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Uncertainties and confidence in stratospheric aerosol injection modelling: a systematic literature review

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Abstract (<250 words)

Introduction: Model projections performed to evaluate the efficacy and impacts of solar geoengineering interventions, such as Stratospheric Aerosol Injection (SAI), include multiple sources of uncertainty, namely scenario, model, and natural variability uncertainty. It is well accepted that a quantitative uncertainty assessment related to SAI modelling is required to provide robust and policy-relevant information on SAI. This study investigates how and to what extent articles using a climate modelling approach on SAI quantify and communicate uncertainty sources. *Methods:* We conducted a systematic literature review of a sample of 60 peer-reviewed articles in order to (a) analyse whether uncertainties were addressed, and if yes, which methods were used to characterize uncertainties, and (b) study how the articles communicated assumptions and limits that contribute to the estimation of confidence in the used models and the resulting projections. *Results:* We present statistics on the uncertainty quantification methods used in the articles and we discuss the vocabulary employed for conveying these uncertainties and model confidence. In the studied article sample, the attention paid to uncertainty estimations in the SAI literature increased with time, and overall, uncertainties were treated using a variety of methods. Model confidence was not always explicitly communicated as the models used are already tested in the literature and their strengths and weaknesses are known to the community although this is often implicit. *Conclusion:* Our results show that it is currently difficult to perform global, quantitative assessments of uncertainty related to SAI research, in line with recent review reports on solar geoengineering.

Lay Summary (<200 words)

We review a sample of 60 articles on literature studying the so-called solar geoengineering method consisting of injecting aerosols into the stratosphere (above 10-15 km of altitude) using climate models. We focus on how these articles address and quantify the uncertainties related to the model results, and we also study the way the articles justify the use of certain models, the confidence attributed to the models, and the vocabulary used to convey all of these aspects. The articles use a variety of methods to address modelling uncertainties, and the attention paid to uncertainty estimation increases with time. Often the used models are implicitly assumed reliable for the purpose they are used for as they are well known in the field. The solar geoengineering community has recently called for a more systematic treatment of uncertainties that will also enable better estimations of the possible risks of solar geoengineering in future assessment reports.

1. Introduction

There is currently a broad scientific consensus that the Earth's climate has experienced human-induced changes over the last century. Past, current and future greenhouse gas emissions will continue to impact the Earth's radiative balance and the climate [1]. In this context, climate-related risks¹ for natural and human systems are projected to increase as global temperature increases from pre-industrial conditions to +1.5°C and beyond [3].

The magnitude of these projected risks, the emphasis on the inertia of the climate-carbon system as well as pessimistic views on humanity's ability to mitigate greenhouse gas emissions in a timely fashion [4] have led a small research community to intensify research activities on solar geoengineering methods. The research aims at evaluating the feasibility, efficacy and specific risks of using these techniques as part of the portfolio of policy options to moderate climate hazards [5–10]. Several review reports on solar radiation management (SRM) research have been published [1,11–13]. They also highlight the high (but not fully quantified) level of uncertainty involved with such techniques.

¹ In this context, "climate-related risks" can be understood as potential adverse consequences of climate hazards for human and natural systems, given the circumstances that characterize the vulnerability and exposure of these systems to these hazards [2].

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3 “Solar geoengineering” refers to technologies that could be used to intentionally modify the
4 Earth’s radiative balance. One of the proposed methods, Stratospheric Aerosol Injection (SAI),
5 consists in injecting aerosol precursors in the stratosphere in order to increase the fraction of
6 sunlight reflected back to space and thus inducing a net global cooling at the surface [8,14–17].
7 This technology has been conceptualized in analogy with volcanic eruptions, such as the Mount
8 Pinatubo eruption in 1991, which had a discernible (about 0.5 K), relatively short-term
9 (approximately one year) cooling effect on the climate [18]. However, volcanic eruptions and
10 intentional injections would not have exactly the same impacts as they are not perfect
11 analogues, differing for instance in terms of stratospheric aerosol size and composition or in the
12 spatio-temporal characteristics of the injection [19–21].

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21 The envisioned scale of SAI deployment is planetary and multidecadal, up to over a century
22 [22]. However, possibilities for obtaining observational data from SAI field experiments are
23 limited to small-scale experiments. Such experiments might help in improving small-scale
24 process descriptions in models and reducing uncertainties related to such processes [10,23], but
25 they cannot inform us on the large-scale climate impacts of SAI nor do they allow for an
26 experimental validation of climate responses to SAI [24,25]. Furthermore, recent attempts to
27 proceed to outdoor field testing (e.g. tests of the delivery system for the SPICE project or the
28 SCoPEX project [26]) have faced systematic opposition from parts of the society and have been
29 abandoned. Hence, any discussion on using SAI as part of the portfolio of options to reduce
30 potential future consequences of climate change has so far predominantly relied on climate
31 simulations investigating related stratospheric processes as well as potential climate response
32 and impacts, and it is likely that it will remain so in the foreseeable future. These simulations
33 are performed with numerical climate models that can explore how characteristics (e.g. global
34 surface temperatures) of the modelled climate system would evolve in response to specific
35 forcings (e.g. under greenhouse gas and aerosol injection scenarios). These results can also be
36 used as input data to other types of models (e.g. crop models, hydrological models, etc.) that
37 simulate specific impacts for a particular climate scenario.

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51 Due to the unprecedented nature and vast scale of the potential SAI interventions, related
52 decision-making processes will necessitate a high level of confidence in model projections [10],
53 both those addressing climate change per se and those on the impact of SAI on the climate, so
54 that all options and the associated uncertainties can be objectively weighed. However, it is not
55 clear how the necessary (“high”) level of confidence for decision-making can and should be
56 defined, but it would require a multidisciplinary approach and a constructive dialogue between
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3 scientists and decision-makers [27]. Generally, the absence of a measure of reliability as well
4 as the non-characterization of uncertainties make the usability of scientific studies in a decision-
5 making context more challenging [28]. In this context it is very important that all the underlying
6 assumptions made (e.g. methodological, epistemological) in producing these projections are
7 discussed and uncertainties systematically characterized to provide a measure of the reliability
8 of the projections [29]. Also, explicitly communicating underlying methodological assumptions
9 and characterizing sources of uncertainty are very important in contextualizing the results of
10 these projections [30].

11
12 While individual scientific articles are mainly written for peers and not for a general audience,
13 these articles might be also used in a policy-making context and in communication to a general
14 public [29], requiring contextualization in the communication of scientific knowledge outside
15 the scientific community. From this viewpoint, assessing uncertainties on a broad topic to be
16 communicated outside the scientific community requires making a synthesis of the aggregated
17 information from a large spectrum of studies, going beyond the treatment of specific
18 uncertainties relevant to a single study. A recent systematic literature review focused on
19 uncertainty treatment in modelling and decision-making research articles on the impact of
20 climate change on forests [31]. They identified an inconsistent use of the notion of uncertainty
21 and a lack of its systematic characterization in the reviewed literature, and showed that
22 modelling and decision-making studies addressed different types of uncertainties. The authors
23 concluded that this difference in uncertainty treatments could make communication of research
24 to decision-makers more difficult, and suggested that the scientific literature should address and
25 communicate uncertainties in a clearer and more comprehensive manner, so that it can fully
26 play its role on providing evidence for decision-making [31]. Two other reviews have recently
27 focused on the communication steps following the production of scientific knowledge. One of
28 them performed a qualitative systematic review of studies in behavioural and cognitive sciences
29 on the communication of uncertainties in climate-related scientific findings, focusing on the
30 communication of climate-related information to its user (e.g., the general public) in a decision-
31 making context [32]. The authors identified three sources of uncertainty in their literature
32 sample, focusing on uncertainty in observations of climate change (the two others being deep
33 uncertainty including ignorance and uncertainty on how well climate models reproduce
34 observations). One of the findings was that presenting ranges to respondents of the studies
35 instead of a single numerical value for a climate parameter improved the understanding of the
36 uncertainty [32]. The authors also noted that the terms in which the ranges were described could
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3 modify the perception of the respondents, underlining the importance of the vocabulary used in
4 communicating scientific uncertainties [32]. The other review focused specifically on
5 communicating model uncertainties to policymakers [27]. The authors concluded that instead
6 of including all possible uncertainties, the clearest communication is acquired with decision-
7 relevant uncertainties that are related to the policymakers' needs and whose relevance is defined
8 through a dialogue [27]. In addition to the above, communication of results to the general public
9 and decision-makers should also take into account inclusivity, cultural differences and
10 particularities of the different regions of the world [30,33].

