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Multidimensional Analysis of Climate Change: Scientific Facts, Impact Assessment, and Response Pathways—A Literature Review Based on Observational Records and Quantitative Models

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Abstract

Human activities are pushing the global climate system towards pronounced change whose principal axis is warming. Organised around the framework "scientific facts—impact assessment—response pathways", this review addresses three progressively nested questions: (1) whether observational indicators drawn from different sources yield warming signals that are consistent in direction and comparable in magnitude; (2) on what chain of evidence and at what confidence level observed changes can be attributed to anthropogenic forcing, and where the respective boundaries of the probability-ratio and attributable-fraction frameworks lie; and (3) whether the responses of ecological, agricultural and economic systems are smooth or exhibit thresholds, and how the location of those thresholds bears upon the trade-off between carbon budgets and adaptation investment. Models were not selected to compete on predictive accuracy; three other criteria were applied instead—parameter transparency, independent reproducibility, and outputs that map directly onto policy variables. Eight simplified quantitative models were accordingly included: the logarithmic parameterisation of radiative forcing, climate sensitivity, probability-ratio attribution, the quadratic sea-level trend, the linear carbon–ice response, the piecewise-linear crop response, the inverted-U macroeconomic response, and the remaining carbon budget. These are used to check orders of magnitude and to locate thresholds, and their respective conditions of application and boundaries of failure are set out explicitly. The main findings are as follows: global surface temperature in 2011–2020 was 1.09 °C above the pre-industrial level (likely range 0.95–1.20 °C); the IPCC assesses human influence on the climate system as "unequivocal"; increases in the probability of extreme-heat events are now detectable; ecological, food and macroeconomic systems exhibit nonlinear and asymmetric responses; and, under the constraint of the remaining carbon budget, global CO_2 emissions must reach net zero around the middle of this century. Two qualifications should be stated at the outset. First, this is a literature review, and all data used are published secondary aggregate data. Second, the eight models derive from independent datasets in different studies and cannot be treated as a like-for-like comparison of accuracy under a common data condition. Because the intervals estimated by different groups for key parameters such as ECS and TCRE overlap, findings are reported as best estimates with intervals, and no ranking of the models is attempted.

Keywords

climate change, global warming, radiative forcing, detection and attribution, impact assessment, carbon budget, mitigation and adaptation, uncertainty

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1. Introduction

1.1 Research Background

Human activities such as fossil-fuel combustion and land-use change have raised the atmospheric concentration of greenhouse gases continuously since the Industrial Revolution. The Working Group I contribution to the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change concludes that "it is unequivocal that human influence has warmed the atmosphere, ocean and land" [1], and that global surface temperature in 2011–2020 was 1.09 °C above the 1850–1900 pre-industrial level (likely range 0.95–1.20 °C) [1]. Climate change has long since spilled beyond the bounds of geophysics to become a compound issue bearing on food security, water security, ecological security, the safety of coastal cities and the architecture of international governance. China itself lies in "a sensitive zone of global climate change and a zone where its impacts are significant", so that the urgency of both disaster prevention and mitigation and green transformation is especially acute [2].

Moving, however, from the climatological fact that "the global mean has warmed by 1.09 °C" to decision problems such as "how much adaptation resource should a given region deploy" or "when should the world reach net zero" requires passing several methodological checkpoints: whether the periods and definitions of observational indicators can legitimately be compared with one another, on what counterfactual specification attribution conclusions rest, whether impact response functions contain thresholds, and whether the intervals reported by different studies support one another. The point of departure of this review is to clarify these links rather than to restate the latest numbers.

1.2 Core Research Questions and Significance of the Study

The following three questions are nested one inside the next and correspond respectively to the three dimensions of the framework; the review is organised around them.

RQ1 (factual layer, comparability). Do the warming signals carried by such heterogeneous observational indicators as temperature, ocean heat content, sea level, ice-sheet mass and sea-ice extent point in the same direction, and are their magnitudes mutually corroborating? To what extent do differences in baseline period, time window and unit convention between studies perturb this judgement?

RQ2 (attribution layer, identifiability). What chain of evidence and what level of confidence are required before long-term change and individual extreme events can be placed on the account of anthropogenic forcing? To which classes of event do the probability ratio (PR) and the fraction of attributable risk (FAR) apply, and where do they break down when the signal-to-noise ratio is too low?

RQ3 (impact and response layer, thresholds and decisions). Are the responses of ecological, agricultural and macroeconomic systems smooth, or do critical thresholds exist? If thresholds do exist, how does their location (about 29 °C for crops, about 13 °C for the macroeconomy) become an operational target for carbon budgets and adaptation investment?

Why these eight models. In screening quantitative tools, this review does not privilege predictive accuracy but three other properties. The first is parameter transparency: every coefficient has a clear physical or economic meaning and can be traced back to the estimate and its uncertainty interval in the original literature. The second is independent reproducibility: a reader can recompute the result from public data without access to proprietary model output. The third is decision relevance: the output of each model corresponds to a variable that can be placed directly on the policy table, such as the remaining carbon budget (Equation (8)), threshold-type damage (Equation (6)) and peak temperature (Equation (7)). By these criteria, tools of higher accuracy but more black-box character—the CMIP6 multi-model ensemble, integrated assessment models (IAMs)—were deliberately excluded. Their strength lies in the completeness of scenario simulation and in spatial resolution, not in transparency of mechanism, and their output can hardly be checked item by item within the compass of a review. What this review undertakes is an "order-of-magnitude check" on key quantities together with an account of mechanism; it does not enter a contest of accuracy between models.

The usefulness of the exercise is broadly threefold. Converting a warming increment into an accountable remaining carbon budget turns the "1.5 °C target" from a slogan into a concrete emission space and a concrete set of sectoral pathways. Locating the thresholds of response functions also grounds the priority ordering of

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adaptation investment: near a threshold the marginal damage per unit of warming is far higher than in stretches remote from it, and resources belong there accordingly. Finally, delimiting the conditions under which the various attribution and extrapolation models apply prevents such errors as applying a global-scale attributable fraction directly to a single event, or extrapolating an acceleration fitted to a twenty-odd-year satellite record all the way to the end of the century.

One thing this review expressly does not do: it does not rank the eight models by predictive accuracy. They come from different studies, different datasets and different spatial and temporal scales, so no common benchmark exists; under such conditions a difference in accuracy could not be attributed to model structure even if it were observed. When this review speaks of "comparison", therefore, it compares mechanisms and conditions of application, not accuracy.

1.3 Methodological Positioning and Limitations of This Review

The methodological positioning of this review can be summarised in three sentences: data are drawn only from published literature, with no new observations and no new numerical experiments; models are screened for transparency of mechanism rather than predictive accuracy; and conclusions are presented as intervals with conditions of application rather than as point estimates. The corresponding limitations should be stated at the outset: the models originate in different studies and lack a common benchmark and evaluation set; some impact estimates do not incorporate full adaptation scenarios; and coverage of the most recent years is constrained by the update cycle of authoritative reports. Sections 4 and 5 return to these points.

1.4 Structure of the Paper

The remainder of the paper is organised as follows. Section 2 sets out the data sources, variable definitions, data-processing rules and model-selection criteria, and specifies the eight quantitative models together with their conditions of application. Section 3 reports the scientific facts and the attribution evidence, compares the boundaries within which different attribution methods apply, and assesses the multidimensional impacts on natural ecosystems and on economic and social systems. Section 4 discusses mitigation pathways and adaptation capacity building under the carbon-budget constraint, together with baseline specification, heterogeneity, robustness and the boundary of validity of the conclusions. Section 5 gives the conclusions and outlook.

