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1. Extended Data

Figure #	Figure title One sentence only	Filename This should be the name the file is saved as when it is uploaded to our system. Please include the file extension. i.e.: *Smith_ED_Fig1.jpg*	Figure Legend If you are citing a reference for the first time in these legends, please include all new references in the main text Methods References section, and carry on the numbering from the main References section of the paper. If your paper does not have a Methods section, include all new references at the end of the main Reference list.
Extended Data Fig. 1	The effect of aerosol forcing uncertainty on future temperature projections under high ambition scenarios	Figure_S1.pdf	a) The 90% confidence range in global mean surface temperature change depicted in (b) as a function of ERF_{aer} uncertainty and mean ERF_{aer} sampled as described in the methods. b) The global surface mean temperature change relative to 1850 under SSP1-1.9 and sampled from an ensemble of simulations[24] consistent with historical temperatures (1850–2019), ocean heat content change (1971–2018) and CO_2 concentration (1750–2014) assuming three different reduced uncertainty ERF_{aer} estimates: weak (blue); medium (green) and strong (red). The 90% confidence range for each subset at the end of the century is indicated to the right of the axis. Observed surface temperatures averaged across four available datasets are shown in black. The underlying heatmap shows the average ERF_{aer} of the ensemble members that produce a given temperature change each year where the ensemble density is greater than 10%. The colormap is

			centred around the median ERF_{aer} in the ensemble and ranges between the 10th-90th percentiles.
Extended Data Fig. 2	The effect of equilibrium climate sensitivity uncertainty on future temperature projections	Figure_S2.pdf	a) The 90% confidence range in global mean surface temperature change depicted in (b) as a function of ECS uncertainty and mean ECS sampled as described in the methods. b) The global surface mean temperature change relative to 1850 under SSP1-2.6 and sampled from an ensemble of simulations[24] consistent with historical temperatures (1850–2019), ocean heat content change (1971–2018) and CO_2 concentration (1750–2014) assuming three different reduced ECS uncertainty estimates: low(blue); medium (green) and high (red). The 90% confidence range for each subset at the end of the century is indicated to the right of the axis. Observed surface temperatures averaged across four available datasets are shown in black. The underlying heatmap shows the average ECS of the ensemble members that produce a given temperature change each year where the ensemble density is greater than 10%. The colormap is centred around the median ECS in the ensemble and ranges between the 10th-90th percentiles.

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Large uncertainty in future warming due to aerosol forcing

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Abstract. Despite a concerted research effort and extensive observational record, uncertainty in climate sensitivity and aerosol forcing, the two largest contributions to future warming uncertainty, remains large. Here we highlight the stark disparity that different aerosol forcing can imply for future warming projections: Paris Agreement compatible scenarios can either easily meet the specified warming limits, or risk missing them completely using plausible samples from the IPCC AR6 assessed uncertainty ranges.

Reducing uncertainty in the response of the climate system could result in trillions of dollars of economic benefits[1] and lead to better mitigation and adaptation planning[2]. However, despite huge amounts of progress in recent years[3,4], the equilibrium climate sensitivity (ECS; the long-term warming expected in response to an instantaneous doubling of atmospheric CO_2 concentrations) and the present-day aerosol effective radiative forcing (ERF_{aer}) still exhibit large uncertainty[5], being recently assessed as very likely (90% probability ranges) to be 2–5°C and –2.0 to –0.6 W m^{-2} (2005–2014 relative to 1750) respectively. ECS and ERF_{aer} are the two factors contributing most to the uncertainty in future warming[6] and while physical mechanisms have been proposed that could link them[7,8] they are often assumed to be independent. Nevertheless, because they have both affected historical temperatures[9], conditioning on observed temperatures necessarily introduces a correlation between them. Therefore, reducing the uncertainty in either ECS or ERF_{aer} would allow us to produce more precise projections of future climate for a given emissions scenario.

ECS is not an observable quantity. Despite recent improvements in estimates of ECS[3] (which are accounted for here) from emergent constraints, palaeo records, the instrumental record, and process understanding, different lines of evidence for ECS do not show a high level of agreement[5]. ERF_{aer} on the other hand can be inferred from the large regional emissions changes over the last few decades[10]; and approaches for reducing uncertainty in model estimates are starting to bear fruit[11,12]. We therefore focus on the implications of potential reductions in ERF_{aer} uncertainty and show that doing so would be at least as effective as reducing uncertainty in ECS for improving confidence in future climate change projections over the near-term.

