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The Engineering of Climate Engineering

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Abstract

While reducing anthropogenic greenhouse gas emissions remains the most essential element of any strategy to manage climate change risk, it is also in principle possible to directly cool the climate by reflecting some sunlight back to space. Such climate engineering approaches include adding aerosols to the stratosphere and marine cloud brightening. Assessing whether these ideas could reduce risk requires a broad, multidisciplinary research effort spanning climate science, social sciences, and governance. However, if such strategies were ever used, the effort would also constitute one of the most critical engineering design and control challenges ever considered: making real-time decisions for a highly uncertain and nonlinear dynamic system with many input variables, many measurements, and a vast number of internal degrees of freedom, the dynamics of which span a wide range of timescales. Here, we review the engineering design aspects of climate engineering, discussing both progress to date and remaining challenges that will need to be addressed.

1. INTRODUCTION

Radiative forcing: a measurement of the net increase or decrease in energy in the climate system that results from a given change, such as increasing CO_2 concentrations

Aerosol: a fine solid or liquid particle in the atmosphere, such as sulfate, black carbon, or dust

As projected more than a century ago by Arrhenius (1), increases in atmospheric greenhouse gas concentrations, primarily CO_2, have warmed the climate. The decade from 2006 to 2015 was almost 1°C warmer than the preindustrial era (2). To avoid dangerous anthropogenic interference in the climate system, the international community has agreed to limit global warming to well below 2°C (3). The only permanently effective strategy for managing climate risk is reducing greenhouse gas emissions (referred to as mitigation), yet the international commitments to mitigation made as part of the 2015 Paris agreement are unlikely to meet this aim (4), with central estimates of the resulting warming projected to be approximately 3°C (5). It is possible to remove CO_2 from the atmosphere after it is emitted (6), but this would need to occur at a scale at least somewhat commensurate with current emissions to avoid temporary overshoots in which global warming greatly exceeds 2°C (7); this scale has never been demonstrated. Furthermore, the global warming associated with a given level of greenhouse gas concentrations remains uncertain, as do the climate impacts resulting from that warming (8). There is thus significant cause for concern that mitigation and CO_2 removal may not be sufficient to avoid serious future climate impacts.

An additional possible tool for managing climate risk is deliberate reflection of some sunlight back to space (9), known as solar geoengineering, solar radiation management, climate intervention, or (our preference) climate engineering. (This term also frequently encompasses CO_2 removal; here, we use it to refer only to sunlight reflection methods.) Increasing Earth's reflectivity (albedo) would reduce the total energy input into the climate system and thus cool the planet; reflecting an additional 1% of incoming solar irradiance would more than offset all of the radiative forcing due to human-emitted CO_2 to date (10).

Although many potential climate engineering ideas have been proposed, two have received the greatest attention (**Figure 1**). The best-understood method would be to add aerosols (such as sulfate) to the stratosphere, the same process by which large volcanic eruptions temporarily cool the climate (see the sidebar titled Stratospheric Sulfate Aerosol Climate Engineering). Although this method was recognized as a possibility in the 1970s (11, 12), relatively little research was conducted until concerns grew that mitigation alone might be insufficient to prevent dangerous anthropogenic climate change (13). Another relatively well-understood approach is marine cloud brightening (see the sidebar titled Marine Cloud Brightening), in which marine clouds are made brighter (more reflective) by adding sea-salt aerosols (14, 15). The climate impacts of these

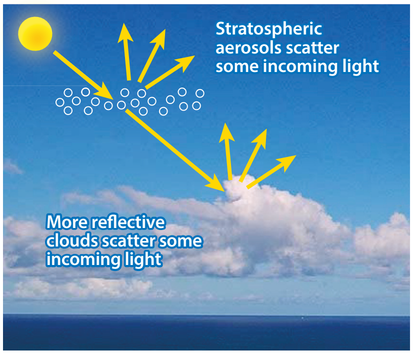

Figure 1

Schematic illustrating the two climate engineering methods discussed in this review. Either stratospheric aerosols or marine cloud brightening could be used to reflect sunlight and cool the climate.

STRATOSPHERIC SULFATE AEROSOL CLIMATE ENGINEERING

The idea of stratospheric sulfate aerosol climate engineering is based on the natural analog of large volcanic eruptions. These eruptions eject (among other things) large amounts of sulfur dioxide (SO_2) gas, sometimes on the order of tens of megatons (20). If the SO_2 is injected with sufficient upward force, it can enter the stratosphere, where it oxidizes into highly reflective sulfate aerosols. Unlike in the troposphere, where aerosol lifetime is on the order of weeks before it is scavenged by precipitation, sulfate aerosols in the stratosphere can last for several years. The aerosols spread around the planet, with the latitudinal extent depending on the injection latitude and time of year (21). The aerosols scatter incoming sunlight, reflecting some back to space; large volcanic eruptions thus temporarily cool the planet (20, 22). Sulfate aerosols also heat the stratosphere, which can impact climate, and they serve as surfaces for stratospheric chemistry (e.g., ozone depletion). For climate engineering, the aerosol layer would need to be sustained with regular injections; aircraft could likely be designed to do so (23–25).

technologies are not yet sufficiently well understood to support informed decisions regarding deployment; Section 2 provides a short summary of the present state of natural science knowledge and dominant uncertainties. In addition to natural science, decisions would also need to take into account societal and governance challenges (16–19) and weigh all of these against the impacts and uncertainties of choosing not to deploy these technologies. If they were deployed, however, then this deliberate management of Earth's climate would be the largest-scale engineering effort ever undertaken by humanity, affecting everyone on the planet for generations.

Decisions about the use of climate engineering will be influenced by projected climate impacts and, in particular, by how well it might compensate for climate changes due to increased CO_2 and other greenhouse gases. However, while climate change can be studied purely as a science problem, climate engineering differs in that it also involves an engineering design aspect. As an example, with stratospheric aerosols, one can choose how much material to inject; at what latitude, altitude, and time of year to do so; and the type of material itself. These design choices affect climate outcomes. For example, introducing aerosols in only one hemisphere would alter

MARINE CLOUD BRIGHTENING

Marine cloud brightening is based on the idea that, as water-soluble aerosols (e.g., sea salt) are added to marine low clouds, they can serve as extra cloud condensation nuclei. For a constant amount of water in a cloud, if that water is distributed among more droplets, those droplets will be smaller and hence brighter (26). This effect, known as the Twomey effect or the first aerosol indirect effect, can be observed in the real world in ship tracks (27). However, there are numerous other feedbacks related to aerosol–cloud interactions that occlude assessments of the fraction of ocean over which this approach may be effective. For example, seeding marine low clouds can induce dynamical circulation patterns, causing those clouds to rain out, with a net effect of reducing albedo rather than increasing it (28). Ascertaining the meteorological conditions under which marine cloud brightening is most likely to be effective is an active area of research. More generally, aerosol–cloud interactions are presently the source of some of the largest uncertainties in climate science (10). As a result, the potential effectiveness of this approach is less certain than that of stratospheric aerosol climate engineering. Because susceptible clouds occur over only a fraction of Earth's surface, the resulting spatially heterogeneous forcing may lead to a more spatially heterogeneous response than stratospheric aerosol climate engineering, but there may also be more ability to tailor the response.

cross-equatorial heat transport, affecting tropical precipitation (29); introducing aerosols at the equator would preferentially cool the tropics relative to the poles; and off-equatorial aerosol injection might preferentially cool higher latitudes (30). Section 3 discusses this design approach and optimization.