2. Materials and Methods

2.1 Data Sources and Their Classification

This paper is a literature review. All data used are published secondary aggregate data; no original observational sample was collected, and no model training or out-of-sample prediction is involved. The sources fall into four classes, which differ in evidential strength and in how they are used, as detailed in Table 1.

Table 1: Stratification of data sources, time coverage and mode of use in this review.

Source type	Specific source	Time coverage	Spatial scale	Main use	Evidential strength and limitations
International assessment reports	IPCC AR6 WGI (2021), WGII (2022), Special Report on Global Warming of 1.5 °C (2018)	1850s–2020s	Global/regional	Backbone findings and parameter ranges for facts and attribution	Highest strength; subject to multiple rounds of government and expert review. Limitation: long update cycle, insufficient coverage of the most recent years
National authoritative institutional reports	China Meteorological Administration, Blue Book on	1901–2022	China and its coast	Regional observational facts; Chinese	High strength; official operational-observation definitions.

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Source type	Specific source	Time coverage	Spatial scale	Main use	Evidential strength and limitations
	Climate Change in China (2023)			policy and targets	Limitation: raw station data not fully public, independent verification difficult
Peer-reviewed primary studies	Primary literature in Nature, Science, PNAS and similar venues	1950s–2020s	Global/national/county level	Parameters and mechanism identification for response functions	Medium-high strength; methods public. Limitation: single-study findings requiring cross-study verification
Annual accounting datasets	Global Carbon Budget 2022	1960–2022	Global/major emitters	Accounting of emissions, sinks and carbon budgets	High strength; updated annually with transparent methods. Limitation: large uncertainty in land-use emissions (±2.6 $GtCO_2\ yr^{-1}$)

Note: evidential strength is a relative judgement made in this review on the basis of verifiability and level of review; it is not a generic scale. Because the present version follows the section order of the target journal, tables are numbered sequentially in order of appearance rather than according to the numbering used in the earlier draft of this manuscript.

2.2 Definitions of Key Variables

Mixing definitions readily produces erroneous conclusions, so the following conventions are applied uniformly. The global mean surface temperature anomaly refers to the deviation from the 1850–1900 baseline period, with land and ocean weighted separately rather than averaged arithmetically. Ocean heat content is restricted to the 0–2000 m layer integral. For sea-level change, satellite altimeter series (from 1993) are preferred; long-term reconstruction series are flagged separately. Arctic sea-ice extent is taken as the September monthly mean, that is, the annual minimum month, which is most sensitive to warming. Effective radiative forcing (ERF) is the net radiative perturbation relative to 1750 after allowing stratospheric and tropospheric rapid adjustments, and is distinguished from instantaneous forcing in which sea-surface temperature alone is held fixed. Equilibrium climate sensitivity (ECS) is the warming realised once the climate system has reached equilibrium after a doubling of CO_2; the transient climate response (TCR) and the transient response to cumulative carbon emissions (TCRE) are flagged separately. The fraction of attributable risk (FAR) is the excess probability share of an event in the "world with human influence". Carbon budgets are always given in $GtCO_2$, with the carbon equivalent (GtC) supplied where necessary.

2.3 Harmonization of Units and Baseline Periods

Definitions are where secondary data most easily go wrong, and three rules were fixed. First, carbon and emission-reduction units are unified as $GtCO_2$, using 1 GtC = 3.664 $GtCO_2$; where the original literature used another convention, values are converted and the conversion noted. It was precisely at this checking step that the review found circulating texts giving 2021 global fossil-fuel emissions of 36.3 $GtCO_2$ as "36.3 GtC"—the two differ by a factor of about 3.7—and the text has been corrected accordingly [14]. Second, the baseline period for temperature anomalies is unified as 1850–1900; where a source used another baseline (1961–1990, 1981–2010), the value is not mixed directly into comparisons but is cited only with the baseline period stated. Third, rate-type indicators (warming rate, rate of sea-level rise) must carry the start and end years, since the rate of the same variable over different windows can differ by more than 60% (see Section 4.7).

2.4 Handling of Missing Values and Outliers

Gaps and conflicts in secondary data cannot be resolved by imputation, and the following rules were applied. For missing values, the supplementary tables of the original literature or public datasets were first traced in an

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attempt to fill the gap; where this failed, the indicator was dropped and the reason stated, with no mean or linear imputation, so as not to fabricate values lacking a source. For outliers, the first check was whether a unit error, a baseline error or a typographical error was involved; where an error was confirmed and could be traced and corrected, the corrected value is cited and noted; where it could not be clarified, the original value is retained and flagged in the table rather than silently altered. Where several estimates of the same parameter exist, this review does not combine them by weighting but sets the intervals side by side and judges consistency of evidence by whether the intervals overlap (Section 4.8).

2.5 Note on Training, Validation and Test Set Partitioning

No model training or out-of-sample prediction is involved here, so dataset partitioning does not in principle apply. One point nevertheless needs stating: if later research were to use the response functions reviewed here (Equations (6) and (7)) for prediction, random partitioning must not be used. Climatic and economic time series carry marked autocorrelation and trend components, and random partitioning places test samples adjacent to, or even interleaved with, training samples in time, producing temporal leakage: test error is systematically understated and the model looks better than it is. The correct procedure is a temporal split—for example 1950–2000 for training, 2001–2010 for validation and post-2011 for testing—with the test set falling entirely after the training set. To make fuller use of the sample, a rolling-origin (walk-forward) scheme can be used instead: at each origin the model is refitted on all preceding history, the next period is predicted, and errors are aggregated across origins. The same constraint applies to cross-validation: standard k-fold cross-validation is invalid for time series and must be replaced by blocked cross-validation or a rolling scheme that holds out h steps ahead.

2.6 Model Selection Criteria and Specification of the Eight Quantitative Models

Eight simplified quantitative models were retained. Their variable relations, parameter values and sources, applicable scales, key assumptions and the circumstances in which they fail or require caution are summarised in Table 2. It should be repeated that the eight models come from different studies, different datasets and different spatial and temporal scales; this review offers no comparison of their predictive accuracy, and the purpose of Table 2 is to delimit conditions of application rather than to rank them.

Table 2: Specification, parameter sources and conditions of application of the eight quantitative models used in this review

No.	Model/equation	Dependent → independent variable	Parameter value and source	Applicable scale	Key assumptions	Circumstances of failure or required caution
Eq. (1)	Logarithmic parameterisation of CO_2 radiative forcing	$F_CO_2 \rightarrow \ln(C/C_0)$	$\alpha \approx 5.35$ W m^{-2} (classical); Etminan et al. revision additionally accounts for shortwave [8]	Global annual mean	Absorption-band saturation; clear-sky column integral; concentration within the fitted range	Extrapolation to high concentrations (>2 × pre-industrial); CH_4 forcing accounting (classical form about 25% low)
Eq. (2)	Linear warming–forcing relation	$\Delta T_eq \rightarrow \Delta F$	λ is the climate feedback parameter; ECS = $\lambda^{-1} \cdot \Delta F_{2x}$, AR6 best estimate 3.0 °C [1]	Global equilibrium	Feedback strength time-invariant; system has reached equilibrium	Transient conditions (equilibrium not reached); TCR/TCRE should be used instead
Eq. (3)	Probability ratio and fraction of attributable risk	$FAR = 1 - P_0/P_1$	P_0 and P_1 supplied by large model	Single event class/region	The model represents the event	Variables with low signal-to-noise ratio

