information

The authors declare no conflicts of interest.

Table 1. Decision Science, with Examples from Applications to Three Domains of Climate Change Mitigation and Adaptation

Case Study	Preparing for sea level rise	Adopting residential smart grid technologies	Investing in energy efficiency in office buildings
Formal analysis	• Feasible options (e.g., retrofitting home) • Valued outcomes (e.g., peace of mind) • Uncertainties (e.g., government coverage of losses)	• Feasible options (e.g., feedback on consumption) • Valued outcomes (e.g., personal comfort) • Uncertainties (e.g., privacy of energy consumption data)	• Feasible options (e.g., efficient lighting) • Valued outcomes (e.g., transaction costs) • Uncertainties (e.g., promised savings)
Descriptive analysis	• Think aloud use of decision aid • Experiment assessing impact of a contextual factors (evoking political beliefs, time horizon)	• Mental models interviews, identifying user concerns • Follow-up survey, assessing underlying dimensions (fear of being controlled, tangible benefits, accountability)	• Mental model interviews, identifying concerns outside formal model • Follow-up survey, assessing prevalence of beliefs
Intervention	• Experimental evaluation of sea level rise decision aid	• Systematic review of field experiments • Experimental evaluation of in-home display designs	• Experimental evaluation of programs addressing concerns (e.g., contractors as change agents)

Figure Legends

Figure 1. Climate Central's Surging Seas Risk Finder for New York City. (a) initial design; (b) design after iterative testing

Source: Wong-Parodi & Strauss (2014)[13]

Figure 2. Risk-of-bias assessment for 32 studies of in-home displays, dynamic pricing, and home automation systems. Most studies were at high risk of bias from participant selection (volunteers), intervention selection (non-random assignment), and attrition (leaving conditions at a high or disproportionate rate). Reporting was insufficient to allow determining risk-of-bias for most studies with respect sequence generation (the order of assignment to conditions), allocation concealment (whether hidden from participants), and blinding (whether hidden from researchers).

Source: Davis et al. (2013)[94]

Figure 3. Screenshot of simulated appliance with specific feedback.

Source: Krishnamurti et al. (2013)[96]

Surging Seas

Sea level rise analysis by CLIMATE CENTRAL

Search by City, State, or Zip

Maps | Basics | Research | Responses | Activate | News

Share view: Like Share 37

List: Cities | Counties

Water level +1ft

Things below +1ft in

New York, New York

Population	64,489	0.8%
Homes	28,780	0.9%
Acres	5,128	2.8%

Over 1 in 6 chance sea level rise + storm surge + tide will overtop +1ft by 2020 at nearest flood risk indicator site: The Battery - New York Harbor, 7.1 miles away.

Learn more:

- New York data download
- New York map | facts | plans
- Surging Seas report
- Map accuracy | speed tip