Robustness: in control theory, the property that the performance of a feedback algorithm does not degrade in the presence of system changes within the bounds of uncertainties

A complicating factor in designing climate engineering is that the climate system response to any imposed forcing can be extraordinarily complex, uncertain, and nonlinear. Even with extensive research efforts, some uncertainties may never be sufficiently reduced to accurately predict the forcing needed to achieve desired objectives. As such, in addition to strategies for reducing uncertainty, strategies must be developed to manage uncertainty in meeting the specified objectives. This challenge is not fundamentally different from many other engineering problems. An effective way to manage uncertainty, discussed in Section 5, is deliberate feedback—observing the climate system response and using information about departures from the objectives to constantly make adjustments. Designing this feedback to manage only the steady-state response to forcing is insufficient; it must also respond fast enough to converge on societally relevant timescales. This requires some understanding of the dynamic (time-evolving) response, considered in Section 4.

The engineering discipline of control theory is dedicated to addressing these problems in optimization, dynamics, and feedback control. The challenge of understanding the impacts of climate engineering is thus both a climate science challenge and a control-systems challenge. From this viewpoint, climate engineering involves a system with (*a*) a vast number of internal degrees of freedom, with relevant dynamics spanning timescales from weeks to centuries; (*b*) a response to imposed perturbations (whether from greenhouse gas forcing or climate engineering) that has significant uncertainty and where nonlinear effects may be significant; (*c*) many input variables (for example, using stratospheric aerosols, one would need to decide how much to inject at multiple different latitudes, different altitudes, and different times of year, with potentially even more choices for marine cloud brightening); (*d*) more variables of importance, and hence potential objectives of climate engineering, than there are independent input degrees of freedom; (*e*) many degrees of freedom that, despite having numerous measurements, remain poorly observed (particularly true for deep ocean states that are critical for behaviors on timescales of decades or longer); (*f*) high internal variability, yielding a poor signal-to-noise ratio on regional variables at societally relevant timescales; and (*g*) substantial consequences for insufficient robustness, but with no possibility of performing full-scale real-world experimentation prior to deployment.

As of 2018, the most advanced climate model simulations of climate engineering use a proportional–integral (PI) feedback algorithm to annually adjust SO_2 injection rates at four different latitudes in response to three degrees of freedom of the simulated response (31, 32) (see **Figure 2**). These simulations demonstrate the possibility of designing stratospheric sulfate aerosol climate engineering and using feedback to manage uncertainty in a somewhat realistic setting. While this is an enormous accomplishment, supporting informed decisions regarding whether and (if so) how to deploy climate engineering would require a great deal of further research.

Figure 2 illustrates that offsetting greenhouse gas warming with stratospheric aerosol cooling results in residual climate changes, which could have consequences for ecosystems and agriculture as well as other concerns. A strategy designed only to maintain global mean temperature will have larger residual changes than the strategy shown here, where the objectives were chosen to maintain not only global mean temperature but also the interhemispheric and equator-to-pole temperature gradients. To inform future policy, it is important to know whether there are different deployment choices that could maintain additional variables and result in better compensation, or whether this level of residual change is an inevitable consequence of any deployment strategy.

Given the constraints imposed by climate physics, there are necessarily limits to which degrees of freedom in the climate system can be managed, but the limits of how well a climate engineering

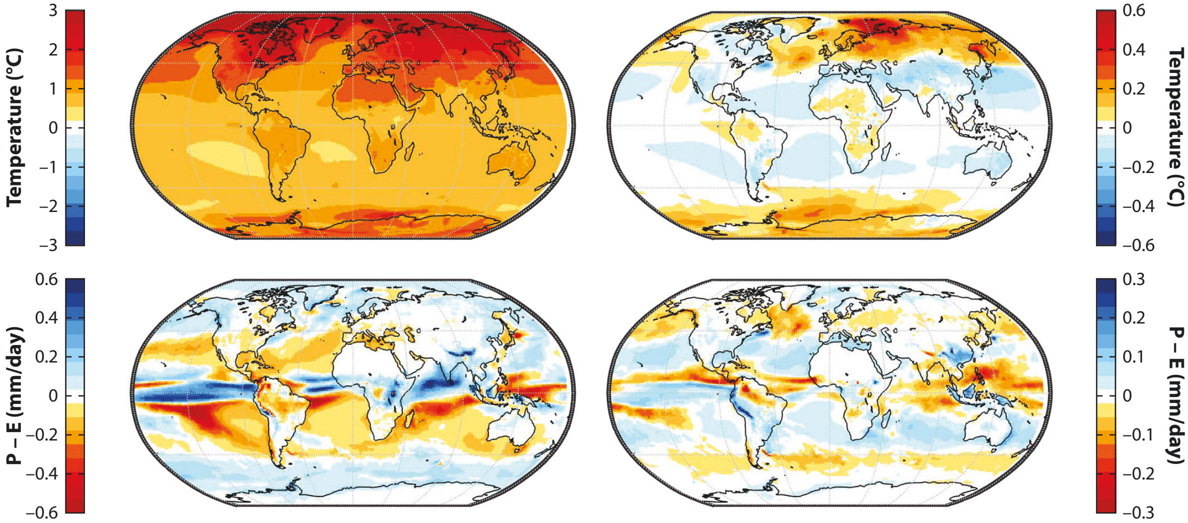

Figure 2

Representative results from simulations of stratospheric aerosol climate engineering, showing changes in temperature (*top row*) and precipitation minus evaporation (P − E) (*bottom row*), a key measure of changes to the hydrological cycle. The left panels show the response due to increased greenhouse gases, scaled per degree of warming. The right panels show the response due to the same increased greenhouse gases but offset by stratospheric aerosol climate engineering; note that the left and right axis scales are different. Even with a strategy that maintains the global mean temperature, interhemispheric temperature gradient, and equator-to-pole gradient, there are still residual changes in regional temperature, P − E, and other variables, which also illustrates the geographical complexity of the response. Figure adapted from Reference 33.

system can be designed and managed are not yet known—we do not know what climate engineering can and cannot do. Based on state-of-the-art simulations, we know that at least 3 things (variables, spatial patterns, etc.) can be controlled, and we are fairly sure that fewer than 100 things can be controlled, but what exactly is the limit? Answering this question is crucial for knowing how well climate engineering might contribute to managing the risks of climate change and thus crucial for informing policy.

The purpose of this article is to outline the basis for understanding the potential and limits of climate engineering, illustrating the ways in which this field sits at a nexus between climate science and engineering, and to both review progress and raise challenges for future research. The next section provides an overview of the present state of knowledge (or lack thereof) regarding the climate science of stratospheric sulfate aerosol climate engineering and marine cloud brightening, providing necessary background for understanding the engineering aspects of the problem. Further details can be found in other recent reviews (9, 34–38). Sections 3–5 then review the progress (as relevant to climate engineering) in design and optimization, dynamics and system identification, and feedback control, respectively. Section 6 summarizes the present state of the field, with a focus on future needs.

2. PHYSICS AND MODELING

2.1. Models and Uncertainty

Unlike many other engineering control problems, full-scale testing (i.e., conducting climate-perturbing experiments in the real world) is not an option. Instead, the tools available are process-level studies or future projections from climate models at a range of scales, from cloud-resolving/large-eddy simulations to general circulation models of the entire climate. These are the same models used to explore the projected climate response to increased greenhouse gas concentrations, though potentially extended to include additional physical processes relevant to climate engineering. These models are informed by observational data (39); future research might also include dedicated small-scale experiments to resolve specific process uncertainties (40–44).