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No.	Model/equation	Dependent → independent variable	Parameter value and source	Applicable scale	Key assumptions	Circumstances of failure or required caution
			ensembles [10,12]		mechanism correctly; sample sufficient to estimate tail probabilities	(e.g. precipitation); events dominated by local circulation
Eq. (4)	Quadratic sea-level trend	$h(t) = a + bt + ct^2$	$b \approx 3.1$ mm yr^{-1}; $c = 0.084 \pm 0.025$ mm yr^{-2} [5]	Global, 1993–2017	Acceleration constant; series corrected for volcanic and ENSO effects	Extrapolation to 2100; c unstable when the start/end years of the series are changed
Eq. (5)	Linear carbon–ice response	$A_ice(E) = A_0 - \beta E$	$\beta \approx 3 \pm 0.3$ m^2 tCO_2^{-1} [13]	Arctic September sea ice	No threshold, no hysteresis, response time-invariant	Near-ice-free conditions (extent → 0); large noise on interannual scales
Eq. (6)	Piecewise-linear crop response	$\Delta Y = g(GDD) - \gamma \cdot \max(0, T - \tau)$	$\tau \approx 29$ °C (maize), $\gamma > 0$ [20]	US county level, growing season	Additive separability of GDD gain and extreme-heat damage	Well-irrigated regions; CO_2 fertilisation not accounted for; coefficient drift after variety replacement
Eq. (7)	Inverted-U macroeconomic response	$g = \beta_0 + \beta_1 T + \beta_2 T^2$	$\beta_1 > 0$, $\beta_2 < 0$, peak temperature $T^* \approx 13$ °C [22]	National mean annual temperature	Comparability across countries; adaptation held at historical levels	Extrapolation into the future (the climate–economy relation changes over time); sub-national scales
Eq. (8)	Remaining carbon budget	$E_budget \approx T/TCRE$	TCRE 0.45 (0.27–0.63) °C per 1000 $GtCO_2$ [1]	Global cumulative emissions	Warming essentially ceases after net zero; non-CO_2 forcing and Earth-system feedbacks already deducted	Direct back-calculation with T/TCRE is not the same quantity as the AR6 remaining budget; the difference can reach a factor of several

Note: the eight models derive from independent datasets in different studies, with different fitting targets and evaluation methods; this review offers no comparison of their accuracy. All models are treated here as fitted in-sample; values beyond the calibration interval are regarded throughout as scenario projections rather than predictions.

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3. Results

3.1 Observed Facts from the Global Scale to China

On a millennium scale, the warming since the second half of the twentieth century is distinctly anomalous, and this emerges in multiple reconstructions. Mann et al. reconstructed the global temperature field of the past six centuries from proxy records including tree rings, ice cores and corals, and found that multi-year temperatures from the late 1980s and the 1990s already exceeded those of any year since AD 1400, greenhouse gases being consequently identified as the dominant forcing of the twentieth century [3]. Once the instrumental era began, the warming signal strengthened steadily: AR6 notes that each of the last four decades has been successively warmer than any decade since 1850, that global surface temperature in 2011–2020 was 1.09 °C above 1850–1900, and that land warmed (1.59 °C) much faster than the ocean (0.88 °C) [1]. The global surface temperature dataset of the China Meteorological Administration records that the 2022 global mean temperature was 1.13 °C above the pre-industrial level, the sixth highest since 1850, and that 2015–2022 constitute the eight warmest years on record [2]. China's own warming rate exceeds the concurrent global rate: mean surface air temperature over China rose by about 0.16 °C per decade over 1901–2022 and by about 0.26 °C per decade over 1951–2022 [2].

The additional heat does not remain in the atmosphere; the great majority of it enters the ocean and the cryosphere. More than 90% of the net energy gain of the climate system is absorbed by the ocean, and global 0–2000 m ocean heat content has risen at an accelerating rate since the 1990s, setting a new record in 2018 [4]. Sea-level observations show that during the satellite altimeter era of 1993–2017 global mean sea level rose at 3.1 ± 0.3 mm yr^{-1}, with a significant acceleration of 0.084 ± 0.025 mm yr^{-2} detected at the same time [5]. Ice-sheet mass-balance accounting shows cumulative losses from the Greenland ice sheet of 3902 ± 342 Gt over 1992–2018, equivalent to about 10.8 mm of sea-level rise, at a loss rate roughly seven times that of the 1990s [6], and cumulative losses from the Antarctic ice sheet of 2720 ± 1390 Gt over 1992–2017, equivalent to about 7.6 mm [7]. Sea ice responds to warming with particular sensitivity: Arctic September sea-ice extent decreased by about 40% between 1979–1988 and 2010–2019 [1]. China's coast is likewise at the risk frontier: coastal sea level rose at 3.5 mm yr^{-1} over 1980–2022 and at 4.0 mm yr^{-1} over 1993–2022, both above the concurrent global average of 3.4 mm yr^{-1} [2].

Trends in extreme events have also formed a clear statistical signal. Data from the Blue Book on Climate Change in China (2023) show that the frequency of extreme high-temperature events in China increased significantly over 1961–2022, with 3501 station-days recorded in 2022, the highest since 1961, and both the high-temperature and the drought risk indices reaching their highest values since 1961 [2]. The key observational indicators are summarised in Table 3.

These indicators agree in direction but not in evidential strength. Temperature and ocean heat content come from direct instrumental measurement, with long series and broad coverage, and constitute strong evidence. Ice-sheet mass balance must be accounted for by gravimetric satellites and the input–output method, and systematic differences exist between methods: the uncertainty of the Antarctic estimate (±1390 Gt) is markedly larger than that of Greenland (±342 Gt), the root cause being weak constraints on ice-flow velocity and snow accumulation rate [6,7]. Sea-ice extent is retrieved from satellite passive microwave data, and no continuous record exists before 1979, so the "40% reduction" holds strictly only for the satellite era. One further point is easily overlooked: the periods covered by the indicators are not synchronised—1993–2017 for sea level, 1992–2018 for the Greenland ice sheet, 1992–2017 for the Antarctic ice sheet and 1979–2019 for sea ice. Cross-indicator comparison of magnitudes can therefore be read only as "parallel presentation against a common background period", not as a strictly contemporaneous joint estimate.

Table 3: Key observational indicators of the global and Chinese climate systems.

Indicator	Change/rate	Period	Source
Global mean surface temperature	+1.09 °C (0.95–1.20 °C)	2011–2020 relative to 1850–1900	[1]
Land surface temperature	+1.59 °C (1.34–1.83 °C)	as above	[1]
Ocean surface temperature	+0.88 °C (0.68–1.01 °C)	as above	[1]

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Indicator	Change/rate	Period	Source
Global mean temperature in 2022	1.13 °C above pre-industrial (sixth highest since 1850)	2022	[2]
Mean surface air temperature over China	about +0.16 °C per decade (1901–2022); about +0.26 °C per decade (1951–2022)	1901–2022	[2]
Global 0–2000 m ocean heat content	significant and accelerating increase; 2018 the warmest year	1990s–2018	[4]
Global mean sea level	3.1 ± 0.3 mm yr^{-1}; acceleration 0.084 ± 0.025 mm yr^{-2}	1993–2017	[5]
Greenland ice-sheet mass	cumulative loss 3902 ± 342 Gt (about 10.8 mm sea-level equivalent)	1992–2018	[6]
Antarctic ice-sheet mass	cumulative loss 2720 ± 1390 Gt (about 7.6 mm sea-level equivalent)	1992–2017	[7]
Arctic September sea-ice extent	decrease of about 40%	1979–1988 to 2010–2019	[1]
Coastal sea level in China	3.5 mm yr^{-1} (1980–2022); 4.0 mm yr^{-1} (1993–2022), above the global 3.4 mm yr^{-1}	1980–2022	[2]
Extreme high temperature in China	3501 station-days in 2022, the highest since 1961; high-temperature and drought risk indices highest since 1961	1961–2022	[2]

Note: "+" denotes an increment relative to the baseline period; data are taken from the original tables or abstracts of the cited sources. The periods covered by the indicators are not synchronised, and this should be borne in mind in cross-indicator comparison.