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12 The communication of lines of evidence in the Intergovernmental Panel on Climate Change
13 (IPCC) assessment reports provides a good example of the transition from scientific knowledge
14 for specialists to information targeted to a larger audience. Glossaries and guidance that frame
15 the use of key concepts such as uncertainty and risk were conceived to homogenize practices
16 among and between the IPCC Working Groups [2,34,35], and climate scientists were asked to
17 evaluate their confidence in conclusions drawn from climate projections, using these guidelines
18 to express the elements of communication, including, when necessary, a varying degree of
19 expert judgement. In the IPCC assessment reports two metrics are produced: (i) the "relative
20 degree of certainty" defined as a combination of the degree of agreement and the consistency
21 of evidence, and (ii) if and when possible, estimated likelihood, defined as the probabilistic
22 estimate of a specific occurrence or attributed to a range of outcomes [34]. These two metrics
23 are the results of informed but subjective processes of weighting theory (perceived
24 understanding of the functioning of underlying processes), data, model simulations and expert
25 judgment. The latter is "only made possible by the large amount of model-based information
26 which resulted from a concerted and timely effort of the climate modeling community" [34].
27 This means that although individual articles studying climate change might not provide
28 thorough uncertainty estimates, the climate research community as a whole has produced
29 sufficient information to enable a reliable estimation of these metrics used in the IPCC reports.
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31 In this article, we focus on the production of information by the scientific community that is
32 needed prior to informing a larger audience.

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34 The SRM research community has recently highlighted the need for a better estimation of
35 uncertainties, also in support for decision-making, and provided perspectives on how to proceed
36 [10,36]. But how has published research so far established and communicated confidence and
37 uncertainties related to modelling studies? The goal of our article is to study the treatment of
38 uncertainties and the attribution of confidence in models in the published SAI modelling

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3 literature. We conduct a systematic literature review of a sample of 60 peer-reviewed research
4 articles to identify the used uncertainty characterization methods and the communication of
5 assumptions, limits and results in the SAI literature. In the following, we first describe our
6 methodology (Section 2), then we present the results (Section 3) and discuss our findings
7 (Section 4), and conclude (Section 5).
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13 14 15 **2. Methodology and terminology**

16 This section discusses the methodology we employed in this study and provides the context for
17 interpreting common practices identified in the SAI literature and discussing their implications
18 on establishing a degree of confidence. We describe the main sources of uncertainty in climate
19 projections and the methods climate modelers use to investigate these uncertainties. We also
20 discuss factors used in assigning confidence in models and projections.
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26 **2.1. A systematic literature review**

27 The questions we try to answer with the systematic literature review method address two topics:
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- 30 • Confidence and uncertainties in SAI modelling studies:
 - 31 ○ Were uncertainties addressed or not?
 - 32 ○ Which types of uncertainty were addressed, and with which methods?
 - 33 ○ How were model performance and confidence estimated?
 - 34 • Communication of confidence in SAI modelling studies:
 - 35 ○ How was confidence communicated, and with which terminology?
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41 We conducted a systematic literature review of a sample of 60 peer-reviewed articles that study
42 different SAI strategies through a climate modelling approach. We used the systematic
43 literature review to reveal common practices for communicating uncertainties and underlying
44 assumptions in the SAI literature. The methodology of systematic literature review is described
45 in the literature [37,38].
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50 We used the Scopus database to search for peer-reviewed research articles published in English
51 with the following search terms: (TAK=Title-Abstract-Key Words) TAK (solar AND
52 geoengineering) OR TAK (strato* AND aerosol AND geoengineering) OR TAK (strato* AND
53 aerosol AND injection) OR TAK (solar AND radiation AND management AND
54 geoengineering). This research string takes into account that different terms are commonly used
55 when referring to these techniques (e.g. solar geoengineering, solar radiation management,
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3 stratospheric aerosol injection). The search string we used might exclude some articles not using
4 the term “geoengineering” at all, but the search substring TITLE-ABS-KEY (strato* AND
5 aerosol AND injection) ensures that SAI articles are in any case included. We did not limit the
6 temporal range of our search so that we sample the full corpus of SAI publications. The search
7 in the Scopus database was conducted on 15 February 2021. These search terms yielded 656
8 articles. Based on the abstracts, we excluded off-topic articles (e.g. those only mentioning
9 stratospheric aerosol injections but not studying them, articles on other solar geoengineering
10 methods) and only kept primary research studies using a climate modelling approach, also
11 including the ones mimicking the impact of stratospheric aerosol injections with a reduction of
12 the solar constant. With these inclusion/exclusion criteria, the sample was reduced to 193
13 articles. From the remaining 193 articles, 60 were randomly selected in order to have a sample
14 size that allowed an in-depth text analysis. Information collected in this analysis was coded in
15 an Excel sheet (provided as a supplementary file). The Scopus database provided information
16 on the year of publication, the authors, the journal and the abstract. We downloaded the full
17 articles as PDF files. Through an in-depth analysis of the entire text and supplementary
18 materials of the reviewed research articles, we collected information on the different elements
19 of uncertainty and confidence that will be discussed more in detail in the following section.

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22 Specifically, for all articles, we coded the following information (see also the supplementary
23 Excel file):

- 24 – The types of uncertainty addressed, and how they were estimated.
- 25 – How model performance was estimated.
- 26 – The way confidence was communicated, and the terminology that was used.

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29 The coding was performed by one of the co-authors, reducing the risk for an inhomogeneous
30 treatment of different articles if made separately by several co-authors.

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33 The assumptions and limitations of our study need to be kept in mind while interpreting the
34 results. We searched only one database, used a certain selection of key words and search strings,
35 and our search was made only on articles in English. We reduced the outcome of the search and
36 exclusion process of 193 articles into a random sample of 60 articles. The 60-article sample we
37 analysed represents only a part of the entire SAI literature. To make sure the sample is
38 representative, we checked that the temporal distribution of the sample (i.e., number of articles
39 per publication year) follows that of the original 193 articles (Figure 1). We also verified that

the first authors of the articles in the sample reflect well the diversity of the field (the number of different first authors over the total number of articles was 116/193 in the original sample and 47/60 in the reduced sample). The entire SAI literature should be studied further in future studies and assessment reports with more efficient methods, such as machine learning for text data mining (e.g. [39]).