Many early climate model simulations simply "turned down the sun" as a proxy for any method that reflected sunlight back to space (45, 46), which could be interpreted as simulating space-based sun shades (47). The field has progressed significantly since then, and to give some idea of the complexities, current simulations of (for example) stratospheric sulfate aerosol climate engineering include a detailed model of stratospheric aerosol microphysics, including oxidation of SO_2 to H_2SO_4, nucleation, condensation, coagulation, evaporation, and sedimentation (48); interactive stratospheric chemistry that is necessary to capture changes in ozone concentrations (49) as well as nonlinear effects on aerosol microphysics due to oxidant depletion (50); the effect of aerosol heating on stratospheric dynamics; and full coupling with land, ocean, and sea-ice models. Changes in stratospheric circulation due to aerosol heating influence surface climate (51); affect modes of stratospheric variability (52, 53); influence stratospheric water vapor concentrations (which has a small effect on radiative forcing but a potentially larger impact on stratospheric chemistry); and, by changing the vertical stability of the upper troposphere, could influence cirrus clouds (54–56) that also affect radiative forcing. Where possible, these models have been validated against available observational evidence, including aerosol properties after the 1991 eruption of Mt. Pinatubo (57, 58), providing some confidence in their ability to represent the effects of climate engineering.

Nonetheless, all of the processes noted above are uncertain to some extent. If one injected SO_2 into the stratosphere at some latitude, there is a good general sense of the broad features of the stratospheric circulation, but also uncertainty both in the stratospheric aerosol processes that determine the amount and spatial pattern of radiative forcing and in the surface climate effects that result from this forcing (59). As an example, while models can be validated against observations after volcanic eruptions, an important difference between the natural stratospheric injection of sulfur from an eruption and hypothetical injection from climate engineering is that the former is a pulse injection, while the latter is in principle sustained. Under sustained injections, gaseous precursors can condense onto existing particles, and aerosols can coagulate, resulting in larger aerosols that are less efficient at scattering solar irradiance and sediment out more quickly (60). Aerosol microphysical growth is thus both uncertain and an important source of nonlinearity in the climate response to stratospheric sulfate aerosol climate engineering (61, 62), yet it will be difficult to fully validate model representations prior to deployment.

Because stratospheric aerosols have a lifetime of a few years, aerosols injected at one location will mix broadly, covering a large portion of one or both hemispheres (**Figure 3**). As such, global climate models are excellent tools for studying the climate effects of stratospheric sulfate aerosol climate engineering. By contrast, aerosols injected into marine boundary-layer clouds have a lifetime on the order of one week, and much more of the physics is spatially localized. Research into marine cloud brightening thus necessitates a hierarchy of models, including cloud-resolving models to understand turbulent mixing, aerosol–cloud interactions, and fine-scale dynamical effects (28) as well as global-scale models to understand the effects on surface climate, large-scale circulation, and climate system feedbacks (44). All of these platforms necessarily have scales on which they operate, and many important features are parameterized, such as aerosol microphysical growth and interactions between aerosols and clouds. These sorts of model uncertainties, which

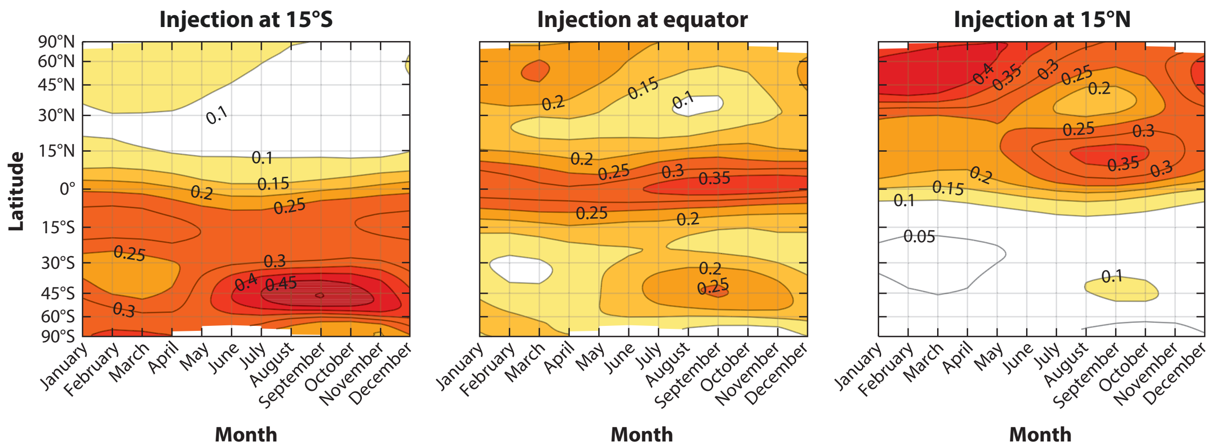

Figure 3

Longitude-averaged seasonal climatology of stratospheric sulfate aerosol optical depth for simulations in which SO_2 was injected into the stratosphere in the Northern Hemisphere at 15°N, at the equator, or in the Southern Hemisphere at 15°S (63). Although the gas is injected at point sources, the aerosols spread to cover either one hemisphere or the entire globe.

can be divided into structural uncertainties (the model is missing or incorrectly represents the physical system) and parametric uncertainties (a subgrid parameter to which model results are sensitive has a range of plausible values), introduce ambiguity and model dependence into conclusions. As these uncertainties may affect strategies for modifying the climate, it is imperative to spend considerable effort to reduce them or devise ways of managing them.

2.2. Climate Engineering Commonalities

Despite uncertainties, there are a few broad conclusions that hold for any implementation of stratospheric aerosol climate engineering or marine cloud brightening. Neither would affect the climate the same way as a reduction in atmospheric CO_2. Nonetheless, if these strategies were used to maintain global mean temperature at some particular value (such as the 1.5°C or 2°C target of the Paris agreement) despite higher CO_2 concentrations, then the climate would be much closer to one with the same global mean temperature due to lower CO_2 levels than it would be to one with the same higher level of CO_2 but without climate engineering and thus with a correspondingly higher temperature (33, 38, 64). While stratospheric sulfate aerosol climate engineering or marine cloud brightening would do little for some impacts, such as ocean acidification, many other climate impacts are also likely to be more like the lower-temperature world than one in which temperatures were allowed to increase (65–68). Because the mechanism of radiative forcing exerted by climate engineering differs from that of an increased CO_2 concentration, changes to the hydrological cycle would result (69–71).

However, current simulations are not sufficient to make much more specific predictions about the impacts of deploying climate engineering. In addition to uncertainties in projections, it is critical to recognize that there is no strict answer to the question "What will happen if society deploys climate engineering?" Without understanding the design space and making deliberate design choices intended to achieve explicitly stated climate goals, the impacts cannot be defined. We therefore next consider climate engineering as a design problem, shifting from the science to the engineering of the problem.