3.2 Radiative Forcing and Climate Sensitivity

The physical quantity actually driving the warming is radiative forcing. In 2019 atmospheric concentrations of CO_2, CH_4 and N_2O reached 410 ppm, 1866 ppb and 332 ppb, about 47%, 156% and 23% above pre-industrial levels [1]. Because the absorption bands of CO_2 saturate, its radiative forcing is approximately proportional to the logarithm of concentration rather than to concentration itself; spectral integration yields the following simplified parameterisation:

$$F_CO_2 \approx \alpha \cdot \ln(C/C_0),\ \alpha \approx 5.35\ \mathrm{W\ m^{-2}} \quad (1)$$

where C is the current concentration and C_0 the reference concentration. Equation (1) gives the radiative forcing increment for a doubling of CO_2 as $\Delta F_{2x} = \alpha \cdot \ln 2 \approx 3.7\ \mathrm{W\ m^{-2}}$. Here a problem arises: the classical form underestimates the absorption contribution of CO_2 in the shortwave band. Etminan et al. re-parameterised the forcing using updated absorption cross-sections and found that, once shortwave absorption is included, the estimated radiative forcing of CO_2 increases somewhat and that of CH_4 by about 25%, with CH_4 forcing at 2011 concentrations reaching about 0.61 W m^{-2}, clearly above earlier assessments [8].

Where exactly the two parameterisations differ is worth stating. The classical form (Equation (1)) was fitted by spectral integration in a one-dimensional radiative–convective model; the expression is compact and convenient for hand calculation, but the concentration range of the fit is narrow, and neither the shortwave absorption of CH_4 nor the overlap of the CH_4–N_2O absorption bands is fully accounted for. The updated parameterisation of Etminan et al. used newer absorption cross-sections and treated band overlap explicitly, yielding CH_4 forcing about 25% higher than earlier assessments [8]. The boundary of applicability is roughly as follows: where CO_2 concentration does not exceed twice the present value and longwave effects dominate, the difference between the two remains within assessment accuracy; once extrapolation to high-concentration scenarios is attempted, or fine accounting of the climate benefit of CH_4 mitigation is required—CH_4 being a short-lived climate pollutant, so that accounting of the benefit of mitigation commitments depends heavily on the accuracy of the forcing parameterisation—the bias of the classical form can no longer be neglected. A more general limitation follows: any empirical parameterisation is reliable only within its own fitting interval, and extrapolation beyond it must be separately validated.

Close to equilibrium, global mean surface warming is approximately linear in radiative forcing:

$$\Delta T_eq = \lambda \cdot \Delta F\ (\lambda \text{ is the climate feedback parameter}) \quad (2)$$

The reciprocal of λ in Equation (2) is conceptually equivalent to climate sensitivity: taking the forcing of a CO_2 doubling as the yardstick, equilibrium climate sensitivity (ECS) is defined precisely as the warming realised after CO_2 concentration has doubled and the climate system has returned to equilibrium. ECS is shaped

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jointly by water-vapour, cloud, ice-albedo and ocean-heat-uptake feedbacks, and is the core parameter for judging long-term warming potential. AR6 gives a likely ECS range of 2.5–4.0 °C with a best estimate of 3.0 °C [1]; Sherwood et al., combining multiple lines of evidence from palaeoclimate, observations and models, estimate a median ECS of about 3.1 °C (66% probability interval 2.6–3.9 °C) [9].

ECS is after all an equilibrium concept, whereas the real climate system is in a transient state and far from equilibrium; for warming over the coming decades to the middle of this century, the transient climate response (TCR) and the transient response to cumulative carbon emissions (TCRE) carry more policy relevance. Using the ECS interval directly as "the warming range for this century" overstates near-term warming, a misuse not uncommon in the citing literature. At the best estimates above, an ECS above 2.5 °C means that even if emissions are cut sharply, the radiative forcing already accumulated will still drive continued warming over multi-decadal scales, so that giving equal weight to mitigation and adaptation is not an empty phrase. Table 4 presents the anthropogenic effective radiative forcing (ERF) of the various drivers in 2019 (relative to 1750), as assessed by AR6 from observations and models.

Table 4: Changes in major greenhouse gas concentrations and anthropogenic effective radiative forcing in 2019 (relative to 1750).

Driver	Concentration in 1750	Concentration in 2019	ERF (W m^{-2})	Source
CO_2	about 278 ppm	410 ppm	+2.16 (1.90–2.41)	[1]
CH_4	about 729 ppb	1866 ppb	+0.54 (0.46–0.62)	[1]
N_2O	about 270 ppb	332 ppb	+0.21 (0.16–0.26)	[1]
Halogenated compounds	near zero	—	+0.41 (0.33–0.49)	[1]
Anthropogenic aerosol (net effect)	—	—	−1.1 (−1.7 to −0.4)	[1]
Total anthropogenic forcing	—	—	+2.72 (1.96–3.48)	[1]

Note: 2019 concentrations are taken from IPCC AR6 (CO_2 410 ppm, CH_4 1866 ppb, N_2O 332 ppb) [1]; the updated parameterisation of Etminan et al. indicates that some longwave estimates are low [8]. For comparison, equilibrium climate sensitivity: AR6 best estimate 3.0 °C (likely range 2.5–4.0 °C) [1]; multi-line-of-evidence median 3.1 °C (66% interval 2.6–3.9 °C) [9]. The aerosol cooling term (−1.7 to −0.4) is the single largest source of uncertainty in total forcing.

3.3 Detection and Attribution: From Statistical Signals to Event Probabilities

Moving from "has warming occurred" to "why has it warmed, and to whose account should an extreme event be placed" depends on the methodological bridge of detection and attribution. It proceeds along two lines: one tests statistically whether a characteristic "fingerprint" corresponding to external forcing (greenhouse gases in particular) can be identified in observed change; the other uses climate models to construct two worlds, "with" and "without" anthropogenic forcing, and compares the probability of the same event in each. AR6 assesses that the globally averaged warming caused by human influence over 1850–1900 to 2010–2019 is likely in the range 0.8–1.3 °C (best estimate 1.07 °C), that greenhouse gases contributed 1.0–2.0 °C of warming, that anthropogenic aerosols and other agents produced about 0.0–0.8 °C of masking cooling, and that the contributions of natural forcing and internal variability both fall within ±0.2 °C [1].