The possibility of a strong ERF_{aer} masking a high climate sensitivity has long been known[15], but since aerosols contribute a diminishing proportion of anthropogenic forcing under high greenhouse gas scenarios they are sometimes viewed as being irrelevant for determining future warming[13]. Under more ambitious mitigation scenarios however, large ERF_{aer} reductions can contribute a significant fraction of warming[14] and air quality policies will play an important role in meeting the Paris agreement. The contribution of ERF_{aer} uncertainty to uncertainty in the year of crossing 1.5°C of warming has recently been demonstrated to be significant[16], but this work relied on a single climate model, only used a very simple approximation of the relationship between ECS and ERF_{aer} and was unable to explore the high-ambition scenarios that are increasingly relevant for policy discussions. The role of aerosol forcing uncertainty on future warming uncertainty, particularly given our improved process understanding and the longer temperature records that are now available[4], has not been robustly quantified.

Here we determine the consequences for future warming uncertainty in two climate mitigation scenarios (SSP1-1.9 and SSP1-2.6, designed to be 1.5°C and 2°C consistent scenarios, respectively[17]) if the uncertainty in $\mathrm{ERF}_{\mathrm{aer}}$ were to be substantially reduced. Starting with an ensemble of constrained climate projections used in the IPCC's Sixth Assessment Report[5], we sub-sample regions of the ensemble that fall into different forcing ranges and highlight three particular ranges reflecting strong (-1.5 ± 0.1 W m^{-2}), moderate (-1.0 ± 0.1 W m^{-2}) and weak (-0.5 ± 0.1 W m^{-2}) $\mathrm{ERF}_{\mathrm{aer}}$ (all ranges expressed as 1-σ and forcing quantities defined for 2005–2014 relative to 1750). We therefore explore the implications of using some of the approaches outlined above to achieve an ambitious increase in the 1-σ precision of $\mathrm{ERF}_{\mathrm{aer}}$ from ±0.3 to ±0.1 W m^{-2}. Secondarily, we also investigate the same projections but subsampling for ECS ranges that are approximately from the lower (10th percentile), central (50th percentile), and upper (90th percentile) of the ECS distribution from the original constrained ensemble (2.2°C, 2.95°C and 4.4°C, each with a ±10% 1-σ range).

The role of $\mathrm{ERF}_{\mathrm{aer}}$ uncertainty in future warming uncertainty is explicitly shown in Figure 1a, which clearly shows the improvements that could be achieved through better knowledge of $\mathrm{ERF}_{\mathrm{aer}}$, particularly for lower $\mathrm{ERF}_{\mathrm{aer}}$ as discussed below. The three sub-sampled projections based on the reduced uncertainty indicated by squares in Figure 1a are shown in Figure 1b, which also shows the average $\mathrm{ERF}_{\mathrm{aer}}$ across the ensemble binned into their temperature response in each year. The members exhibiting a strong $\mathrm{ERF}_{\mathrm{aer}}$ show a stronger than average cooling before 2000 and stronger than average warming after 2020, and vice versa. (This highlights the value of using estimates of the 2000-2020 trend in $\mathrm{ERF}_{\mathrm{aer}}$ to constrain future warming[18].) The subset of strong $\mathrm{ERF}_{\mathrm{aer}}$ members results in SSP1-2.6 temperatures just remaining under 2°C with 50% probability (it would be a "Higher 2°C" scenario in the IPCC's Special Report[19]), whereas the weak $\mathrm{ERF}_{\mathrm{aer}}$ results in the same socio-economic scenario remaining under 1.5°C with >50% probability (a "Below 1.5°C" scenario). Such large differences undermine adaptation and mitigation efforts: there is a substantial disparity in the climate impacts of 1.5°C and 2°C of warming on heat extremes, tropical coral reefs, water availability and agricultural yield[20]. Similarly large differences are found for SSP1-1.9 with a 50% chance of returning below 1.0°C by the end of the century under a weak $\mathrm{ERF}_{\mathrm{aer}}$, and >50 % chance of exceeding 1.5°C assuming a strong $\mathrm{ERF}_{\mathrm{aer}}$ (see Extended Data Fig. 1).