3. DESIGN AND OPTIMIZATION

Aerosol optical depth (AOD): a measure of how much solar irradiance is attenuated (prevented from reaching the surface) by an aerosol layer in an atmospheric column; it depends on aerosol concentration, size distribution, and refractive index

Much of the research to date involves climate model simulations of decreases in the solar constant, injection of some amount of sulfate aerosols into the stratosphere at the equator, or idealized changes in cloud properties to increase albedo over the ocean. While these simulations are essential for exploring general characteristics of climate model responses to climate engineering and to define simulations that can be readily conducted in multiple models for intercomparison studies, they are not well suited to assessing what climate engineering can and cannot do. For stratospheric sulfate aerosol climate engineering, for example, the stratospheric Brewer–Dobson circulation largely acts to transport air poleward. As a result, aerosols injected in one hemisphere tend to stay mostly in that hemisphere, and aerosols injected further poleward tend to increase aerosol concentrations mostly toward the poles (see **Figure 3**). This implies at least three degrees of freedom in terms of aerosol burden and surface climate effects: the overall mean, the relative focus on the Northern Hemisphere versus the Southern Hemisphere, and the relative focus on high latitudes versus low latitudes.

Recognizing this potential, several early studies considered Arctic-only climate engineering (72, 73). Haywood et al. (29) later simulated stratospheric sulfate injection isolated to either the Northern or Southern Hemisphere, with the key observation being a consequent shift in tropical precipitation, which is relevant to subsequent design studies. Building on this work, MacCracken et al. (74) improved on the Arctic-only approaches by including forcing at both poles to avoid the tropical precipitation impact of hemispherically asymmetric forcing. All of these studies could be interpreted as considering a design approach to the problem, although they were not explicitly framed that way.

The first to take an explicit design perspective were Ban-Weiss & Caldeira (30). Offsetting a CO_2 concentration increase with a reduction in total solar irradiance results in overcooling of the tropics and undercooling of the poles (45, 46). In addition, the net effects of these two forcings differ between the Northern and Southern Hemispheres, largely due to different land areas and hence total heat capacities; this differential can drive shifts in tropical precipitation, as noted above. To offset these effects, Ban-Weiss & Caldeira (30) independently adjusted aerosol optical depth (AOD) in three independent degrees of freedom, better compensating for the temperature changes due to increased CO_2. The three input degrees of freedom they (and a number of subsequent studies) considered were the area-weighted Legendre polynomials in latitude ψ:

$$\mathrm{L0} = 1, \tag{1}$$

$$\mathrm{L1} = \sin(\psi), \tag{2}$$

$$\mathrm{L2} = \frac{1}{2}[3\sin^2(\psi) - 1]. \tag{3}$$

One can similarly define T0, T1, and T2 as projections of temperature onto these three polynomials, representing the global mean temperature, the interhemispheric temperature gradient, and the equator-to-pole temperature gradient, respectively.

Using solar reduction as a proxy for AOD, MacMartin et al. (75) expanded the input space by considering the same spatial distributions as in Equations 1–3 but also introduced seasonal variations, enabling better management of the response, particularly as it relates to achieving multiple simultaneous climate objectives under a variety of performance metrics. Kravitz et al. (76) further expanded on these studies by considering two separate strategies: (*a*) independently modifying forcing at both poles to achieve simultaneous objectives in high-latitude temperature and tropical precipitation and (*b*) independently imposing three patterns of solar reduction described by Equations 1–3 to simultaneously meet three global temperature objectives in T0, T1, and T2. This study also included a system identification and feedback element that is discussed in Sections 4 and 5.

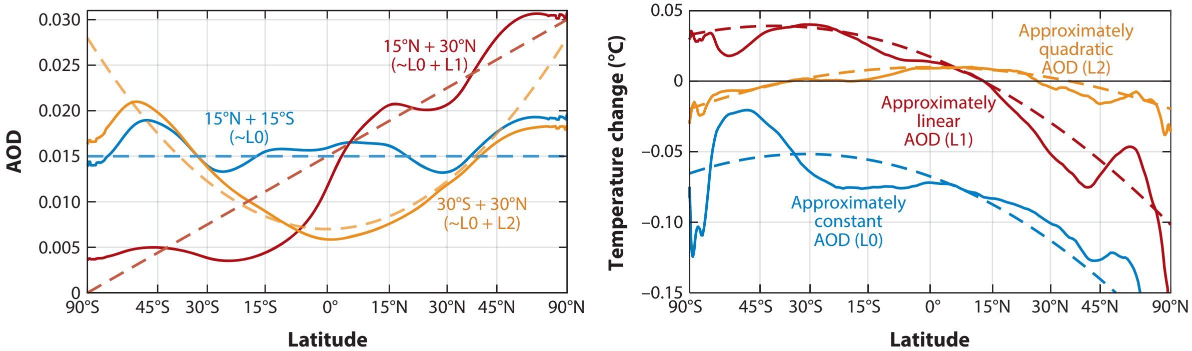

Figure 4

Aerosol optical depth (AOD) as a function of latitude for different combinations of injection at different latitudes (*left*), designed to roughly approximate constant (L0), linear (L0 + L1), and quadratic (L0 + L2) dependence, and the corresponding zonal mean surface air temperature for each AOD pattern (*right*), after subtracting the mean AOD from the linear and quadratic cases. Results were simulated in CESM1(WACCM). Figure adapted from Reference 79.

While instructive, simulations involving solar reduction ultimately have limited applicability to stratospheric aerosol climate engineering. An important difference is that while one can model exact geographic boundaries of forcing via solar reduction, one cannot wall off the stratosphere, and as such, stratospheric circulation limits the achievable degrees of freedom. Dai et al. (77) recently conducted a comprehensive survey of the effects of injection at different latitudes and altitudes in a relatively simple 2-D model, along with some limited exploration of the time of year of injection. Tilmes et al. (63, 78) contemporaneously conducted a more limited survey of latitudes and altitudes but used the much more comprehensive Community Earth System Model version 1, with the Whole Atmosphere Community Climate Model as the atmospheric component [CESM1(WACCM)] (58). MacMartin et al. (79) then demonstrated how injection of SO_2 at four stratospheric locations can achieve patterns of AOD that correspond to L0, L1, and L2 and the resulting temperature changes from imposing those patterns (see **Figure 4**).

There remains considerable scope for further exploring and expanding the design space with stratospheric aerosols, including more thorough exploration of the time of year of injection and the aerosol composition itself. Different aerosols (80–84) will have both different chemical effects and different radiative effects, especially the ratio of light scattering to stratospheric heating, potentially influencing outcomes. Even with sulfate aerosol, the method of emission (e.g., SO_2 versus direct condensation of H_2SO_4) can influence the aerosol size distribution and hence outcomes (60, 77, 85).

Most of the design-focused research above focuses on stratospheric aerosols. Marine cloud brightening might enable even more independent degrees of freedom, with different forcing being applied over different regions and faster temporal adjustment possible. In principle, the two methods can be combined to achieve outcomes that no one method could alone (86). However, because there is substantial uncertainty as to what cloud and meteorological conditions are favorable for altering cloud albedo, there has been little exploration of how one can tune the forcing over different regions to improve outcomes.

4. DYNAMICS AND SYSTEM IDENTIFICATION

Nearly all of the studies described above consider only steady-state optimizations and further assume that the climate response to each imposed degree of freedom is known, linear, and

Transfer function: a complex-valued function of frequency that contains quantitative information about an input–output relationship, including the gain and phase

independent of the others so that the responses can be linearly combined and optimized. Although these assumptions are useful starting points for understanding what might be possible, they are known to be false (79) and are thus insufficient for assessing what might be achievable under uncertainty. The design and assessment of feedback algorithms that can manage uncertainty, described in Section 5, rely on a description of the dynamic responses of the system to perturbations. This requires system identification—introducing a time-varying input signal, simulating the response, and constructing a simplified model or emulator. For a linear system, the result is an estimate of the impulse response or (equivalently in the frequency domain) the transfer function (87, 88) between the inputs and outputs. The resulting dynamic description is simpler than the full climate model, easing computations and interpretation, and also permits inverse modeling—estimating the inputs that would be needed to achieve a particular set of climate outcomes. We thus first consider the dynamics relevant to climate engineering, as estimated from climate models.