Map Beta release.
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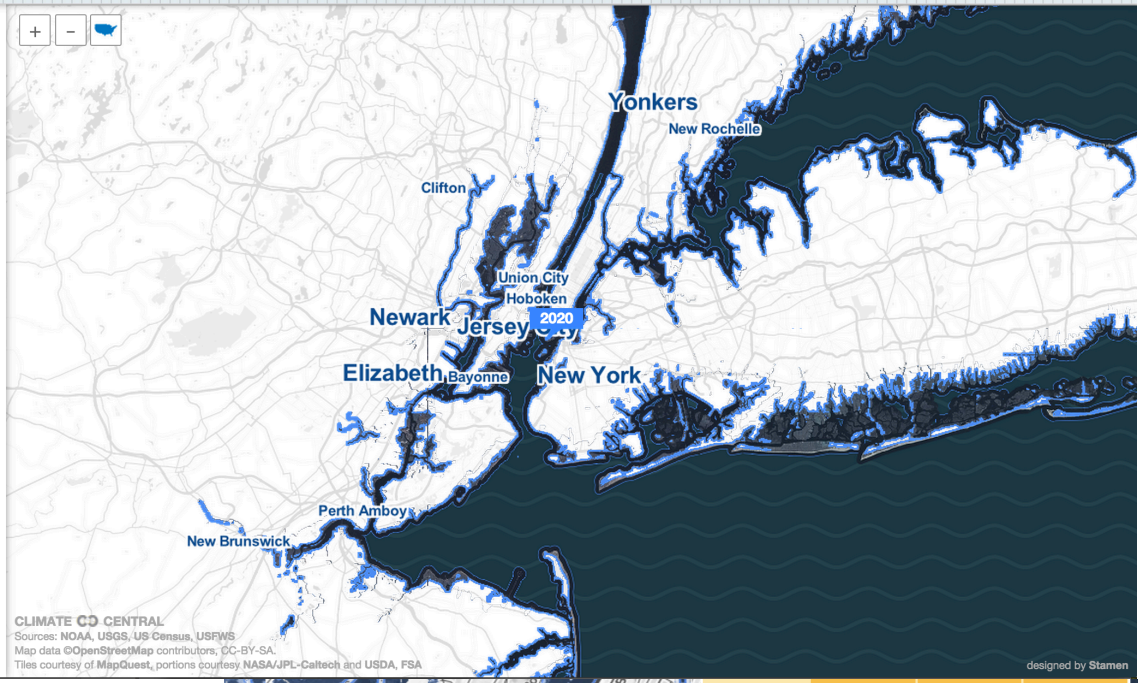