While we use representative reductions in $\mathrm{ERF}_{\mathrm{aer}}$ uncertainty to demonstrate the effect of reducing future temperature change uncertainties, it should be noted that a lower (most negative) bound on $\mathrm{ERF}_{\mathrm{aer}}$ would also provide a valuable constraint. Indeed, the recently proposed[21] lower bound of -1.0 Wm^{-2} is included in Figure 1a and would reduce the upper (90% confidence) estimate or temperature change at the end of the century from 2.2°C to 1.7°C for SSP1-2.6 (although this bound is contested and relied on historical temperature trends which are already accounted for here).

The joint distribution between ECS and $\mathrm{ERF}_{\mathrm{aer}}$ in the full ensemble and the three reduced uncertainty aerosol subsamples is shown in Fig. 2 and clearly shows the source of this behaviour. A stronger present-day $\mathrm{ERF}_{\mathrm{aer}}$ is masking a more sensitive climate in the constrained ensemble, which would imply more warming in the future as clean air legislation continues to reduce aerosol burdens. The distribution is not symmetric though: by ruling out strong $\mathrm{ERF}_{\mathrm{aer}}$ we would be able to rule out high values of ECS, while better quantifying a strong $\mathrm{ERF}_{\mathrm{aer}}$ leaves weaker constraints on ECS and hence leads to larger temperature uncertainties. This is demonstrated by the larger uncertainties in temperature change of the strong aerosol distribution in SSP1-2.6 of Figure 1, and even more so for SSP1-1.9 (Extended Data Fig. 1). The similarly ambitious reductions in uncertainty of ECS described above, although harder to achieve in practice, lead to very similar reductions in uncertainty in future projections (see Extended Data Fig. 2).

Two extensive assessments of ECS[3] and $\mathrm{ERF_{aer}}$[4] were recently published which reviewed the available lines of evidence supporting the various ranges of each quantity independently. Given the close relationship which emerges between the two when applying the best constraint we currently have (the observed temperature record), we would urge closer coordination between the two communities to reduce the joint uncertainty in these quantities which is so important for increasing confidence in future temperature projections. To make the required progress these top-down constraints must be complemented by bottom-up process-based constraints, which have recently been demonstrated in individual models, and novel approaches of combining the two should be explored as a matter of urgency.

As has been recently highlighted[22], separate reporting of emissions of Short-Lived Climate Forcers (SLCFs; such as methane) from long-lived climate forcers (LLCFs; such as nitrous oxide) is key for unambiguous global temperature outcomes. Given the very short lifetime of both black carbon and sulphate aerosol, their non-linear forcing response and importance for future warming we would encourage emissions of these aerosol species to also be reported separately.

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Author contributions: Duncan Watson-Parris: Conceptualization, Formal Analysis, Visualization, Writing – original draft, Writing – reviewing & editing; Christopher J Smith: Formal Analysis, Writing – original draft, Writing – reviewing & editing.

Competing interests: The authors declare no competing interests.

Figure captions:

Figure 1 - The effect of aerosol forcing uncertainty on future temperature projections: a) The 90% confidence range in global mean surface temperature change depicted in (b) as a function of $\mathrm{ERF_{aer}}$ uncertainty and mean $\mathrm{ERF_{aer}}$ sampled as described in the methods. Using a lower bound on $\mathrm{ERF_{aer}}$ of 1 W m^{-2} is denoted with a triangle. b) The surface mean temperature change under SSP1-2.6 assuming three different reduced $\mathrm{ERF_{aer}}$ uncertainty estimates. The 90% confidence range for each subset at the end of the century is indicated to the right of the axis (with the original range indicated in grey). Observed surface temperatures averaged across four available datasets are shown in black. The heatmap shows the mean $\mathrm{ERF_{aer}}$ of the ensemble members for a given temperature change.