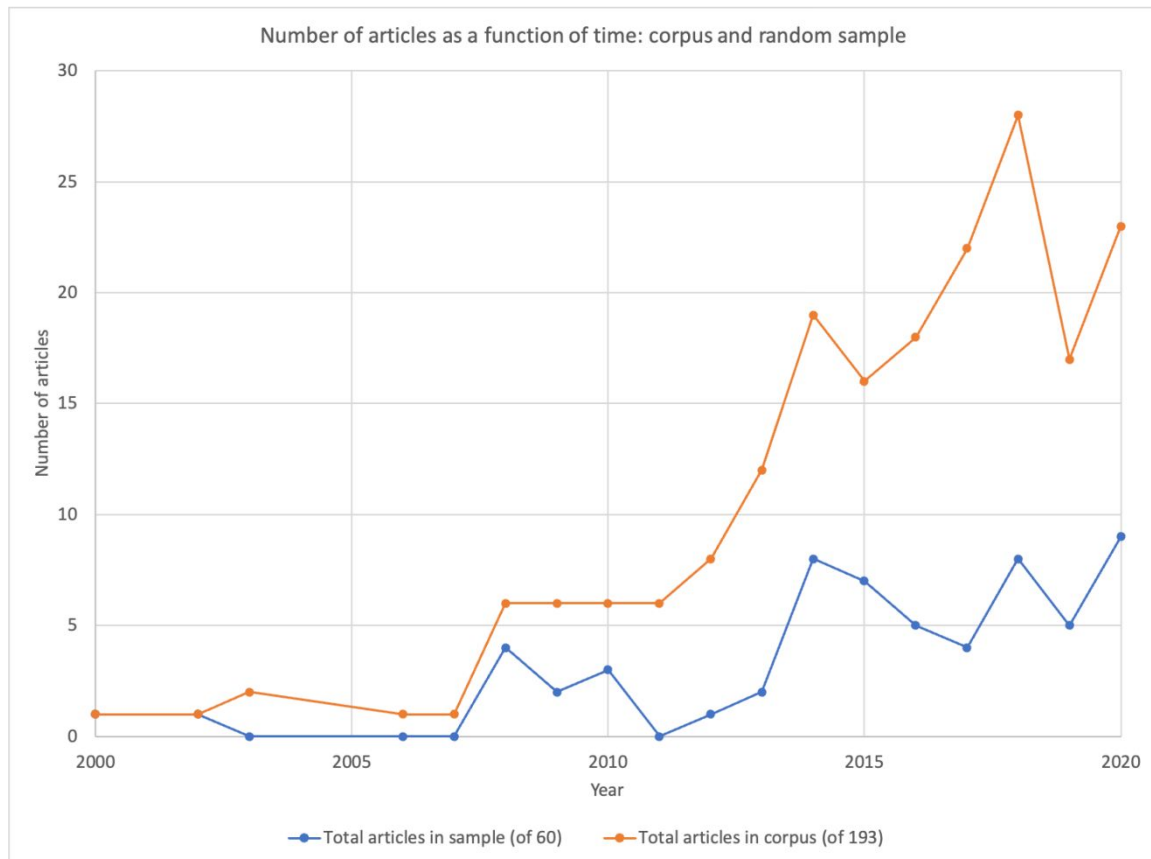


Figure 1: Number of articles in the full corpus of 193 articles (orange) and in the sample of 60 articles (blue) as a function of publication year.

2.2. Three types of modelling uncertainty and how to deal with them

The notion of uncertainty has many definitions, depending on the field of research. Addressing uncertainties is an integral part of research in natural sciences: their sources need to be defined and the uncertainties quantified in the best possible way in order to assess the robustness of the results. In this article, we will refer to uncertainty as “any departure from the unachievable ideal of complete determinism” [40]. This definition emphasizes the existence of irreducible components of uncertainty in our understanding of the climate system and thus in decision-making about climate change.