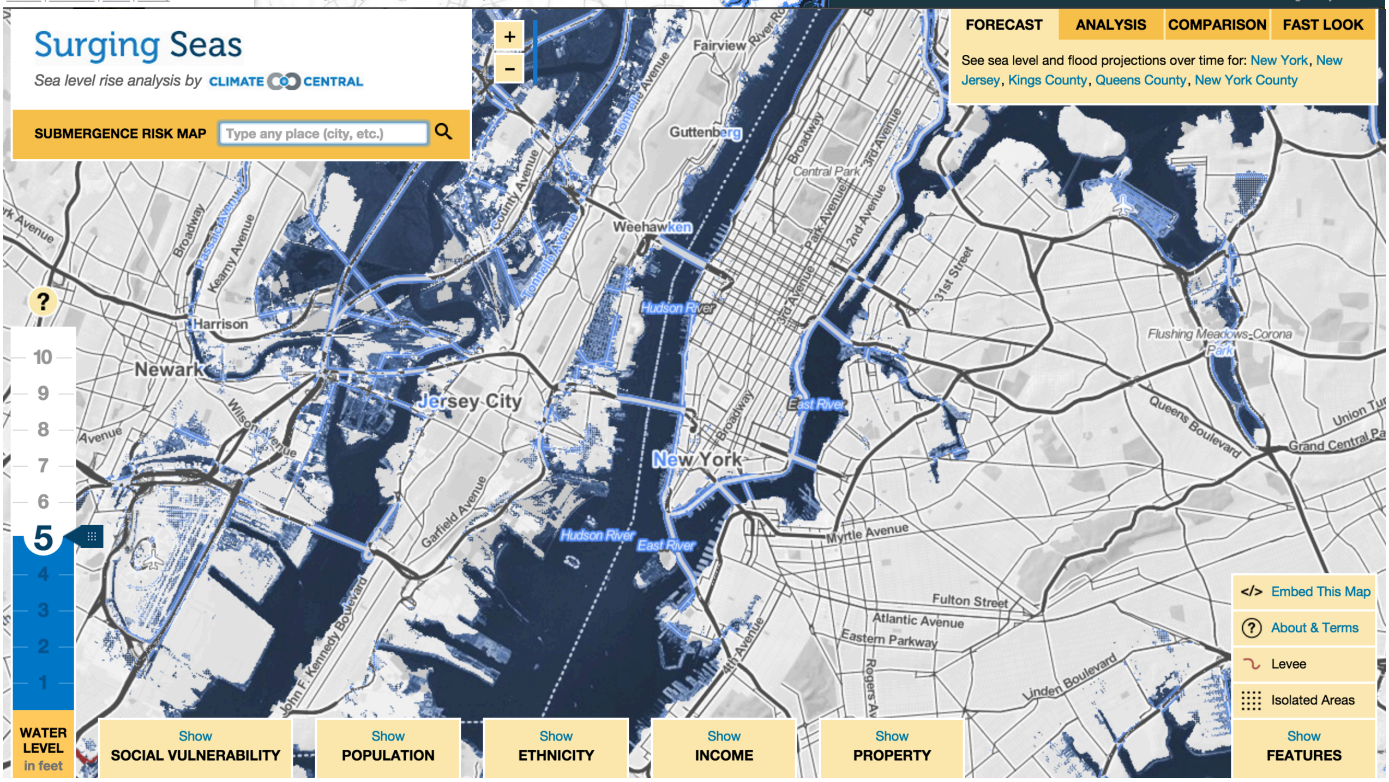
Surging Seas

Sea level rise analysis by CLIMATE CENTRAL

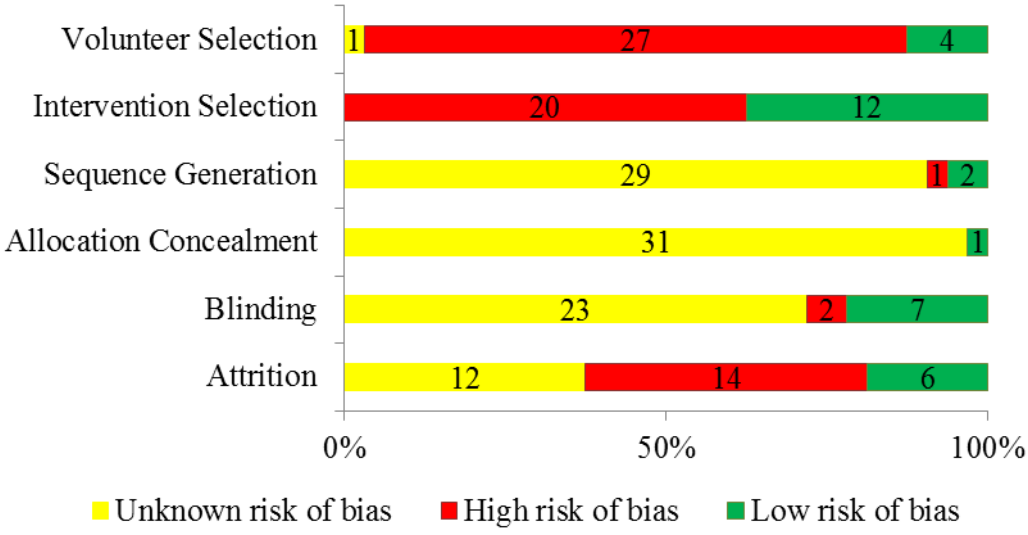
SUBMERGENCE RISK MAP | Type any place (city, etc.)

FORECAST | ANALYSIS | COMPARISON | FAST LOOK

See sea level and flood projections over time for: New York, New Jersey, Kings County, Queens County, New York County



Show SOCIAL VULNERABILITY | Show POPULATION | Show ETHNICITY | Show INCOME | Show PROPERTY | Show FEATURES


Volunteer Selection
1
27
4
Intervention Selection
20
12
Sequence Generation
29
1
2
Allocation Concealment
31
1
Blinding
23
2
7
Attrition
12
14
6
0%
50%
100%
Unknown risk of bias
High risk of bias
Low risk of bias

Appliance	Status	Hours	
Air Conditioner	78.0 ° F	0.00	Reset
Water Heater	120.0° F	0.00	Reset
Indoor Lights	OFF	0.00	Reset
Outdoor Lights	OFF	0.00	Reset
Refrigerator	38.0 ° F	0.00	Reset
Freezer	-15.0° F	0.00	Reset
Oven	OFF	0.00	Reset
Microwave	OFF	0.00	Reset
Television	OFF	0.00	Reset
Washing Machine	OFF	0.00	Reset
Dryer	OFF	0.00	Reset

Total kWh

Total kWh: 0.0000 **Reset All**