Figure 2 – the close relationship between ECS and ERF_{aer}: The joint and marginal densities of ECS and ERF_{aer} in the constrained ensemble (grey). Also shown are the joint and marginal densities of each subsampled ensemble of strong (red), medium (green) and weak ERF_{aer} (blue), each to within ±0.1 W m^{-2}

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Methods

We use a recalibration of the observationally constrained ensemble produced from the FaIR simple climate model (v1.6.2)[23] for the IPCC Sixth Assessment Report Working Group 1 (available from https://github.com/chrisroadmap/ar6). FaIR takes emissions of greenhouse gases and short-lived climate forcers and calculates atmospheric concentrations, radiative forcing and global mean surface temperature through simplified carbon cycle, greenhouse gas and atmospheric chemistry relationships coupled to a two-layer ocean. A simple functional form is used to relate aerosol emissions to direct and indirect aerosol forcing which is nevertheless found to fit a variety of CMIP6 models very well[18]. A 1-million-member Monte Carlo ensemble of climate projections is generated that samples the uncertainty ranges in climate response, carbon cycle and radiative forcing (including aerosol forcing) based on assessed ranges in the IPCC AR6[5] and calibrations to CMIP6 Earth System Models. The resulting ensemble is constrained based on observations of historical global mean surface temperature (1850–2019), ocean heat content change (1971–2018) and CO_2 concentration (1750–2014)[24]. Two differences between this ensemble and AR6 are as follows: first, we relax the strict requirement for ensemble members to match the assessment of future airborne fraction of CO_2 from AR6, leaving 3751 ensemble members that match the observational constraints rather than the 2237-member set in AR6, and second, we switch off solar forcing when re-running these pathways through FaIR to isolate the anthropogenic warming signal.

The resulting 3751-member ensemble is then subsampled around five values for ECS (between 2.2°C and 4.4°C, with a range of uncertainties between ±30% and ±10% 1-σ) and ERF_{aer} in 2005–2014 (between –1.5 and –0.5 W m^{-2}, with a range of uncertainties between ±0.3 W m^{-2} and ±0.1 W m^{-2} 1-σ). A relative uncertainty constraint is used in the case of ECS since it is heavily right-skewed and, since any reduced distribution is likely to retain this feature, feel this is a more appropriate sampling strategy. We highlight the low, mid and high samples at the lowest uncertainty bracket for the projections shown in e.g., Figure 1a. Subsampling is performed using a Gaussian acceptance criterion on the original ensemble. The original 3751-member constrained ensemble has an ERF_{aer} of –1.15 ± 0.33 W m^{-2} for 2005–2014 relative to 1750, which is less negative and with lower uncertainty than the headline assessment in AR6[5] (–1.3 ± 0.43 W m^{-2}). This is due to the documented difficulties in reconciling a strong assessed ERF_{aer} with energy budget (temperature and ocean heat content) constraints and that strong ERF_{aer} is likely to produce too little observed warming[18,4,24]. The energy budget constraints are also likely acting to reduce the spread of estimates around the mean, making exceptionally strong or weak $\mathrm{ERF}_{\mathrm{aer}}$ less likely than would be permitted by observational or model evidence on $\mathrm{ERF}_{\mathrm{aer}}$ alone [4,5].

While FaIR includes a forced pattern effect from ocean warming changes over long timescales, which reproduces CMIP6 model responses, it does not include any unforced pattern effect which may introduce additional (potentially large) uncertainties on future warming unaccounted for here. A full assessment is beyond the scope of this paper, but recent work has suggested a non-negligible, negative (stabilising) pattern effect[25] which would imply either a weak aerosol forcing or low climate sensitivity in order to reproduce observed warming. Even though such a pattern effect would entail additional warming as the Earth system reaches equilibrium, the weak aerosol / low ECS requirement implies the eventual forced response would still be on the lower end of expectations.

The temperature changes shown in Figures 1, Extended Data Fig. 1 and Extended Data Fig. 2 are relative to the observed 1850-1900 mean.

Data availability: The full ensemble and constrained subsets that support the findings of this study are available in zenodo with the DOI: 10.5281/zenodo.7103014[26].

Code availability: The notebooks used to perform analysis and generate all plots in this manuscript are available in zenodo with the DOI: 10.5281/zenodo.7103014[26].