At the level of event attribution, the analysis by Stott et al. of the 2003 European heatwave counts as a landmark: model simulations showed that anthropogenic warming at least doubled the risk of such a heatwave (confidence level > 90%) [10]. Hansen et al. used the metaphor of "loading the climate dice" to show that the whole distribution is shifting rightwards—relative to the 1951–1980 baseline, hot anomalies exceeding three standard deviations (3σ) covered less than 1% of land area, whereas by about 2006–2011 this fraction typically reached about 10% [11]. The global analysis of Fischer and Knutti further supplies quantitative shares: against a realised warming of about 0.85 °C, roughly 75% of extreme high-temperature events and roughly 18% of extreme precipitation events globally can be attributed to human influence [12]. These shares fit into a rather compact probabilistic framework: letting P_1 be the probability of the event in the "world with human influence" and P_0 the probability in the "world without",

$$\text{Probability ratio } PR = P_1/P_0;\ \text{Fraction of attributable risk } FAR = 1 - P_0/P_1 \quad (3)$$

When $P_1 \gg P_0$, FAR approaches 1, meaning that such an event would be almost impossible in a "world without warming".

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The three classes of attribution method each have their own boundary of applicability and deserve to be compared side by side. The "fingerprint" method (optimal fingerprint regression) regresses the observed field on response patterns simulated by multiple models as basis functions, and suits long-term, large-scale trend attribution; its strength is that it can separate greenhouse gas, aerosol and natural forcings simultaneously, while its weakness is dependence on the models' rendering of the spatial structure of the response pattern and considerable sensitivity to the estimate of internal variability [1]. Event attribution (the FAR framework) uses large model ensembles of the "with/without anthropogenic forcing" worlds to compare the probability of a specific event, and applies to meteorological extremes; intuitive outputs (PR, FAR) usable directly in risk communication are its advantage, while dependence on the model's ability to simulate that event class and the need for ensembles large enough to support tail-probability estimation are its soft spots [10,12]. The distribution-shift method ("climate dice") does not target a single event but characterises the shift and broadening of the whole distribution; its robustness is good and its dependence on model detail low, at the cost of being unable to answer "was this particular event caused by climate change" [11].

All three share one soft spot: each depends on the unobservable counterfactual of a "world without anthropogenic forcing", so their credibility rests more on the models themselves than on the statistical method. The difference in signal-to-noise ratio provides directly observable evidence: against the same warming of 0.85 °C, the attributable fraction is about 75% for extreme heat but only about 18% for extreme precipitation [12]. This gap should not be read simply as "human influence on precipitation is small"; the more reasonable explanation is that precipitation variability is large and internal noise strong, so that the same forcing signal is far harder to detect in precipitation than in temperature. The strength of an attribution conclusion thus depends on the signal-to-noise ratio of the variable and not only on the actual size of the anthropogenic forcing. The attribution results are summarised in Table 5. It should also be noted that event-attribution conclusions depend on the model's ability to represent local circulation, soil moisture and related processes, so that attribution of a single event remains uncertain, which is why the IPCC expresses its assessment findings in "confidence language" [1].

Table 5: Representative quantitative results of detection and attribution of climate change.

Object/event	Key finding	Method	Source
Global surface temperature (1850–1900 to 2010–2019)	anthropogenic warming 0.8–1.3 °C (best estimate 1.07 °C); greenhouse gases 1.0–2.0 °C, aerosol cooling 0.0–0.8 °C	multi-model attribution	[1]
European heatwave of 2003	anthropogenic warming at least doubled the risk of occurrence (confidence > 90%)	event attribution	[10]
Extreme summer heat (> 3σ)	covered area rose from < 1% in 1951–1980 to about 10% in 2006–2011	statistical distribution (climate dice)	[11]
Global temperature and heavy-precipitation extremes	about 75% of high-temperature extremes and about 18% of heavy-precipitation extremes attributable to human influence (0.85 °C background)	probabilistic attribution (FAR)	[12]
Extreme high temperature/climate risk in China	frequency increased significantly over 1961–2022; 3501 station-days of extreme high temperature in 2022; high-temperature and drought risk indices highest	observational statistics	[2]

Note: FAR = 1 − P_0/P_1, the excess probability share of the event in the world with human influence. The difference in attributable share between temperature and precipitation mainly reflects the difference in signal-to-noise ratio rather than a difference in the actual size of anthropogenic forcing.

3.4 Quantitative Relationships Among Sea Level, Sea Ice and the Carbon Cycle

Sea-level rise is not proceeding at a uniform rate. Nerem et al. fitted a quadratic trend to the satellite altimeter series:

$$h(t) = a + b \cdot t + c \cdot t^2,\ dh/dt = b + 2c \cdot t \quad (4)$$

where $b \approx 3.1$ mm yr^{-1} represents the baseline rate and $c = 0.084 \pm 0.025$ mm yr^{-2} is the acceleration. The quadratic term is significantly positive, indicating that sea level is rising at an accelerating rate, the physical reason being that the contribution of ice-sheet and glacier meltwater grows with time [5–7].

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The range of validity of Equation (4) needs emphasis. This quadratic trend is fitted to roughly 25 years of satellite altimetry from 1993–2017; although the acceleration term c is statistically significant, twenty-odd years remains short on the decadal to multi-decadal scales of sea-level change, and the estimate of acceleration is fairly sensitive to the start and end years of the series and to how volcanic and El Niño events are removed. Extrapolating c as a constant to 2100 is therefore not recommended here: a quadratic over an eighty-year span gives results well above those of process-based models and lacks observational constraint. The more defensible statement is that sea-level rise shows an accelerating character over the observation period, and that if the contribution of ice-sheet dynamical processes continues to grow, long-term rise will exceed linear extrapolation, though the magnitude must be supplied by process models and scenarios.

The cryosphere response to cumulative emissions is, by contrast, highly linear. Combining observations with climate models, Notz and Stroeve found a robust linear relationship between Arctic September sea-ice extent and cumulative anthropogenic CO_2 emissions:

$$A_ice(E) = A_0 - \beta \cdot E,\ \beta \approx 3 \pm 0.3\ m^2\ tCO_2^{-1} \quad (5)$$

Equation (5) means that each additional tonne of CO_2 emitted reduces September sea-ice extent by about 3 m^2 on average, with no evident threshold or hysteresis; this "carbon–ice budget" anchors cryospheric loss directly to cumulative emissions and supplies an intuitive Earth-system constraint for setting mitigation targets [13]. It should nevertheless be noted that the linear relationship cannot be extrapolated indefinitely in physical terms: as September sea-ice extent approaches zero the linear relation must truncate, and both observations and models suggest that an accelerated transition may occur near ice-free conditions. The value of this relationship lies in supplying an intuitive constraint, not in predicting precisely when an ice-free year will arrive.

The global account of emissions and sinks is equally clear. The Global Carbon Budget 2022 estimates 2021 global fossil-fuel CO_2 emissions at 36.3 ± 1.8 $GtCO_2$ (about 9.9 ± 0.5 GtC), back to the pre-pandemic level of 2019; mean atmospheric CO_2 concentration was 414.71 ppm in 2021 and was projected to reach 417.2 ppm in 2022, more than 50% above the pre-industrial level of about 278 ppm. Land and ocean sinks absorb more than half of anthropogenic emissions each year (about 56% over the 1960s–2020s), slowing the accumulation of atmospheric CO_2 to some extent at the cost of continuing ocean acidification [1,14]. These budget data form the basis of the carbon-budget analysis in Section 3.8.