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3 Different categorizations are proposed to define sub-classes of the broader concept of
4 uncertainty in the specific context of model-based decision support [40–42]. In this article, we
5 follow the climate modelling community in distinguishing three main sources of uncertainty:
6 model uncertainty, scenario uncertainty, and uncertainty related to internal climate variability
7 [42–45]. These sources of uncertainty are common to all fields using the climate modelling
8 approach, and many of the uncertainties in SRM modelling are the same that arise in modelling
9 future climate change. Moreover, the uncertainties related to aerosol and cloud processes in
10 climate research are very high [1], and as these are the key processes involved in SRM, there is
11 a very strong link between uncertainties in climate and SRM research.
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19 First, **model uncertainty** arises from the difference between the real climate system and the
20 model used to represent it. There are two main sources of model uncertainty. Our incomplete
21 knowledge about the functioning of the climate system and its processes as well as
22 simplifications made in the representation of the system (e.g. included processes, resolution,
23 parametrization of sub-grid scale processes) produce uncertainty arising from the model
24 structure (**model structure uncertainty**). The *a priori* values assigned to model parameters
25 also generate **parameter uncertainty** [46]. Further uncertainty (unknown unknowns) could
26 arise from processes that are not currently considered but that could play an important role in
27 future climate conditions.
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35 Second, **scenario uncertainty**, also called driving force uncertainty, reflects the inherent
36 uncertainty on the possible futures described by the used scenarios. A climate scenario is a
37 “plausible description of a possible future state of the world” composed of different radiative
38 forcing factors (e.g. forcing corresponding to a particular greenhouse gas emission path, forcing
39 corresponding to the injection of stratospheric aerosols) [47]. When exploring the effects of a
40 certain scenario of solar geoengineering deployment, assumptions are made about (i) the
41 context in which this particular strategy would be deployed (future emission pathways, future
42 radiative forcings, etc.) and (ii) the feasibility of the deployment (technically, politically,
43 socially, economically, etc.). Particularly, the political and social components of feasibility are
44 subjected to a particular type of uncertainties that are difficult to anticipate and quantify.
45 Political and social acceptability is a construct highly dependent on national politics and cultural
46 features. Therefore, a scenario is a single combination of “what-if” conditions among the
47 infinite range of possible future states of the world [46]. Scenario uncertainty is difficult to
48 quantify, inherently irreducible, and increases the farther we are from present-day conditions.
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3 Third, **uncertainty related to internal climate variability** reflects that, even in the absence of
4 external forcing, the climate system varies naturally, due to the existence of non-linear dynamic
5 processes. It is therefore also necessary to differentiate internal climate variability and forcing
6 response in climate projections by using long time scales and different initial conditions [48].
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10 There are different ways to quantify each type of uncertainty. First, model uncertainty (model
11 structure and parameter uncertainty) can be explored through different methods. The discussion
12 on and quantification of these uncertainties in sulphate aerosol models, relevant to both climate
13 modelling and SAI started over 25 years ago [49]. The “**Multiple Model Ensemble**” (MME)
14 method performs simulations with multiple climate models that incorporate similar climate
15 processes and use the same set of scenarios and simulate the same time period. This method
16 addresses uncertainty originating from the model structure and parameter values [50]. Using
17 different models with alternative structures and specifications to simulate the functioning of the
18 climate system allows to partially distinguish their consequences on model outputs. These
19 alternative model structures can be seen as different approximations of the real climate system,
20 constrained by complexity and computational cost. However, the extent to which this approach
21 can contribute to the characterization of uncertainty depends on different elements; for instance,
22 interdependence of the chosen models and choices made to build the ensemble [46]. Model
23 ensembles are often opportunistic and rarely designed through a well thought-through
24 approach. The Geoengineering Model Intercomparison Project (GeoMIP) designed
25 standardized scenarios to perform these MME studies on solar geoengineering [51].
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39 Specific **sensitivity analysis** explores the sensitivity of projections to changes in elements of
40 the model structure or in parameter values. This definition does not include exploration of the
41 sensitivity of projections to changes in scenario parameters. **Perturbed Physics Ensemble**
42 (PPE) modelling, a subcategory of sensitivity analysis, also sometimes addresses model
43 structure uncertainty, and more specifically, uncertainty regarding parameter values (Parameter
44 uncertainty). PPE uses a single model, and proceeds to multiple model runs differing from one
45 another by perturbations of a limited number of model parameters, under similar scenarios,
46 preferably with large ensemble size and systematic sampling [52]. As the size of the space
47 representing all the combinations of model parameters is tremendous, sampling the full
48 parameter uncertainty in climate models is impossible because of the computational cost and
49 human time required for result analysis. Hence, simpler versions of climate models or emulators
50 are often used in exploring this uncertainty. As PPE are conducted with a single model, the
51 interpretation of results from PPE are constrained by the structural characteristics of the model
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3 used [53]. Both approaches, PPE and MME, can be combined to improve the understanding of
4 key uncertainties in modelling. In SAI literature, one study combined and compared MME and
5 PPE to investigate the different types of uncertainties using standardized GeoMIP scenarios and
6 models, and they called for future studies building upon their approach to better understand the
7 uncertainties in modelling of solar geoengineering [54].
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12 Second, **scenario analyses** address scenario uncertainty. They explore a broad range of possible
13 future conditions [47]. The computational cost and the time needed to analyse the data limit the
14 possibilities to analyse a large number of scenarios. A systematic sampling of the space of
15 possible futures is not possible, but using multiple scenarios allows to explore degrees of
16 freedom and how they might impact the modelled response. Nevertheless, standardizing
17 scenarios, such as those of GeoMIP, or others that have been recently proposed, are also
18 important in order to facilitate the comparison between models and to assess if a certain feature
19 is recurrent in these projections [51,55,56]. It should be mentioned that there are SAI studies
20 that specifically focus on scenario uncertainties by exploring multiple SAI scenarios (e.g.
21 [55,57]).
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31 Third, to further explore uncertainty arising from the internal natural variability of the climate
32 system in the models and try to separate the climate response to forcing from this internal
33 climate variability, several model runs can be carried out with the same model but with different
34 initial conditions. This is called **Single-Model Initial Condition (Large) Ensemble
35 Modelling**. It allows to quantify the natural climate variability uncertainty with ensemble
36 statistics. The ensemble size is a primordial criterion for the interpretation of the ensemble
37 results as it is considered to determine their significance. However, there is no unique, ideal
38 ensemble size; the necessary ensemble size depends on many aspects, such as the studied
39 variable and the acceptable level of error [58]. Large ensembles are particularly important for
40 the assessment of regional climate responses, yet the computational cost of this approach limits
41 the extent to which large ensembles are employed [42]. The stratospheric aerosol
42 Geoengineering Large Ensemble Project (GLENS) was created for the purpose of quantifying
43 the natural variability in the modelled climate response to SAI [59]. A more recent effort with
44 a similar approach has been conducted in the ARISE-SAI project [60]. Other, computationally
45 less expensive approaches can be used as well. These generally look at the statistical
46 significance of the change or difference of a mean value of a parameter with respect to internal
47 climate variability.
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3 These different methods make it possible to quantify the different types of uncertainties. They
4 provide a lower bound of the total uncertainty, but computational cost often limits their
5 extensive use.
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10 11 **2.3. Model performance and perceived accuracy in climate projections**

12 The characterization of uncertainties and the explicit communication of known limits and
13 assumptions contribute to the perceived accuracy of modelled projections [29]. We distinguish
14 here two dimensions of the model performance: model fit to past and present observations and
15 ‘robustness’.
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20 First, **model fit** is widely used to estimate confidence in the model [61]. This hypothesis
21 consists in extrapolating a model’s ability to produce results for past and present-day conditions
22 that fit well the available observational data (model fit) as an indication of its projection skills
23 for multidecadal and century-timescales in the future. Different indicators of model
24 performance (instances of fit) are used to estimate this empirical accuracy and to compare
25 performance between models [62]. A debate exists on whether these different instances of fit
26 should be considered as a confirmation of the entire model or of its adequacy for particular
27 purposes [63]. In this adequacy-for-purpose perspective, climate modelers often justify the
28 choice of a model for a given purpose by its ability to represent particular processes that they
29 consider relevant for the study. This “empirical accuracy” factor is crucial in the confidence for
30 interpreting climate projections, but it cannot be verified. The inference from model fit has other
31 known limitations, such as the possible existence of compensating biases introduced during the
32 model calibration process to fit the data, and the fact that future climate conditions could be
33 significantly different from those for which the model has been calibrated [61,64].
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45 Second, the ‘**robustness**’ of results from a model projection corresponds to how well these
46 results agree with those obtained with other models or reported in other studies in the literature.
47 In order to be able to state that a result from a model projection is robust thanks to a good
48 agreement with results from other studies, it is necessary to explain why alternative
49 explanations for the agreement are ruled out. For instance, it could be clarified why the
50 agreement between models in a multi-model ensemble is not a result of models sharing common
51 biases due to interdependence between models [46,65]. In fact, obtaining consistent results from
52 different models does not necessarily mean that they are accurate. The concept of climate model
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3 robustness and its different usages have also been discussed in the field of philosophy of science
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5 (see e.g. [66]).
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7 In summary, climate model projections are inherently uncertain, as a result of model structure
8 uncertainty, scenario uncertainty, and uncertainty related to internal climate variability. These
9 uncertainties can be characterized and quantified through different methods, helping to establish
10 confidence in the modelled results. Confidence is also related to model performance, expressed
11 as model fit and robustness. Finally, it is also important how uncertainty and confidence are
12 communicated: that is, which terminology is used, and how. All of the above applies to both
13 climate change projections and to other topics, such as SAI, studied with the climate modelling
14 approach.
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26 **3. Results of the systematic literature review**

27 In this section, we provide quantitative and qualitative evidence on the different factors used in
28 the discussion on the confidence and uncertainties in SAI simulations in the studied articles of
29 our sample. We first discuss if and how the different types of uncertainties were studied. Then
30 we address how model confidence was expressed in the studied articles. Finally, we map the
31 vocabulary used for conveying these aspects in the reviewed literature. The full dataset with
32 further details can be found in supplementary materials.
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39 **3.1. Types of uncertainties and how they were dealt with**

40 As the sample of analysed articles contained a large variety of non-standardized scenarios and
41 experiments and the articles did not perform quantitative scenario uncertainty estimations, we
42 are not discussing scenario uncertainty in this analysis. Only results concerning model
43 uncertainty and natural climate variability uncertainty are presented in the following, and show
44 that, when uncertainties are discussed, the SAI studies apply a large variety of methods to
45 estimate the different types of uncertainties.
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51 Model structure uncertainty was mainly investigated with Multiple Model Ensemble (MME)
52 using similar scenarios. Among the 60 reviewed articles, 21 performed MME modelling with
53 2-13 models (Table 1). Sixteen studies shared common methodologies (e.g. similar set of
54 models and scenarios) as they were part of the Geoengineering Model Intercomparison Project
55 (GeoMIP). In particular, four articles (see Table 1) used results of eight Earth System Models
56 from GeoMIP [67–70]. Results from MME modelling were communicated and represented in
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different ways: (i) by focusing on the unweighted multi-model mean with different complementary metrics on the spread of the results, such as the across-model spread (range, under the form of shading, parentheses), the ensemble standard deviation (in the form of an error bar, or \pm) as well as stippling on maps to represent areas where a certain proportion of the involved models agree on the sign of change; and (ii) by representing results of the individual models separately to better identify differences between models.