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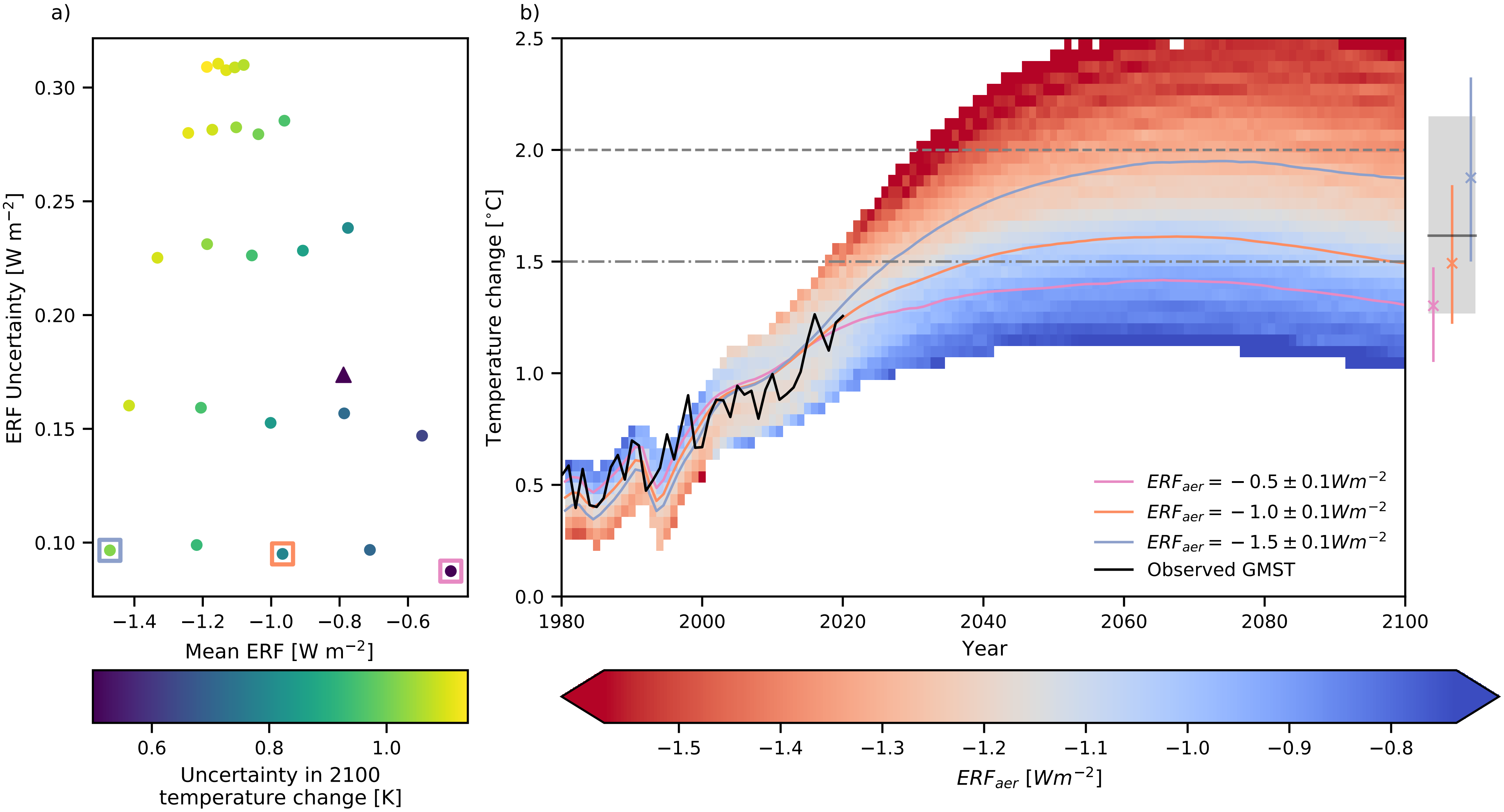
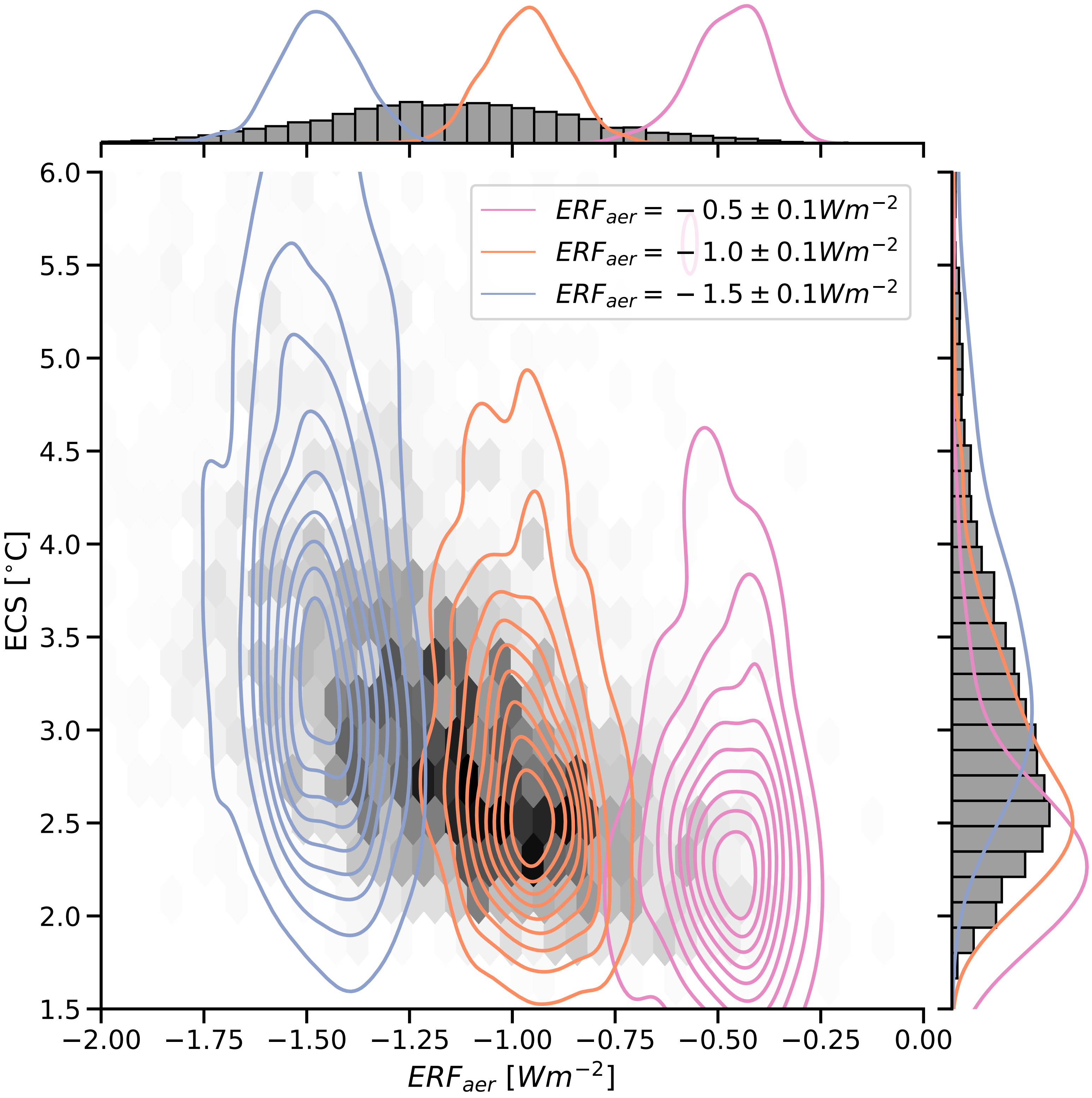