One further point deserves mention: during data checking this review noticed that some circulating texts give 2021 global fossil-fuel emissions as "36.3 GtC". According to the Global Carbon Budget 2022, 36.3 $GtCO_2$ corresponds to about 9.9 GtC, and the two units cannot be used interchangeably; this review uses $GtCO_2$ throughout and states the carbon equivalent, so as to keep numerical conventions consistent [14].

3.5 Impacts on Natural Ecosystems

Species responses to climate change carry a globally coherent "fingerprint". In a meta-analysis of more than 1700 species and systems, Parmesan and Yohe found that temperate species' ranges shifted polewards at a mean rate of 6.1 km per decade and that spring phenology advanced by 2.3 days per decade, the direction of change matching closely what would be expected from twentieth-century warming [17]. A systematic review of wildlife studies by Root et al. likewise confirms that spring events (leaf unfolding, flowering, migration, breeding) have advanced significantly in many species, that ranges have moved to higher latitudes and altitudes, and that the magnitude of change correlates with the local rate of warming [18]. In the ocean, the analysis of global coral bleaching by Hughes et al. shows that the recurrence interval of severe bleaching has shortened continuously since the 1980s, falling to a median of about six years by 2016—far shorter than the time coral communities need to recover—so that World Heritage sites such as the Great Barrier Reef face the threat of repeated bleaching [19]. In cryospheric ecosystems, the linear loss of about 3 m^2 of Arctic sea ice per tonne of CO_2 means that the habitat of ice-dependent species shrinks monotonically with cumulative emissions [13]. In China, representative glaciers such as Urumqi River Head Glacier No. 1 in the Tianshan are retreating at an accelerating rate, and the active-layer thickness in permafrost regions along the Qinghai–Tibet Highway thickened by an average of 19.9 cm per decade over 1981–2022, reaching a record 256 cm in 2022 [2]; permafrost degradation in turn alters the hydrology and carbon cycling of alpine meadows.

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These two representative studies are methodologically complementary, and their differences are worth noting. Parmesan and Yohe used meta-analysis, quantitatively aggregating the direction and rate of change across many studies; the advantage is a comparable effect size, while the problem is that the periods, regions and methods of the primary studies are not uniform, so the aggregated rate should be read as an average trend across studies rather than as the expectation for any specific site [17]. Root et al. took the systematic-review route, covering a wider range of species and geography, but aggregating mainly by qualitative direction without a unified effect size, which makes comparison of magnitudes across studies difficult [18]. The two agree in direction and corroborate each other, yet both concentrate on temperate species in North America and Europe, with relatively thin evidence for tropical species and marine invertebrates. This geographic and taxonomic bias means that the claim of a "globally coherent fingerprint" holds at the global scale, but that the evidence base becomes thin once it is applied directly to risk assessment in a particular tropical region. In addition, the shortening of the bleaching interval from several decades to about six years [19] is far shorter than the recovery cycle of the community, indicating an irreversible threshold risk in such systems—categorically different from the "gradual" responses of range shift and phenological advance. These responses are summarised in Table 6.

Table 6: Observed responses of natural ecosystems to climate change.

System/object	Observed response	Rate/magnitude	Source
Temperate species' ranges	poleward range shift	about 6.1 km per decade	[17]
Spring phenology (plants/animals)	advance of leaf unfolding, flowering, breeding	about 2.3 days per decade	[17,18]
Reef-building corals	shortened recurrence interval of severe bleaching (median 6 years in 2016)	from several decades to about 6 years	[19]
Arctic September sea ice	extent declining linearly with cumulative CO_2 emissions	about 3 ± 0.3 m² tCO_2^{-1}	[13]
Glaciers in China (e.g. Urumqi River Head Glacier No. 1)	continuing accelerating ablation and retreat	monitoring reported in successive Blue Books	[2]
Permafrost along the Qinghai–Tibet Highway	significant thickening of the active layer	about 19.9 cm per decade (1981–2022)	[2]

Note: the rate estimates of Parmesan and Yohe are multi-species meta-analytic averages [17]. Meta-analysis and systematic review do not carry the same evidential weight: the former yields an effect size, the latter aggregates mainly by direction, and the two cannot be combined directly.

3.6 Impacts on Agriculture and Food Security

Crop-yield response to temperature is clearly nonlinear. Using US county-level yields and fine-resolution weather data, Schlenker and Roberts found that maize and soybean yields rise with growing-season temperature up to a point, but that a "breakpoint" threshold exists: once daily maximum temperature exceeds about 29 °C (for maize), each additional "extreme heat degree day" brings significant yield loss, and the harm from high temperature far exceeds the benefit from an equal amount of low temperature, giving an overall piecewise-linear (kinked) response function:

$$\Delta Y = g(GDD) - \gamma \cdot \max(0, T - \tau),\ \tau \approx 29\ ^\circ C \text{ for maize},\ \gamma > 0 \quad (6)$$

where GDD is growing degree days (beneficial heat) and T is daily maximum temperature, the part exceeding the threshold τ entering damage through the coefficient γ; this form explains why the average effect of warming on yields often masks the strongly nonlinear damage of extreme heat [20]. At the global scale, Lobell et al. isolated the net effect of climate trends using global crop statistics and climate data for 1980–2008: relative to a no-warming case, global maize production was about 3.8% lower and wheat about 5.5% lower, with rice and soybean less affected [21]. China, situated at low to middle latitudes with irrigation-based agriculture predominant, faces increased heat and water stress in major grain-producing regions such as North China and the Yangtze basin as extreme high-temperature and drought events multiply (the 2022 high-temperature and drought risk index was the highest since 1961 [2]); subsequent assessments will need to couple in mitigating factors such as CO_2 fertilisation, irrigation adaptation and cultivar improvement, so as to avoid over- or underestimating net risk.

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Comparison of the two studies is equally important. Schlenker and Roberts used a US county-level yield panel with high-resolution weather data, absorbing time-invariant county heterogeneity through fixed effects and identifying the piecewise-linear effects of growing degree days and extreme heat; the advantage is relatively clean causal identification and the ability to locate the threshold, while the limitation is that the sample is confined to the United States, so extrapolation to other climate zones and other cultivars and management conditions requires caution [20]. Lobell et al. used national-scale statistics and climate data worldwide, with broad coverage and a direct answer to the global aggregate question, but national aggregation conceals within-country variation, control for cross-country differences in technology and management is weak, and the estimate is closer to correlation than to causation [21]. The magnitudes given by the two do not conflict, but they can be neither added together nor substituted for one another: the former answers "mechanism and threshold", the latter "global aggregate"—the questions posed are simply different.

The two studies also share a common shortcoming: incomplete accounting of CO_2 fertilisation, irrigation adaptation and cultivar improvement. Rising CO_2 concentration has some yield-enhancing effect on C3 crops (wheat, rice, soybean) and a weaker effect on C4 crops (maize); irrigation can substantially relieve heat stress but is constrained by water availability; and cultivar improvement is entangled with technological progress in historical data and hard to separate out. The historical estimates above should therefore be read as "the net effect without full accounting of these mitigating factors": future net risk may lie either below or above this estimate, and the direction is not determined. This too is why the present review refrains from giving a single damage figure in its conclusions.