Table 1 Number (and percentage) of models used per article in the full sample

Number of models	1	2	4-7	8	9-10	12-13
Number of articles (%)	39 (65.0)	5 (8.3)	4 (6.7)	4 (6.7)	4 (6.7)	4 (6.7)

Ten of the 60 reviewed articles explicitly conducted sensitivity analyses. These sensitivity analyses were implemented by removing (in four articles) entire modules from the climate/impact model structure (e.g. projections with or without interactive chemistry [71]), or processes (with or without heat and water stress in crop modules [72]), as well by changing (in six articles) parameter values (e.g. sensitivity of crop yields to temperature and precipitation changes, crop failure threshold [73,74]). Results were often presented through comparing the results of the model runs with varied parameters (e.g. global mean radiative forcing for the different model runs) as curves in a plot or as values tabulated in tables for easy comparison.

Two of the 60 reviewed studies explicitly used a Perturbed Physics Ensemble (PPE) in order to explore the parameter uncertainty. One of them used a crop model with perturbations of 20 parameters [72]. The resulting ensemble grouped 19 parameter sets for the historical climate and 76 for projections (19 parameter sets for 4 different parametrizations of the response to CO₂). The other PPE was conducted with HadCM3, an older generation climate model (CMIP3), with a PPE ensemble size of 20 members, perturbing 8 parameters [54]. The authors explicitly stated that the small ensemble size, the small number of perturbed parameters and the shared model structure undermined the strength of the interpretation of the PPE results [54]. This also applies to the capability of the PPE to inform us on the climate response in a Multiple Model Ensemble [54]. In both PPE articles, methodologies to select tested parameter sets and choose which parameter to perturb were extensively communicated. Results from the PPE using HadCM3, such as the surface air temperature change between geoengineering and control

scenarios, were communicated with the ensemble mean complemented with the ensemble standard deviation as well as the range (minimum and maximum of the ensemble) [54]. For graphical representations, the PPE ensemble mean was sometimes shown alone (with or without standard deviation and range) or along with individual PPE members.

18 articles addressed uncertainty related to internal climate variability by carrying out several model runs with the same model but with differing initial conditions. These articles have more than one Single Model Initial Condition Ensemble member with ensemble sizes from 2 to 30 members. Six articles use a Large Ensemble with at least 10 ensemble members. Three of these studies used a large ensemble generated in the context of the Stratospheric Aerosol Geoengineering Large Ensemble (GLENS) Project [9,75,76]. Results corresponding to the different ensemble members were represented either (i) by regrouping them with the ensemble mean, complemented by information about the spread (with the range, standard deviation or standard error in shading); or (ii) by communicating the results individually. Other, computationally less expensive methods were used in a majority of publications (42 articles) looking at the statistical significance of the change or difference of a mean value of a parameter providing a significant enough signal with respect to internal climate variability (noise). In some cases, both methods were used (15 articles).

Table 2 Number/percent of articles using different uncertainty analysis methods

Method	MME	PPE	Sensitivity analysis	Internal variability (ensembles)	Internal variability (signal-to-noise)
Number (%)	10 (16.7)	2 (3.3)	10 (16.7)	18 (30)	42 (70)

The statistics on the uncertainty estimation methods are given in Table 2. None of the articles systematically addressed all of these different sources of uncertainty. As our sample spans two decades of SAI modelling research, we have also taken a look at the temporal evolution of uncertainty estimation in the articles (Figure 2). We note that, in the studied articles, there has been an increase in interest concerning parameter and model structure uncertainty especially since 2010, the earlier studies (before 2010) looking nearly exclusively at natural variability uncertainty. This points to an increasing importance of uncertainty quantification in the field.

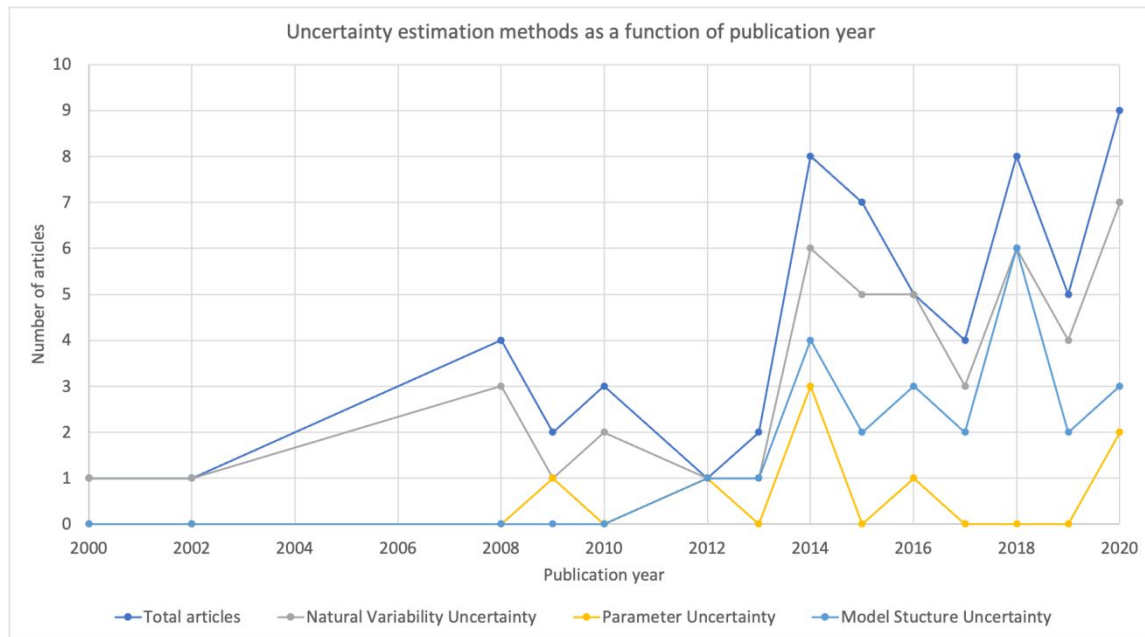


Figure 2: Evolution of uncertainty estimation methods in the articles as a function of publication year. The total number of articles (dark blue) is plotted in addition to natural variability (grey), parameter (yellow) and model structure uncertainty (light blue).