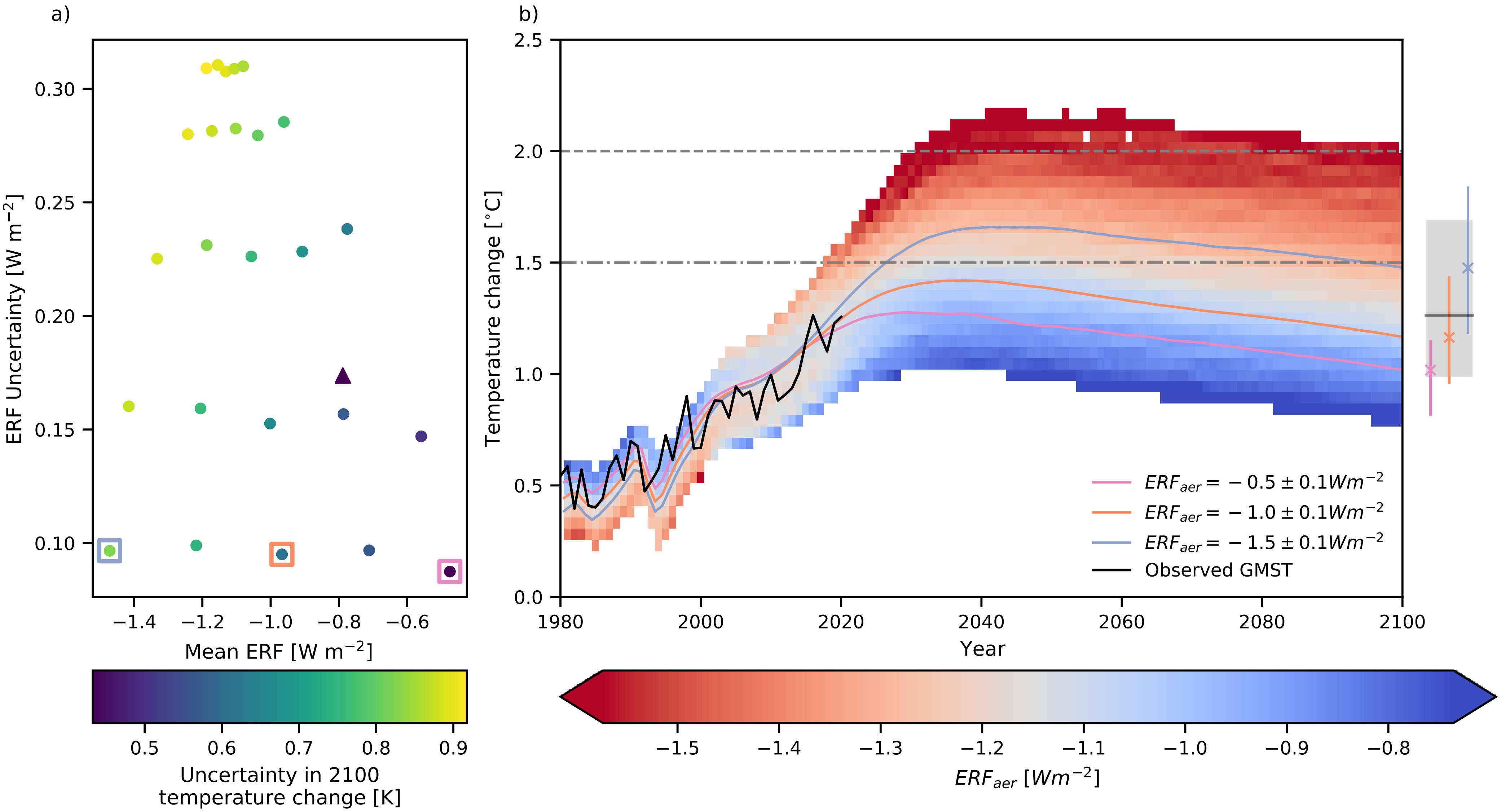
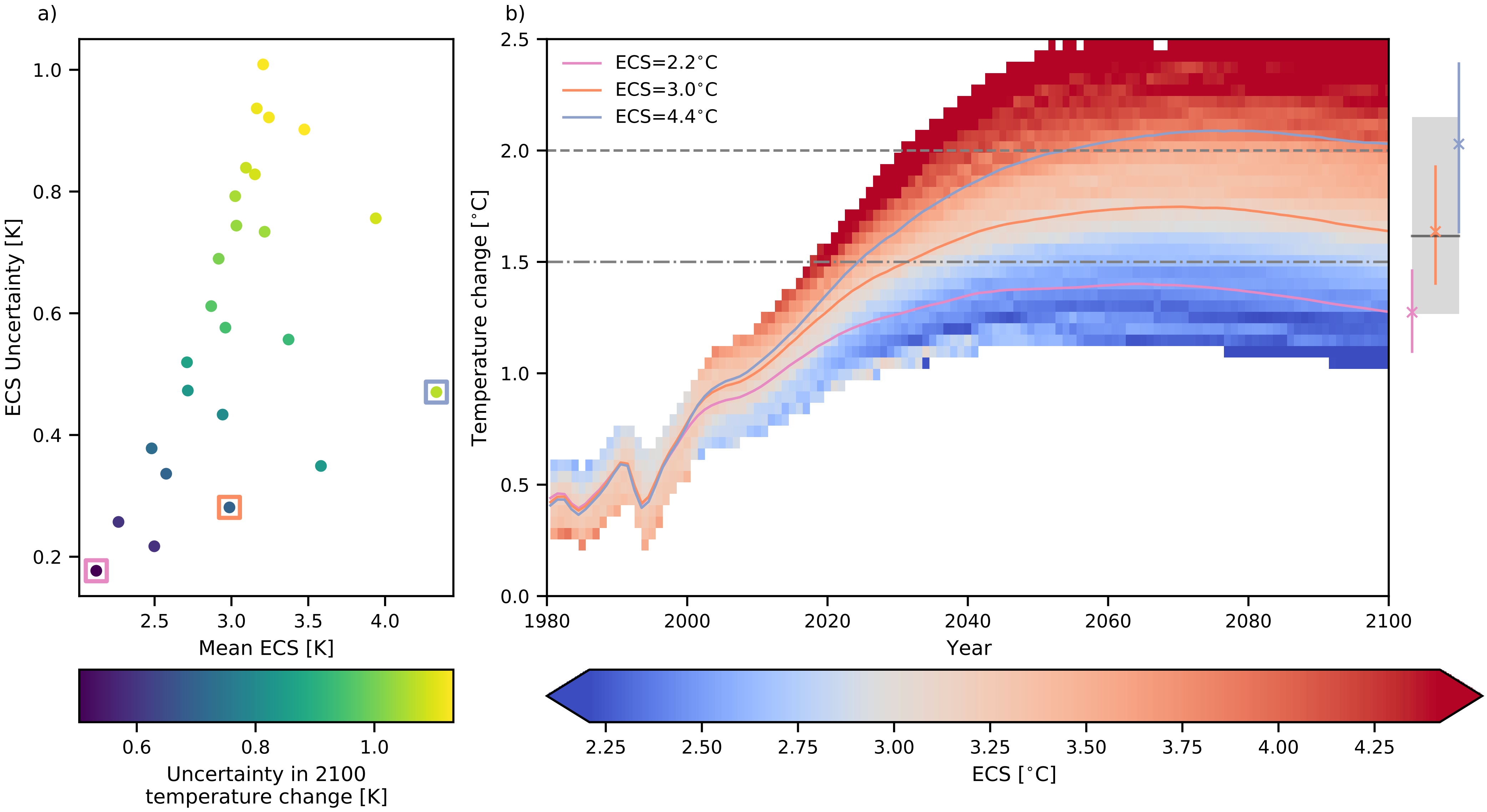