If information is needed over a broad range of frequencies, then there are various choices for the input signal for system identification, including step changes, which contain all frequencies but emphasize steady-state behavior, multiple (preferably noncommensurate) sinusoids, or filtered broadband noise, where the filtering can be chosen to emphasize the relevant range of timescales (89). Different approaches have been taken in various studies.

4.1. Single Input, Single Output: The Global Mean Response

In the first paper to take an explicitly frequency-domain approach to system identification of a climate model response, MacMynowski et al. (90) conducted sinusoidal response simulations across a range of frequencies (see **Figure 5**) in the Hadley Centre Coupled Model version 3 (HadCM3L) climate model (91) and found that the global-mean-temperature response to changes in total solar irradiance can be quite well approximated by the output of a semi-infinite diffusion model (**Figure 5**), consistent with earlier hypotheses (92). Multiple studies have confirmed this behavior for CO_2 forcing using step inputs (38, 93). With this assumption, the impulse response

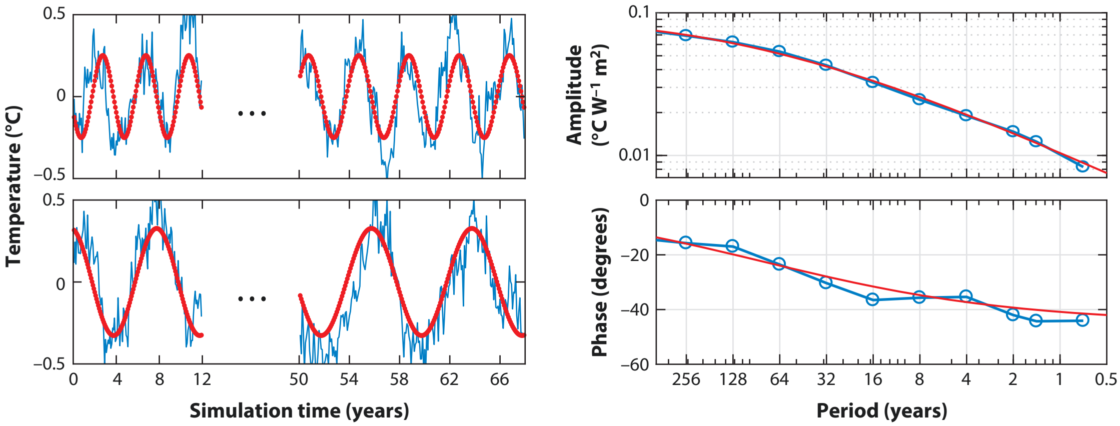

Figure 5

Illustration of system identification using sinusoidal input signals in HadCM3L. Sinusoidal variations in solar radiation were introduced at many different periods, as illustrated at left for four- and eight-year periods; the smooth line is the fit to a sinusoid. The right panels show the resulting frequency response (magnitude and phase) of global mean temperature and a fit to a semi-infinite diffusion model. Figure adapted from Reference 90.

$h(t)$ and step response $g(t)$ satisfy

$$h(t) = \frac{\mu}{\tau}\left[\frac{1}{\sqrt{\pi t/\tau}} - e^{t/\tau}\operatorname{erfc}(\sqrt{t/\tau})\right], \tag{4.}$$

$$g(t) = \mu\left[1 - e^{t/\tau}\operatorname{erfc}(\sqrt{t/\tau})\right], \tag{5.}$$

where erfc is the complementary error function. The corresponding transfer function (in frequency space s) from forcing to global mean temperature (as in **Figure 5**) is

$$H(s) = \frac{\mu}{1+\sqrt{\tau s}}. \tag{6.}$$

The response is characterized by only two parameters: a timescale τ and the equilibrium sensitivity μ. These parameters can be estimated from a least squares fit to either the frequency response or the time-domain response to any particular forcing scenario. The time-domain response to any other forcing can then be obtained through convolution (87, 94).

4.2. Multivariable Dynamics

Even with a single input variable, not all output variables respond the same way (90). When designing feedback algorithms for climate engineering, we are interested in the response of potentially many climate variables to many different inputs.

Section 3 described the ability to independently manage three degrees of freedom of temperature (T0, T1, and T2) by appropriately choosing the three input variables (L0, L1, and L2)—either by using patterns of solar reduction or by combining SO_2 injection at different latitudes to achieve these patterns of AOD. For reasons that will be clearer in the next section, the system identification simulations conducted by Kravitz et al. (76) for this 3×3 system used sinusoidal simulations at only a single frequency. Step response simulations, which are easier to interpret (see **Figure 6**), reveal three key observations. First, robust assessments of the input–output relationships for even these three simple degrees of freedom are obscured by considerable natural variability. Second, the matrix of relationships is lower triangular: A zero-mean change in solar constant (by changing either L1 or L2) does not significantly affect the global mean temperature T0, and a quadratic change in solar constant (by changing L2) has minimal impact on the interhemispheric gradient T1, behavior that is also evident in **Figure 4**. This lower-triangular property is useful for designing multivariate feedback strategies and is revisited in Section 5. Third, the time constants are not independent of either the spatial pattern of forcing or the spatial pattern of response; indeed, the semi-infinite diffusion model that does a good job of matching the relationship between L0 and T0 is likely not a reasonable functional form to use in fitting the remaining transfer functions. Note that if it were, then knowledge of the response at a single frequency (both gain and phase) would be sufficient to estimate the two parameters in Equation 6.

Simulated changes in solar irradiance are only idealizations. The dynamics between stratospheric SO_2 injection and surface climate response are more complicated, as they involve not only the climate response to different spatial patterns of radiative forcing but also the dynamics associated with achieving a steady-state sulfate aerosol burden, which are determined both by the microphysics of conversion from SO_2 to sulfate and by stratospheric transport. In simulations with the computationally expensive CESM1(WACCM) climate model, Tilmes et al. (63) applied step changes in the SO_2 injection rate. Step changes add energy at all frequencies but add more at low frequencies. They are thus well suited to assessing quasi-static optimization (which motivated this choice), although it is unclear whether this is the ideal input signal to use for developing dynamic models for feedback design.