3.2 Estimation of model performance and confidence

In the reviewed publications, indications of model performance were given in three forms. First, articles generally stated that (i) relevant processes were included in the model configuration, and/or (ii) the used model could be considered as being “state-of-the-art”, as it was participating in intercomparison works (CMIP) and assessment reports of the IPCC. Second, 27 articles referred to other publications in which some form of model evaluation in past or present-day conditions had been conducted. Third, 15 articles stated that the study included a comparison of model results to past or present-day observational data or to results from other studies performed with another model of similar or higher complexity. These elements were sometimes communicated with figures (e.g. Figure 2 in [77]; Figure 1 in [78]) showing the comparison between a simulation of historical baseline and observational data, sometimes with error bars to show the statistical significance and correlation factor. More often, the indications were expressed with qualitative statements (using terms such as “good agreement”, “realistic”, “reproduce reasonably well”, “accurately simulate”, “simulate consistently”, “compares very well”). 20 of the reviewed articles (33% of the sample) did not include any explicit elements about model performance. Furthermore, the reviewed articles mentioning the model performance for past or present-day conditions did not explicitly state that the inference from model fit hypothesis was the basis for the extrapolation to the model’s ability to produce reliable projections of the future. Both the lack of explicit elements on model performance and the lack

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3 of statements on model fit hypothesis can be explained by the fact that the extent to which
4 models that have been used for a long time in the field are reliable or considered to be reliable
5 for a particular purpose is known to the authors and to the community as it has been extensively
6 tested and documented in different settings.
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10 11 12 **3.3 Terminology used to communicate uncertainty and confidence**

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14 Finally, we also explored how the articles used different notions when speaking about
15 uncertainty and confidence in their results. A variety of terms were employed and we have
16 classified them into three categories: terms related to the methodology of the studies, to the
17 effects of SRM, and to the uncertainty metrics (Figure 3).
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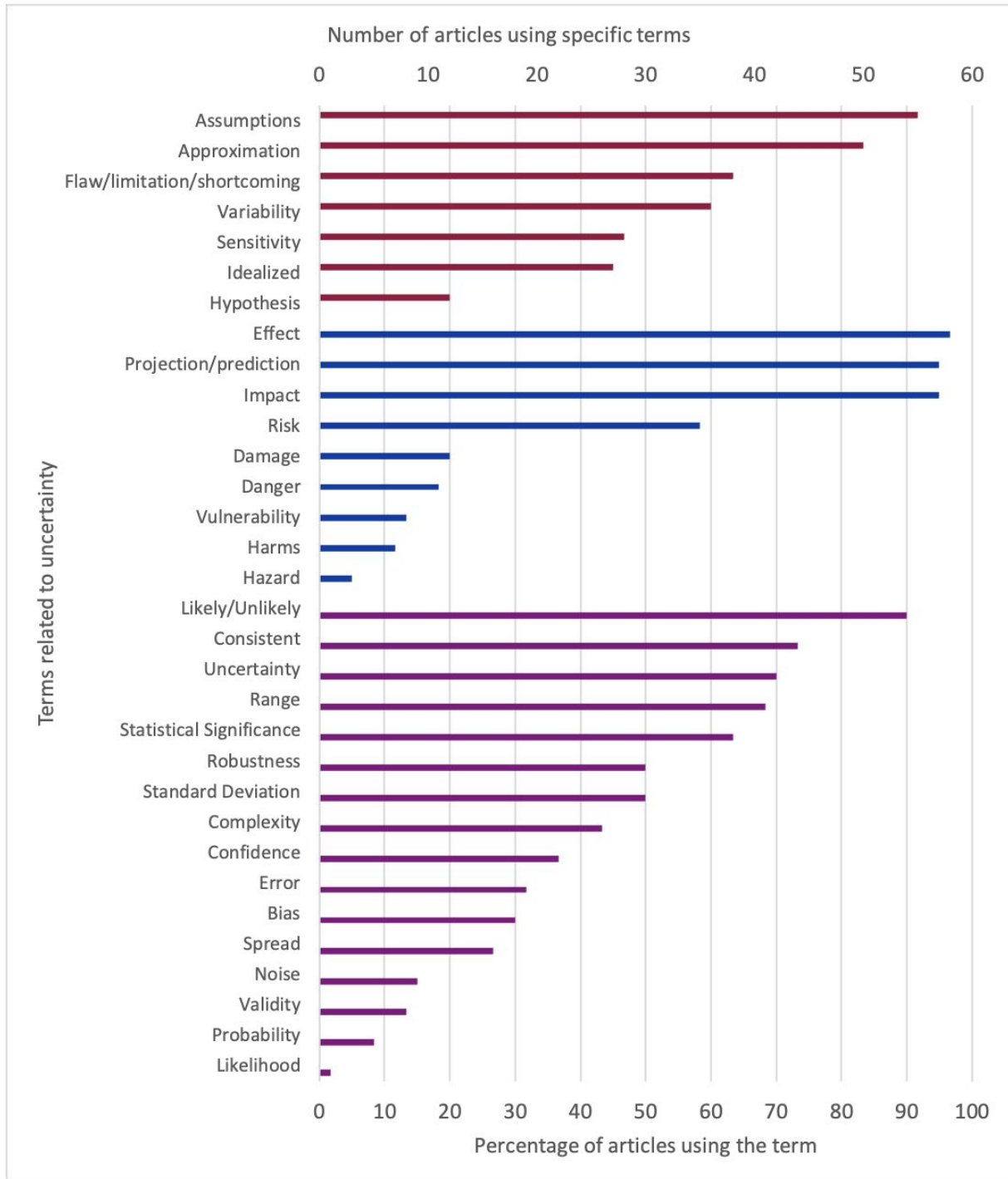


Figure 3 Number (top x-axis) and percentage (bottom x-axis) of articles using the listed terms related to uncertainty. The terms are grouped in three categories: Methodology (red, top group), effects (blue, middle group) and uncertainty metrics (violet, bottom group).

The first category on methodology (red bars in Figure 3) is also related to the above discussion on model confidence, as terms such as “assumptions”, “approximation” and “hypothesis” are found in this category. The results show (blue bars in Figure 3) that nearly all of the articles refer to effects and impacts of SRM, more than half mention risks, and more detailed terms such as damage and harm were used in 10-20 % of the articles. Statements about the effects of