a)
ERF Uncertainty [W m^{-2}]
0.30
0.25
0.20
0.15
0.10
−1.4
−1.2
−1.0
−0.8
−0.6
Mean ERF [W m^{-2}]
0.6
0.8
1.0
Uncertainty in 2100
temperature change [K]
b)
Temperature change [°C]
2.5
2.0
1.5
1.0
0.5
0.0
1980
2000
2020
2040
2060
2080
2100
Year
$ERF_{aer} = -0.5 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.0 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.5 \pm 0.1 Wm^{-2}$
Observed GMST
−1.5
−1.4
−1.3
−1.2
−1.1
−1.0
−0.9
−0.8
ERF_{aer} [Wm^{-2}]


$ERF_{aer} = -0.5 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.0 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.5 \pm 0.1 Wm^{-2}$
ECS [°C]
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
−2.00
−1.75
−1.50
−1.25
−1.00
−0.75
−0.50
−0.25
0.00
ERF_{aer} [Wm^{-2}]


a)
ERF Uncertainty [W m^{-2}]
0.30
0.25
0.20
0.15
0.10
−1.4
−1.2
−1.0
−0.8
−0.6
Mean ERF [W m^{-2}]
0.5
0.6
0.7
0.8
0.9
Uncertainty in 2100 temperature change [K]
b)
Temperature change [°C]
2.5
2.0
1.5
1.0
0.5
0.0
1980
2000
2020
2040
2060
2080
2100
Year
$ERF_{aer} = -0.5 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.0 \pm 0.1 Wm^{-2}$
$ERF_{aer} = -1.5 \pm 0.1 Wm^{-2}$
Observed GMST
−1.5
−1.4
−1.3
−1.2
−1.1
−1.0
−0.9
−0.8
ERF_{aer} $[Wm^{-2}]$


a)
b)
ECS Uncertainty [K]
0.2
0.4
0.6
0.8
1.0
2.5
3.0
3.5
4.0
Mean ECS [K]
0.6
0.8
1.0
Uncertainty in 2100
temperature change [K]
ECS=2.2°C
ECS=3.0°C
ECS=4.4°C
Temperature change [°C]
0.0
0.5
1.0
1.5
2.0
2.5
1980
2000
2020
2040
2060
2080
2100
Year
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
ECS [°C]