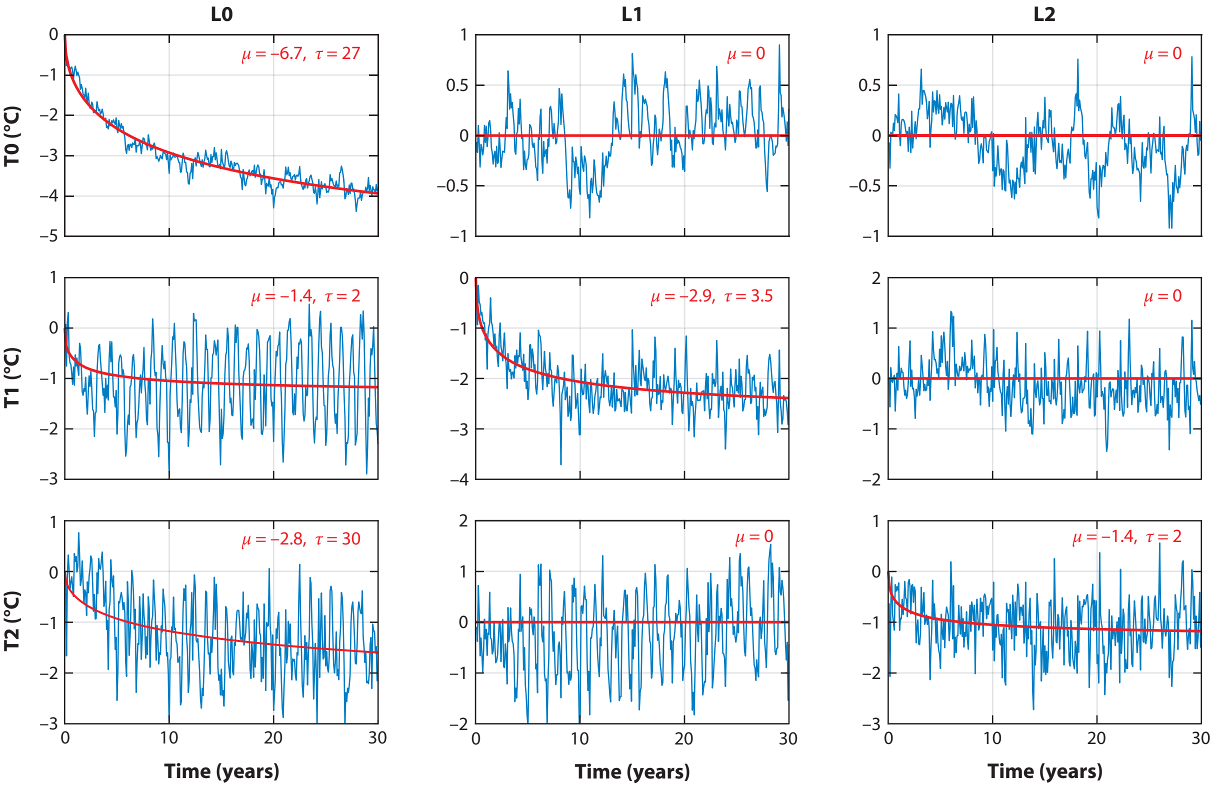

Figure 6

Matrix of input/output step responses simulated in CESM1 between three patterns of solar reduction and the three temperature patterns T0, T1, and T2. Red lines are best fits to semi-infinite diffusion, with estimated parameter values given in each panel.

The effects of a step change in the SO_2 injection rate at different combinations of locations on three patterns of AOD (L0, L1, and L2) and temperature (T0, T1, and T2) were calculated by MacMartin et al. (79; see their figure 4). The dynamics between injection rate and the resulting pattern of AOD were reasonably approximated as the output of a first-order system with a one-year time constant, and the global mean temperature was reasonably well approximated by the convolution of this one-year response with the semi-infinite diffusion model. Thus, at least for a combination of SO_2 injections that leads to a relatively spatially uniform AOD (i.e., L0), the transfer function between injection rates and the global mean temperature T0 is of the form

$$H_{00}(s) = \left(\frac{\alpha}{1+s}\right) \times \left(\frac{\mu}{1+\sqrt{\tau s}}\right), \qquad 7.$$

which can be used as a basis for feedback algorithm design and analysis. The appropriate functional form for the remaining nonzero entries of the 3×3 transfer function matrix is again unclear from these simulations.

MacMartin et al. (79) also evaluated whether the response to a combination of injections at different locations can be adequately predicted from the responses simulated for each injection location separately. At injection rates sufficient to give 2°C global cooling, the interaction effects were on the order of 20%—large enough to necessitate a feedback approach to compensate, but small enough that the simple feedback algorithm described in the next section was sufficient.

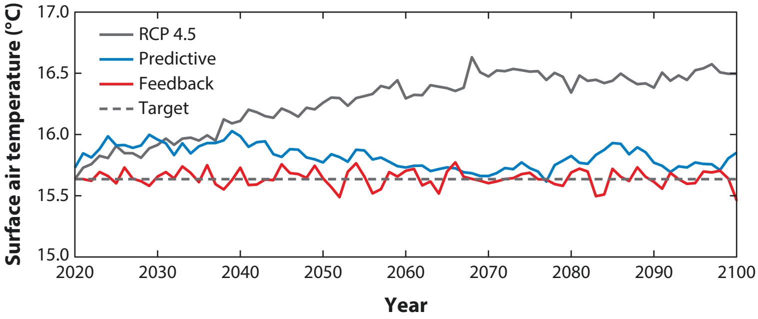

Figure 7

Illustration of the importance of using feedback of observations (in this case, climate model output) to adjust the amount of forcing. Estimates of the solar reduction required to maintain global mean temperature were made based on simulations with HadCM3L (91), and a blind test was conducted in a second general circulation model, Goddard Institute for Space Studies (GISS) ModelE2-R (96), for both this prescribed strategy and a feedback strategy. Absent perfect knowledge of the system, feedback is essential to meet the objectives, even in this relatively simple case. Uncertainty is higher in simulations of SO_2 injection and for more regional goals. Feedback is thus an essential element of any assessment of how well geoengineering could meet specific goals. Abbreviation: RCP, Representative Concentration Pathway. Figure adapted from Reference 95 with permission.

5. FEEDBACK

If climate engineering were ever deployed, it is implausible that choices such as the amount of SO_2 to inject at each latitude would follow some predetermined function of time regardless of what actually occurred in the climate system. Indeed, even for the simplest case of using global solar reduction to meet a global-mean-temperature objective, following such a strategy would likely lead to significant differences between the actual and desired temperature due to uncertainty (95) (**Figure 7**). More likely, the initial estimates for the injection rates needed to meet some particular goals would be reevaluated throughout deployment and updated regularly. Regardless of whether this follows a formal algorithm or is decided through some social process, it constitutes a feedback.

Using a feedback algorithm to manage uncertainty in climate engineering was first suggested as an aid in running climate model simulations to find the right amount of forcing to achieve a particular goal, such as a constant global mean temperature (97). The first explicit feedback algorithm was used by MacMartin et al. (98), who utilized a single degree of freedom (the solar constant) and a PI controller to manage either the global mean temperature or land-averaged precipitation. The PI gains were designed using the frequency response in **Figure 5**, enabling successful prediction of the dynamic behavior of the algorithm.

However, this study used the same climate model for both extensive system identification and demonstration of the feedback algorithm. This does not represent the situation that would be faced in reality, where one would develop strategies based on climate model simulations but would need them to work in the actual world. As a better test of this scenario, the same algorithm was subsequently validated in a blind test in a second climate model in which no system identification simulations were conducted (95). The feedback algorithm was robust to 50% errors in the gain, i.e., in how sensitive the climate model was to solar forcing as compared with CO_2 forcing (**Figure 7**).