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3 SRM could be expected to be accompanied by, for example, an estimation of the probability of
4 such effects taking place or the uncertainties related to the impacts and risks (violet bars). In
5 what follows, we analyse the way the articles use the notions related to uncertainty to back up
6 statements on the effects of SRM.
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10 The adverbs “likely” and “unlikely” were used in a qualitative manner in the great majority (54)
11 of the reviewed articles. First, they were used to express authors’ confidence in the results of
12 the projections (examples: “In particular, it is likely that ice loss will be greater than predicted
13 by the icesheet model, resulting in a higher level of SRM geoengineering needed to avert a
14 given sea-level rise” [79]; “hence the main conclusions reached in this study are unlikely to be
15 altered by distributing the aerosols within the stratosphere” [80]). Second, they could also
16 indicate a probable (but not directly demonstrated) explanation for a certain phenomenon
17 showing up in the studied experiments (examples: “Decreasing plant water use due to a decrease
18 in transpiration is likely driving the increase in global soil moisture” [81]; “This is likely due
19 to the following reason” [82]).
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28 The term “Consistent” was used in 44 studies, also with different usages. This term was mainly
29 used (30 articles) to describe how the results agreed with results of other studies in the literature,
30 with (28) or without (2) reference to precise studies. This term was also employed to indicate
31 when there seemed to be an agreement between models on the effects or climate responses that
32 were considered significant (8), sometimes with a defined threshold (e.g. consistency for at
33 least 75% of all models). Another usage of “consistent” was to highlight that projected effects
34 and climate responses were coherent between each other in light of expected relationships
35 between them (10) based on our understanding of physics (e.g. “physically consistent” [75];
36 “consistent with Clausius-Clapeyron relation” [83]).
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45 “(Statistical) significance” (38 articles) and “confidence” (22) were used to describe the
46 statistical significance of the results. Among the 60 reviewed articles, 34 used at least one
47 statistical procedure to test the statistical significance of the results. The procedures included
48 Student’s *t*-test (16), Kolmogorov-Smirnov test (3), Wilcoxon signed-rank test (2), Mann–
49 Whitney U test (1), Kappa statistics (1), and tests not explicitly described in the article. Metrics
50 communicated in relation to the tests were the *p*-value interpreted as the “confidence level” on
51 the statistical significance of the results, e.g. $p \leq 0.05$ interpreted as a confidence level of 95%.
52 Different *p*-values were used: most frequently 0.05, and rarely 0.01 or 0.1. In most of these
53 studies, only the differences that were deemed statistically significant were further analysed
54 and interpreted.
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3 The notion of “robustness” of results is one of the most frequently used terms, being mentioned
4 in half of the reviewed publications (30 articles), and associated with different criteria. The term
5 is commonly used in climate sciences, especially when describing converging lines of evidence,
6 including but not restricted to convergent predictions of a group of more or less independent
7 models, and has sparked a discussion among philosophers of science. A study has reviewed the
8 philosophical literature on types of robustness, in particular related to climate modelling [66].
9 They describe a distinct type of “model robustness” that is not only supported by the converging
10 results of the models sharing a common causal core, but also by the independently and
11 empirically verified parameterizations in these models [66]. In practice, this term was used in
12 various ways in the studied articles. “Robustness” was most commonly used in association with
13 results from multi-model ensembles, when there seemed to be a good agreement on a particular
14 climate response between models (15 articles). This was done either without mention of criteria
15 of “good” agreement, or with explicitly mentioned criteria (e.g. 75% of the models [84], or 10
16 out of 13 models agreeing on the sign of change [85]). This usage of “robustness” was found
17 mainly for results from the GeoMIP project that included up to 13 models, but also in studies
18 using only two models. In contrast, seven studies, particularly those using a single model,
19 mention that further work, with other models, is needed to determine whether the effects
20 produced in their individual study can be considered as “robust”. Another usage of “robustness”
21 to describe results on climate response to SAI scenarios is related to the perceived recurrence
22 of projected climate response in other studies in the literature (7 articles), with or without direct
23 references to particular studies. The use of the term “robust” was also found in association with
24 characteristics of the model (e.g. the model resolution, or the model configuration including
25 aerosol microphysics presented as “realistic” [86]), characteristics of the simulation (e.g. long
26 simulations [87]), and of the initial condition ensemble size. For example, a study may have
27 “robustly” separated signal from internal variability (“noise”), where “robust” is used as
28 synonym to “statistically significant” for differences between projections using control and
29 SRM scenarios (“This experiment thus depicts a strongly forced case of geoengineering with
30 carbon dioxide concentrations at 1139 ppm, providing a robust signal-to-noise ratio relative to
31 internal variability” [84]). Seven studies explicitly mention limitations to the “robustness” of
32 their results for different reasons. These included large uncertainties in the representation of
33 particular processes (e.g. El Niño – Southern oscillation [87]; changes in precipitation patterns
34 [88]), current disagreement among studies in the literature, dependence on the climate
35 sensitivity of the model or on the assumptions of the SRM termination [88], the large
36 disagreement between different models used in the study [89], and the small ensemble size of
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3 a Perturbed Parameter Ensemble [54]. Six studies used complementary terms (conditional,
4 modal verbs) to moderate the statement about the “robustness” of the results (e.g. “is likely to
5 be robust”, “relatively robust”, “could be robust”, “reasonably robust”, “If the results and
6 reasoning described above are robust”). The other studies did not use such complementary
7 terms, but included stronger statements (e.g. “a robust result is”, “is a robust climate response”).
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12 Quantitative “likelihoods” (one article) or “probabilities” (five articles) of the outcomes were
13 rarely produced in these articles, resulting from the numerous uncertainties and the
14 deterministic nature of the projections [70,76,84,88,90].
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20 **4. Discussion**

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22 As we have seen, the SAI modelling literature deploys a variety of uncertainty estimation
23 methods focusing on the different types of modelling uncertainties. When discussing these
24 uncertainties, we need to keep the nature of the uncertainty sources in mind.
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28 **4.1 Model uncertainty**

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30 Around one third (21 articles) of the reviewed articles were using more than one model in order
31 to explore model uncertainty. However, the multi-model spread is an imperfect measure of
32 uncertainty and should not be overinterpreted, as the spread is a biased estimate of the
33 uncertainty because climate models used in these experiments are generally not independent,
34 sharing more or less important similarities and thus, they can have similar biases (same model
35 structure, same unknowns) [91,92]. The spread can also result from individual models lacking
36 sufficient descriptions of the relevant processes. Thus, results of individual models are also
37 important to analyse because they can contribute to identifying sources and locations of model
38 uncertainty. This is particularly important in SAI studies where the models represent some of
39 the relevant processes (e.g. aerosol injection) in a simplified way, leading to difficulties in
40 interpreting the inter-model spread in a meaningful way [36,93,94]. Also, a sufficient multi-
41 model ensemble size depends on the research question [58]. These ensemble sizes are often
42 limited due to practical reasons, such as computational constraints and available human
43 resources, and as a result of the number of models available to the scientists performing these
44 studies. The ensembles are largely opportunistic in nature rather than constructed in a
45 systematic way to sample model uncertainty, although in relatively large multiple model
46 ensembles, such as GeoMIP, the models include different parametrizations [51]. Thus, the
47 strength of the statements on robustness arising from agreement between models depends on
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3 the independence and the diversity of the used models. Furthermore, interpreting equally-
4 weighted multi-model mean as providing more robust projections than individual models relies
5 on the implicit assumption that individual biases of the different models are partially cancelled
6 out in the averaging process. This assumption is an extrapolation of results showing that a multi-
7 model mean generally provides better results for simulation of present-day climate than
8 individual models [46,95]. It may not be always true: for instance, if weaker models are
9 included in the multi-model ensemble, it could also be that the model spread overestimates the
10 actual uncertainty.

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12 Perturbed Physics Ensemble (2 articles) and Sensitivity Analysis (10 articles) were occasionally
13 used in the reviewed articles to explore uncertainty in model parameters or structure. These
14 methods were only used to explore a limited number of parameters and model features, and did
15 so with older generation models, mainly because of computational constraints. Perturbed
16 physics ensemble may gain back some popularity with the advent of automatic (or machine-
17 assisted) model tuning methods. It has been shown [96] how iterative waves of short
18 simulations could be used to train an emulator to predict a range of model performance metrics.
19 The emulator is thus a key element of this "history matching" procedure to explore the
20 parameter space more systematically and select parameter combinations for which the model
21 emerging properties satisfy some set criteria. Perturbed physics ensemble can then be focused
22 on a small set of configurations that are equally plausible rather than on a large and arbitrary
23 sample of the parameter space as it is often currently done. This method could be applied to
24 investigate parametric uncertainties on the climate sensitivity [97] but other types of
25 uncertainties (e.g. those related to stratospheric aerosol processes) could be investigated in a
26 similar way.

27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 **4.2 Natural variability uncertainty**

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46 For the investigation of the natural variability uncertainty, initial condition large ensembles
47 remained rare in the sample (only 6 articles with at least 10 ensemble members). Initial
48 condition ensembles require further computing and storage resources and human time for
49 analysing results. These are necessary when there is insufficient signal-to-noise ratio in a single
50 simulation either because the signal is small or the simulation not long enough (e.g. because it
51 is part of a scenario). A key question, which is rarely addressed, is whether such an ensemble
52 is required or not. Furthermore, it is important to remember that internal variability uncertainty
53 also varies from one model to another and is thus impacted by model uncertainty. Any estimates
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of internal variability uncertainty for a model are therefore biased but nonetheless useful in characterizing different dimensions of uncertainty [98].