3.7 Macroeconomic, Health and Conflict Impacts

The temperature response of the macroeconomy is likewise nonlinear, rising first and then falling. Using panel data for 166 countries over 1950–2010, Burke et al. estimate an inverted-U relationship between national economic growth rate and mean annual temperature, with the peak falling at about 13 °C:

$$g = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot T^2 + X'\gamma,\ \beta_1 > 0,\ \beta_2 < 0,\ \text{peak temperature } T^* = -\beta_1/(2\beta_2) \approx 13\ ^\circ\text{C} \quad (7)$$

Equation (7) means that temperatures below the peak favour growth (as in cold high-latitude countries) whereas temperatures above it markedly suppress growth; since most low-income countries lie in hot regions, climate change will widen the North–South gap further. On this basis Burke et al. estimate that, in the absence of significant adaptation and under a high-emission scenario, global per capita income in 2100 could be about 23% lower than in a no-climate-change case [22]. On social conflict, the synthesis of multiple empirical studies by Hsiang et al. indicates that each one-standard-deviation increase in temperature or precipitation anomaly raises interpersonal violence by about 4% and intergroup conflict by about 14% [23], suggesting that climate stress can amplify social instability through food prices, migration and resource competition. For human health, heatwaves directly raise the risk of heat-related illness and excess mortality, and the IPCC WGII assessment lists this as a highly credible health threat [16]; the China Blue Book likewise notes the upward trend in extreme high temperature and in the climate risk index [2].

The conditions of application of these estimates need stating. The strength of Burke et al. is a long sample spanning different income levels; the limitations are threefold: national aggregation conceals large within-country variation, so policy implications are limited; identification relies on year-to-year temperature fluctuations, and the response to short-term fluctuation is not necessarily the same as the response to long-term climate change—short-term fluctuation can be smoothed through saving and inventories, whereas long-term change involves altered capital accumulation and technology choice, and the two cannot simply be interchanged; and adaptation in the model is implicitly held at historical levels, so that if future adaptation investment increases substantially the slope of the damage function may flatten. The estimate that global per capita income in 2100 will be about 23% lower should therefore be read as "a reference upper bound under RCP8.5 with no additional adaptation", not as a central projection [22].

The synthesis by Hsiang et al. on social conflict faces a comparable comparability problem: the primary studies differ substantially in how conflict is defined, in data sources and in spatial units, so the effect sizes of +4% and +14% should be read as order-of-magnitude indications across studies rather than as precise coefficients that can be extrapolated [23]. Moreover, the climate–conflict chain runs through food prices, migration and resource competition, and its strength depends heavily on institutional context, while institutional variables are typically under-controlled in existing empirical designs. It should also be stressed

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that impact assessment is strongly scenario- and adaptation-dependent, and that the estimates above mostly represent "no additional adaptation" reference cases; actual risk depends on the combination of mitigation effort and adaptation investment. These estimates are summarised in Table 7.

Table 7: Key quantitative impact estimates for agriculture, the economy and society.

Object/system	Key quantitative estimate	Period/scenario	Source
US maize/soybean yields	significant loss once daily maximum temperature exceeds about 29 °C (maize); piecewise-linear nonlinearity	historical county-level panel	[20]
Global crop production (four major crops)	climate trends reduced maize by about 3.8% and wheat by about 5.5%	1980–2008	[21]
Global macroeconomy	inverted-U: growth peaks at about 13 °C mean annual temperature; about 23% lower global per capita income in 2100 under a high-emission, no-adaptation scenario	1950–2010 panel; RCP8.5	[22]
Social conflict	per +1σ of temperature/precipitation anomaly: interpersonal violence +4%, intergroup conflict +14%	synthesis of multiple studies	[23]
Agriculture and health in China	high-temperature and drought risk indices highest since 1961 in 2022, threatening food security and population health	1961–2022	[2,16]

Note: most of these estimates do not incorporate full adaptive response and can be regarded as reference upper bounds of the risk interval rather than central projections. The thresholds (29 °C, 13 °C) are region- and sample-dependent, and extrapolation requires caution.

3.8 Carbon Budget Constraints, Current Emissions and Mitigation Targets

Global warming is approximately linear in cumulative CO_2 emissions, and the slope of this line is the "transient climate response to cumulative carbon emissions" (TCRE). AR6 estimates a likely TCRE range of 0.27–0.63 °C per 1000 $GtCO_2$, with a best estimate of about 0.45 °C per 1000 $GtCO_2$ [1]. With it, a warming target can be inverted into a remaining carbon budget:

$$E_budget(T) \approx T/TCRE \text{ (T is the target warming)} \quad (8)$$

Two cautions are needed. Equation (8) is itself a highly simplified expression, and the TCRE fed into it carries a rather wide uncertainty interval. More importantly, the magnitude obtained by direct inversion with T/TCRE is not the same quantity as the "remaining carbon budget" given by AR6: the latter is counted from the beginning of 2020 and further deducts the warming corresponding to historical cumulative emissions, the additional warming from non-CO_2 forcing, continued warming after net zero (ZEC), and Earth-system feedbacks not contained in TCRE (such as permafrost carbon release). The two figures differ by a factor of several, and the difference is precisely the sum of the deductions above. This difference itself shows that carbon-budget values depend heavily on the starting year, the target probability and the treatment of non-CO_2 forcing, and that the convention must be stated when citing them, since otherwise misreadings of an order of magnitude readily arise.

The AR6 assessment (counted from the beginning of 2020) is that the remaining carbon budget for limiting warming to 1.5 °C (about 50% probability) is about 500 $GtCO_2$, and for limiting it to 2 °C (about 67% probability) about 1150 $GtCO_2$ [1]. Against actual emissions—36.3 ± 1.8 $GtCO_2$ of global fossil-fuel emissions in 2021, or about 40 $GtCO_2\ yr^{-1}$ once land-use emissions are included [14]—the 1.5 °C budget covers little more than a decade at current levels, from which the urgency of the net-zero transition is evident. The IPCC Special Report on Global Warming of 1.5 °C states that keeping warming within 1.5 °C requires global CO_2 emissions to reach net zero around 2050, together with deep reductions in non-CO_2 greenhouse gases such as CH_4 [15]. Because the TCRE framework holds on the premise that "global warming essentially ceases after net zero", what determines peak warming is the timing of net zero rather than the detail of the cumulative pathway [1,15].

All eight quantitative models used in this review have now been presented. Table 8 assembles the global carbon budget, current emissions and principal mitigation targets so that the extrapolation boundaries of the various settings become explicit and can be checked item by item.

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Table 8: Global carbon budget, current emissions and principal mitigation targets.

Indicator/target	Value	Time point	Source
Global anthropogenic CO_2 emissions (fossil + land use)	about 40.0 ± 2.9 $GtCO_2$ in 2021 in total (of which fossil 36.3 ± 1.8 $GtCO_2$)	2021	[14]
Atmospheric CO_2 concentration	414.7 ppm (2021); projected 417.2 ppm (2022), more than 50% above pre-industrial	2021–2022	[14]
Remaining carbon budget for 1.5 °C	about 500 $GtCO_2$ (50% probability, counted from 2020)	from 2020	[1]
Remaining carbon budget for 2 °C	about 1150 $GtCO_2$ (67% probability, counted from 2020)	from 2020	[1]
Global CO_2 net zero (1.5 °C pathway)	achieved around 2050	mid-century	[15]
China's carbon peaking	peak CO_2 emissions before 2030	before 2030	[25,26]
China's carbon neutrality	carbon neutrality before 2060	before 2060	[25,26]
China's 2030 nationally determined contribution targets	CO_2 per unit of GDP down by more than 65% from 2005; non-fossil energy share about 25%; wind and solar installed capacity above 1.2 billion kW	2030	[25]
China's fossil-fuel CO_2 emissions (reference)	about 11.4 $GtCO_2$ projected for 2022 (about 3.1 GtC), roughly 30% of the global total	2022	[14]

Note: carbon-budget values change as the starting year and methods are updated, and the convention should be stated when citing them (here, AR6 counted from 2020). The 50% and 67% figures are two different probability conventions and their magnitudes cannot be compared directly.