Feedforward: a preliminary estimate of the amount of climate engineering that needs to be imposed at a particular time to meet the chosen objectives

Rather than relying entirely on the feedback algorithm to determine the right input, MacMartin et al. (99) added a model-predictive feedforward component so that the overall solar reduction in

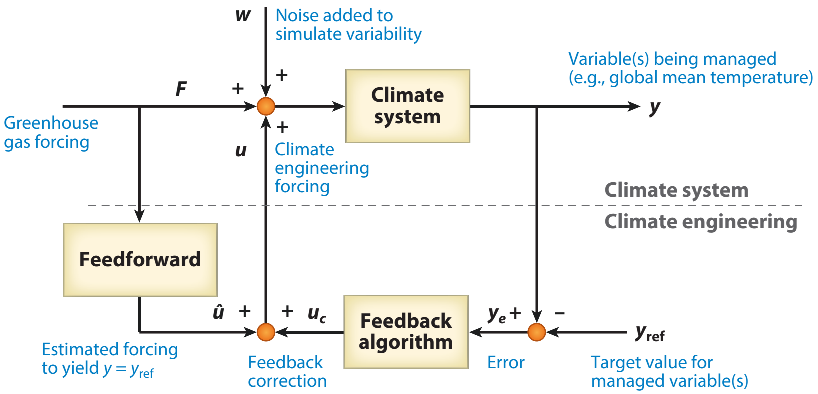

Figure 8

Block diagram of climate engineering feedback, assuming for simplicity that radiative forcing from climate engineering (u) and from other sources (F) simply add. Radiative forcing noise w can be included to simulate natural climate variability. The climate system yields anomaly y in response to radiative forcing. The feedback algorithm computes the appropriate updated climate engineering forcing in response to the deviation between observed and desired climate (e.g., temperature), written $y - y_{\mathrm{ref}}$. Also included is a feedforward of the best estimate of the climate engineering radiative forcing $\hat{u}$ required to maintain $y = y_{\mathrm{ref}}$ in the presence of the disturbance F. Studies to date have used a one-year update rate: One year of model simulation is conducted, the value of the climate engineering forcing is updated, and the climate model simulation is conducted for the next year. Figure adapted from Reference 98.

year k, $u[k]$, is calculated as a function of the objective (e.g., temperature) in previous years $y[j]$, $j \le k$, and desired value y_{d} (which could also be a function of time) as

$$u[k] = \hat{u}[k] + K_{\mathrm{P}}(y[k] - y_{\mathrm{d}}) + K_{\mathrm{I}} \sum_{j=0}^{j=k} (y[j] - y_{\mathrm{d}}) \qquad 8.$$

for proportional and integral gains K_{P} and K_{I}. The feedforward $\hat{u}[k]$ is estimated assuming a semi-infinite diffusion model (Equation 4) and convolution to predict the response to the CO_2-forcing time history. The overall algorithm is illustrated as a block diagram in **Figure 8**.

Bandwidth: the highest frequency in disturbance that the feedback system corrects; this is the inverse of the time constant for convergence (for a more formal definition, see Reference 87)

Phase margin: the additional phase lag (e.g., from time delay) between input and response before a feedback system becomes unstable; poor phase margin impacts performance (see, e.g., Reference 87)

Several of these ideas have been used in other studies. Cao & Jiang (100) used a PI controller to manage global mean temperature in a different climate model with an interactive carbon cycle, and Jackson et al. (101) applied model-predictive control for sulfate aerosol injection to manage Arctic sea ice extent. The idea of feedback has been extended for multi-input, multi-output control, in which solar reduction (76) or stratospheric SO_2 injection (31, 32) was used to adjust three patterns (L0, L1, and L2) of solar reduction or AOD, respectively, to meet temperature objectives T0, T1, and T2 (**Figure 9**).

To design a PI feedback algorithm for a single-input, single-output relationship, it is sufficient to know the magnitude and phase relationships of the transfer function at a single frequency (76, 98), corresponding to the desired bandwidth or convergence time. This observation motivated the single-frequency perturbations used for system identification by Kravitz et al. (76), although this approach, while sufficient to set a desired phase margin, provides no information about the overall functional form of the transfer function and hence no ability to make trade-offs with different bandwidths. For multi-input, multi-output control, if the transfer function matrix is triangular, one can design a feedback algorithm through sequential loop closure. For the 3 × 3 matrix discussed above, the only degree of freedom affecting T0 is L0, so designing a feedback loop

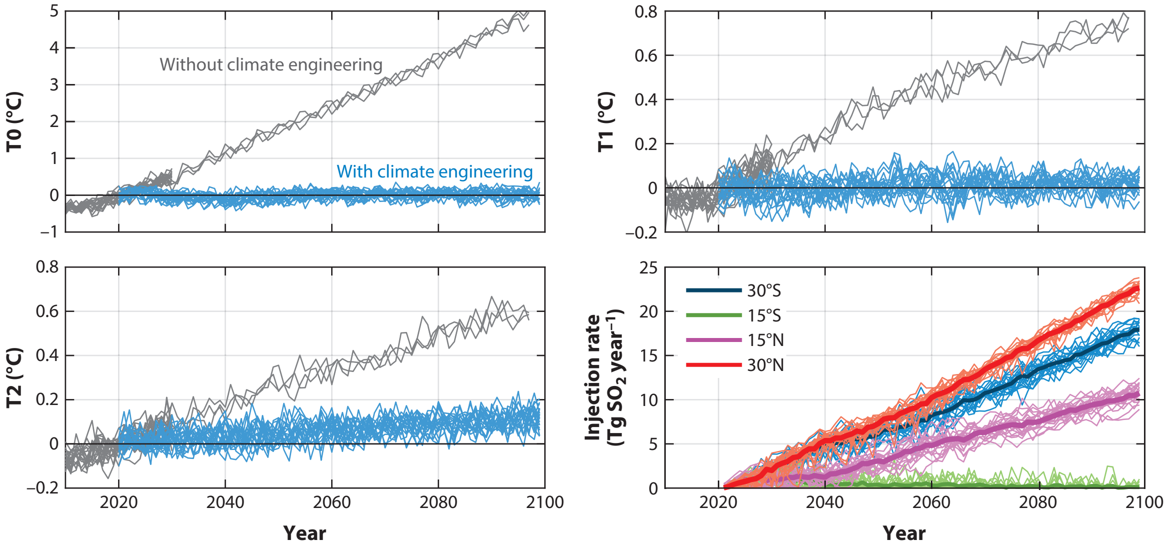

Figure 9

Feedback to manage multiple degrees of freedom in a 20-member ensemble of CESM1(WACCM) simulations. SO_2 injection rates at each of four latitudes (*lower right*) were adjusted in each year of each simulation to simultaneously meet goals in T0, T1, and T2 despite rising CO_2 levels. Temperatures without climate engineering are shown in gray. Figure adapted from Reference 32.

for that component is a 1 × 1 relationship. For effects on T1, one then designs a 1 × 1 relationship for L1 versus T1 and subtracts the known effects of L0 on T1. This process is continued until all (effective) 1 × 1 loops are closed. Transfer function matrices that are not triangular (or readily triangularizable) require more complicated approaches that have not yet been explored in climate science. We discuss potential approaches in the next section.

6. STATUS AND FUTURE DIRECTIONS

To support future informed decisions regarding whether to deploy climate engineering, research will ultimately need to address three main questions: How might one deploy climate engineering? What are the resulting impacts? And what range of outcomes are plausible given uncertainties? These questions are not fully separable, as both the impacts and the uncertainties depend on design decisions, while these decisions will be influenced both by projected impacts and by which strategies might be most robust to uncertainty. Indeed, this set of interleaved questions arguably forms the core of the climate engineering challenge: how to design robust feedback control algorithms that can achieve desired climate outcomes despite uncertainty. Control theory, including optimization, dynamics, and feedback design, is thus central to climate engineering research.