4.3 Scenario uncertainty

Although scenario uncertainty was not analysed in this study, we note that implications of the different assumptions made in the design of the SAI scenarios were not systematically discussed in the studied literature. However, these scenarios entail assumptions about the technical feasibility (e.g. ability to deliver a projected intervention, no technical failure), human dimensions of uncertainty (e.g. emission trajectories, social/political acceptability of the interventions, global agreement to proceed to an intervention, no disruption of the intervention) as well as other climate forcings such as volcanic eruptions. The reviewed articles using a modelling approach on SAI mainly aimed at gaining a better understanding of the physical aspects of these deployments. However, the assumptions included in the SAI scenarios also create further uncertainty in the interpretation of the projected outcomes. A community approach for producing a range of plausible SAI scenarios to be systematically used in SAI modelling will be helpful for investigating the uncertainties [36,51,55,56].

4.4 Model confidence

The terms used for communicating the reliability of the used models and the degree of confidence in the projections are important to choose in a way that adequately reflects the scientific basis of the statements.

Different factors contribute to the communication and thus the perception of the degree of confidence in climate projections, resulting in the use of specific adjectives (e.g. robust, consistent, significant) or adverbs (e.g. likely, unlikely). The meaning of these words and notions used to describe the results of climate projections is of high importance and it is not always clear if they are used in a qualitative or quantitative manner (for example, using “likely” with an associated likelihood as is done in the latest IPCC reports, [34]). These words related to the stated degree of confidence can strongly impact the interpretation made of the model projections and thus, the perceived informational value attributed to their results.

A common assumption, not only in the solar geoengineering community but also more generally in climate change research, is that good model performance for observed past and present-day conditions is an indication of the model’s ability to make accurate projections in the future (extrapolation of the model performance). It appears that as the degree of reliability

of commonly used and continuously developed models is implicitly known and acknowledged in the field, many (more than a third) of the reviewed articles did not mention the model performance for present-day or past conditions to justify that the model chosen to perform these particular projections was adequate. This is very probably not dissimilar to what is done in modelling studies on climate change. Despite the implicit knowledge in the field, it would be important to explicitly mention and discuss the adequacy of the models for this particular purpose, as the ability of climate models to provide accurate long-term projections cannot be verified and models are calibrated for present-day conditions. Such a discussion could include explanations about a) the choice of model performance metrics (instances of model fit) used to assess the empirical accuracy of the model for present-day conditions and b) the link between these instances of model fit and the assumptions made on the model quality for projecting scenarios in the future [61,63]. Another element used in justifying the adequacy of a model for this purpose was to state that model configurations included processes that were considered crucial for the quality of the SAI projections (e.g. detailed aerosol chemistry and microphysics). This argument relies on the support from background knowledge about the climate system to strengthen the confidence in the quality of the projections and on the assumption that we have already identified and included all of the processes that could significantly impact results of the climate projections based on SAI scenarios. As a counterexample, most of the current models are missing a detailed treatment of the small-scale physics related to the injection strategy, such as what happens in the plume after the injection, showing that more research and model development is still needed.

5. Conclusion

Recent assessment reports mention a “high” level of uncertainty related to SRM, but do not provide systematic or quantitative estimates of the uncertainties [1,11–13]. The SRM community has called for a more comprehensive investigation of modelling uncertainties (see e.g. [10,36]). As the field is rapidly evolving there is no doubt that these questions will be investigated. A stocktake of the published literature can provide a baseline for future studies and assessments. Our study provides a quantitative assessment of if and how the uncertainties have typically been estimated in the published literature through a systematic literature review using a representative sample of the SAI modelling literature. Our results show that, overall, the identification and quantification of uncertainties greatly varies between studies, but over time, the SAI literature has started paying increasing attention to uncertainty estimation. We also noticed that assumptions made in the interpretation of results are sometimes considered

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3 implicitly known instead of being reported. The reasons for the varying methods of reporting
4 uncertainties and assumptions are probably related to, for example, the computational cost
5 associated with uncertainty quantification, the preliminary and exploratory character of some
6 studies, and implicit knowledge in the community on the adequacy and validity of the models
7 and protocols being used. These elements are important factors to back up statements on the
8 confidence in modelling results and thus in the ability to estimate potential impacts of SAI
9 interventions. Our study is by no means an exhaustive review and needs to be complemented
10 by others. Moreover, our study does not provide a quantitative assessment of the uncertainties
11 related to SRM: such a full assessment should be accomplished in the future through a wide
12 effort of the whole research community [10,36].

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21 In the growing community, more studies aim to identify the knowledge gaps. This provides a
22 step towards specifically designed projects that will address the uncertainties in a systematic
23 and comprehensive manner, also ensuring that uncertainties will be more systematically
24 estimated in the literature (see e.g. discussion in [36]). This does not mean that every single
25 article needs to have a comprehensive uncertainty treatment, since some topics are still
26 exploratory (such as the physics that takes place in the injection plume) and their uncertainties
27 can be more comprehensively quantified in later work. In addition, other means of reducing the
28 uncertainties should be kept in mind [10,23,24]. Observations of analogous phenomena and
29 their impacts, such as volcanic eruptions or significant changes in tropospheric particle mass
30 (e.g. air pollution measures or reduction of particle emissions by marine transport), can also
31 provide a means to reduce the uncertainties. Better estimates of uncertainties can be acquired
32 with targeted small-scale or laboratory experiments of relevant processes, such as
33 microphysical processes related to aerosol-cloud interactions and the ensuing radiative impact
34 at local scale, or impacts of different materials on atmospheric chemistry. However, such small-
35 scale experiments will not address the question of uncertainties in global scale climate response
36 to solar geoengineering. Moreover, there is no consensus on whether such experiments,
37 specifically targeting solar geoengineering goals, should be performed [99].

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51 Beyond the production of scientific knowledge, in future meta-analyses and assessments,
52 including a discussion on model confidence and establishing a common framework similar to
53 the IPCC guidelines on communication of uncertainties will be of great added value, especially
54 if and when SAI modelling results are to be used in the political arena.

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Other types of uncertainties that are somewhat outside the scope of purely climate modelling studies of SRM should not be downplayed. For instance, to avoid any problems related to rapid

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3 temperature changes caused sudden discontinuation of SRM ('termination shock', [100,101]),
4 a resilient SRM infrastructure would be needed for effective global deployment [100]. This
5 could be achieved with a commitment through, for example, international agreements to
6 oversee SRM in the long run and at the planetary scale. Not only scientific but also geopolitical
7 and political uncertainties, such as the emergence of a coalition supporting a non-use
8 agreement, have thus to be evaluated when considering SRM [99,102,103]. These issues are
9 also intertwined with the important ethical questions that are raised by SRM [104]. It is of
10 course not expected that all studies address all types of uncertainties. How to combine such
11 uncertainties from a range of studies is thus an important topic for future research and
12 assessments.
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23 **Acknowledgements**

24 We are grateful for financial support from the Institut de la transition environnementale de
25 l'Alliance Sorbonne Université (SU-ITE).
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28 **Data availability statement**

29 The data underlying this article are available in the article and in its online supplementary
30 material. The article database is provided as a Supplementary File (Excel format).
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