Research in stratospheric aerosol climate engineering has begun to transition from asking questions like "What happens if climate engineering were deployed like this?" to "How could we achieve desired outcomes?" Similar questions have not yet been asked for marine cloud brightening because of insufficient understanding of the locations and meteorological conditions under which albedo can be increased. This progression toward treating climate engineering as an engineering problem is essential to ultimately address whether and (if so) how these ideas can reduce climate risk. However, all of the components of this research are still in their infancy; in this section, we briefly comment on future challenges that will need to be addressed.

6.1. Expanding the Design Space

Figure 2 illustrates what might be achievable with the three degrees of freedom of SO_2 injection used by Kravitz et al. (31), Tilmes et al. (63), and MacMartin et al. (79) and described in Sections 3–5. Gaining a better understanding of the limits of what climate engineering can do will require expanding the design space—for example, to consider more latitudes and altitudes (as in Reference 77 but in more comprehensive climate models), different seasons of injection, different methods of injection, and different aerosol compositions. It is clear, for example, in **Figure 3** (see also figure 2 of Reference 63) that stratospheric circulation varies considerably with season, as does the solar radiation at any latitude; an injection strategy that does not vary with season is obviously not optimal. In principle, expanding the input space is straightforward; the challenge will lie in assessing how many degrees of freedom are practically independent when one considers both the climate variability (which can obscure small differences) and consistency, not only across different climate models but also between models and reality.

With N independent inputs, one might manage N independent climate variables, and presumably larger N yields better compensation for climate changes. Yet there are vastly more climate variables that affect humans and ecosystems than any plausible value for N. How well can all of the impacts of climate change be compensated for? If one were to optimize for one set of metrics, how would that affect the rest of the climate system? Are there distinctly different deployment strategies that might arise depending on what variables one optimizes for, and do these lead to distinctly different distributions of benefits and harms? The answers to these questions could have significant implications for governance and the question of who makes decisions regarding this technology—about not only whether to deploy but also how to do so.

6.2. Dynamics and Emulators

While general circulation models of the climate are useful tools for making projections of how the climate might respond to forcing, they are not well suited for the development of feedback algorithms due to their computational expense and the difficulty of generating inverse models (to predict the forcing needed to achieve a particular effect). The ability to develop pragmatic multivariable reduced-order dynamic and possibly nonlinear models that strike a balance between fidelity and complexity will be essential; in the climate literature, such models are referred to as emulators (94).

There is an extensive body of literature available for developing linear dynamic models—for example, projecting spatial patterns of response onto empirical orthogonal functions and using tools such as linear-inverse modeling (102). However, nonlinearities (e.g., in aerosol microphysical growth) may introduce challenges with purely linear approaches. Tools such as deep neural networks are advancing rapidly and might be useful for nonlinear system identification. Regardless of the tool, there will be two broad challenges. Because of the computational expense of general circulation model simulations, one challenge will be the ability to estimate simplified representations from relatively limited sets of general circulation model output. The second challenge will be ensuring that the resulting behavior is meaningful. To that end, retaining physical insight is essential to establish confidence that the estimated behavior will carry over to the real world.

As the field progresses to expand the design space, including both more input variables and more output variables, there will inevitably be greater challenges with poor signal-to-noise ratio. This ratio will be poorer at more regional spatial scales and for some variables, such as precipitation changes, yet these will be critical inputs to societal assessments of this technology. The problem may be even more challenging for marine cloud brightening than for stratospheric aerosols, as one might want to understand the impact of making changes to albedo over relatively small spatial areas and for many different areas and times of year; an initial exploration in a highly idealized setting illustrated ideas but found significant challenges with a poor signal-to-noise ratio (89).

Additional tools from dynamical systems theory (103) could be invaluable both for understanding subgrid-cell mixing characteristics and for gaining greater insight into large-scale stratospheric aerosol transport barriers to help assess trade-offs with injection locations.

6.3. Managing Uncertainty Through Feedback

The above-described approach of sequential loop closure to produce a set of decoupled single-input, single-output PI controllers will rapidly reach its limits of applicability as more complex objectives are pursued. In that context, there are several useful research directions.

Better system identification can lead to better dynamic input–output models and hence better predictions of the required forcing. This might allow a feedforward that can respond quickly to nonanthropogenic forcings, such as volcanic eruptions, or to known components of natural variability, such as El Niño cycles.

One could also incorporate information about the state of the system beyond just observations of the chosen objectives. Climate variables such as temperature and precipitation evolve slowly, so adjustments to SO_2 injection amounts must wait until the effects of adjustments are apparent in the surface climate. However, for stratospheric aerosol climate engineering, the AOD itself can be measured at a high signal-to-noise ratio, and the AOD responds more rapidly to injection changes, with time constants on the order of one year. A higher bandwidth could thus be achieved on a feedback loop that adjusts injection rates to maintain a particular spatial pattern of AOD, and then a lower-bandwidth adjustment could monitor the relevant climate variables and adjust the desired AOD values. A similar approach could be used for marine cloud albedo. Insofar as much of the nonlinearity and uncertainty are in the stratospheric processes (or marine cloud–aerosol interactions), this method might greatly improve robustness.

While this is a pragmatic, physically motivated strategy, the eventual solution might involve model-predictive or receding-horizon control (101, 104). Given a state estimate that incorporates all available climate measurements and a sufficiently computationally tractable forward model, the optimal choices (e.g., SO_2 injection rates at all latitudes and seasons) could be made based on the best available information. Such an approach could in principle take into account nonlinearities, model uncertainty (by using multiple forward models), and state uncertainty and might consider nonquadratic or constrained optimization criteria.

Physical uncertainties will always remain a critical limitation in any feedback strategy. For example, the sign of the global-mean-temperature change in response to a change in incoming sunlight is clear from basic physics, although there may be uncertainty in the magnitude of the response. However, for other variables, such as regional precipitation, even the sign of the response is uncertain. As such, the ability to design and manage climate engineering to compensate for regional impacts of climate change remains unclear.

6.4. The Bigger Picture

All of the research described here is, at least for the time being, a means to an end: to provide a balanced assessment of expected impacts from climate engineering to inform future societal decisions. Uncertainty, nonlinearity, and climate variability are fundamental features of the climate engineering challenge. How well can these be managed? That is, the original design question posed in Section 1 could be phrased in a more nuanced way: How well can climate engineering meet different climate objectives in the presence of uncertainty, nonlinearity, and climate variability?

While independent verification of the feedback algorithms in a different model (76, 95) demonstrates robustness to uncertainty, bridging the model-to-real-world gap, overcoming poor signal-to-noise ratios in highly variable fields, optimizing the feedback algorithm to meet the chosen objectives, and minimizing the side effects of any hypothetical deployment will require far more research. Finally, these questions lead to an overarching and heretofore unaddressed question: How good does one's model of the system need to be?

SUMMARY POINTS

1. Climate engineering, by reflecting some sunlight, could cool the climate and potentially help manage some impacts of climate change.
2. If implemented, climate engineering would be humanity's largest engineering and control challenge.
3. Design choices can be made to at least partially tailor outcomes, but the limits of such strategies are not yet known.
4. Using feedback of observations to adjust the strategy will be essential to meet objectives despite uncertainty.

FUTURE ISSUES

1. The design space of climate engineering needs to be more fully explored to determine what it can and cannot achieve.
2. Multi-input, multi-output reduced-order dynamic models will need to be developed that balance fidelity with computational simplicity.
3. Multi-input, multi-output feedback strategies will need to be developed that take advantage of all available observations and adjust many input variables to meet multiple simultaneous climate objectives.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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Errata

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