4. Discussion

4.1 Consensus, Divergence and the Contribution of the Present Review

Looking back over Section 3, existing research has reached consensus on several points: the fact of global warming is well established; anthropogenic forcing is the dominant factor in warming over the past half-century; and the response directions of the atmosphere, ocean and cryosphere agree. Divergences and shortcomings are equally present, however.

First, the intervals of parameter estimates remain too wide. The likely range of ECS spans 2.5–4.0 °C [1], and the 66% interval of the multi-line-of-evidence synthesis is 2.6–3.9 °C [9]; the two intervals overlap heavily, yet neither has narrowed sufficiently to distinguish the consequences of different emission pathways. The likely range of TCRE (0.27–0.63 °C per 1000 $GtCO_2$) spans more than a factor of two, and this uncertainty propagates directly into the estimate of the remaining carbon budget.

Second, there is no unified standard for the relative weighting of different lines of evidence. The ECS estimates given by the palaeoclimate, instrumental and modelling lines of evidence do not agree completely, and AR6 adopts expert-judgement weighting rather than a purely statistical combination [1]; necessary as this treatment is, it also means that the conclusion is sensitive to the composition of the expert group and to how weights are set.

Third, attribution capability at the regional scale is clearly weaker than at the global scale. Temperature attribution at the global scale is already fairly robust, whereas variables such as precipitation and drought are strongly disturbed by internal variability, and the confidence of regional-scale conclusions is generally lower than that of global-scale ones [1].

Fourth, the reliability of extrapolating parameterisations lacks systematic assessment. The logarithmic form of radiative forcing, the quadratic sea-level trend and the linear carbon–ice relation all perform well within their own calibration intervals, but the literature has examined their extrapolation behaviour relatively little.

The present review does not respond to these shortcomings by adding new observations or model experiments. It does three things instead: it tabulates systematically the parameter values, sources, applicable scales and failure conditions of each model (Table 2 in Section 2.6), making the extrapolation boundary explicit;

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it sets estimates from several studies of the same parameter side by side and judges evidential consistency by whether the intervals overlap (Table 9 in Section 4.8); and it distinguishes strictly between "interpolation within the fitting interval" and "scenario projection beyond it", flagging the latter and noting that its uncertainty grows with the time span.

4.2 Mechanistic Interpretation of Response Functions and Their Boundaries of Validity

The impact estimates presented above share one feature: they are nonlinear and asymmetric—the damage from warming far exceeds the benefit from cooling of equal magnitude. Reporting coefficient sizes alone is not enough to understand this; a mechanistic explanation is also required.

Why thresholds appear. The crop threshold (about 29 °C for maize) corresponds to two physiological processes: first, the activity of enzymes associated with photosynthesis falls rapidly once the optimum temperature is exceeded; second, high temperature intensifies transpiration and the vapour-pressure deficit (VPD), leading to stomatal closure and water stress. The crux is that the harm from high temperature concentrates in a very short window of reproductive growth (the tasselling–silking stage); even if the mean temperature over the whole growth period changes little, yield is significantly damaged as soon as this window coincides with extreme heat—which explains why assessments based on growing-season mean temperature systematically underestimate the damage from extreme heat [20]. The macroeconomic peak (about 13 °C) reflects structural factors more than physiological ones: countries with low mean annual temperature are mostly high-latitude developed economies, whereas hot countries are over-represented among low-income groups, with a large weight of agriculture and outdoor labour and low accessibility of air conditioning and other adaptation measures, so that the direct exposure of labour productivity to temperature is more complete [22]. The shortening of the coral bleaching interval belongs to another class of mechanism: it is not smooth marginal damage but a "state switch" occurring once the tolerance window of the symbiotic algae is exceeded, with a recovery period far longer than the disturbance period and hence cumulative and irreversible in character [19].

When the models perform better. The simple models above have greater explanatory power under the following conditions: the variable falls within the historical observational range; the time scale is between annual and decadal; the spatial unit matches that of the original study (a county-level model applied at county level, a national model at national level); and the response mechanism is mainly physiological or physical rather than institutional or behavioural. Conversely, they tend to fail under the following conditions: extrapolation beyond the historical range (Equation (5) near ice-free conditions, Equation (4) extrapolated to 2100); entry of the variable into a nonlinear region (the linear approximation behind Equation (6) failing beyond the threshold); structural change (technological progress, irrigation expansion and cultivar replacement all make the coefficients of Equations (6) and (7) drift over time); and a focus on the tails of the distribution—mean regression characterises the conditional expectation, whereas the risk of extreme events is determined by the tails, so assessing tail risk with a mean model systematically underestimates it.

Why they fail in certain circumstances. One directly testable example is that the attributable fraction for extreme heat (about 75%) is far higher than that for extreme precipitation (about 18%) [12]; this is not because human influence on precipitation is weak, but because the internal variability of precipitation is large and the signal-to-noise ratio low, so that the same forcing increment is detected in precipitation with far lower probability than in temperature. Reading "low attributable share" as "no influence" is a common misreading. Similarly, the quadratic sea-level trend fits the data well over the observation period but loses observational constraint once extrapolated to the end of the century—not because the model has "deteriorated", but because it has never been tested in that range. Again, Equation (6) applies less well in well-irrigated regions, because the model assumes that high temperature acts through water stress whereas irrigation severs that pathway, so that the same temperature increase causes markedly less damage under irrigation than under rain-fed conditions. These examples jointly show that model validity is relative to a particular mechanism, a particular scale and a particular interval, and that asking "which model is better" outside those conditions has no testable meaning.

4.3 Energy Transition and China's "Dual Carbon" Actions

Mitigation turns on two things: decarbonising the energy system and protecting carbon sinks. From the global carbon budget, land-use emissions averaged about 4.5 ± 2.6 $GtCO_2$ yr^{-1} over 2012–2021, of which

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deforestation emissions reached 1.8 ± 0.4 GtC yr^{-1} while afforestation and reforestation offset only about half, so that the mitigation potential of "halting deforestation" is immediately effective [14]; over the same period land and ocean sinks absorbed about 56% of anthropogenic CO_2 emissions each year, making the protection and enhancement of sinks an important low-cost component of mitigation [1,14]. One further phenomenon deserves mention: over 2012–2021, 24 countries reduced fossil-fuel emissions while growing economically, and together they account for about a quarter of global emissions, showing that "decoupling emissions from growth" is practically feasible [14].

China has embedded climate response deeply in its national development strategy. In September 2020, China announced that it would strive to peak CO_2 emissions before 2030 and achieve carbon neutrality before 2060; the white paper China's Policies and Actions for Addressing Climate Change, issued in October 2021, set out the top-level design of this "dual carbon" goal, proposing the construction of a "1+N" policy system and updating the nationally determined contribution targets: by 2030, CO_2 emissions per unit of GDP are to fall by more than 65% from the 2005 level, the share of non-fossil energy in primary energy consumption is to reach about 25%, and total installed wind and solar capacity is to exceed 1.2 billion kW [25]. The 2021 annual report of the National Development Commission further summarised progress including the launch and operation of the national carbon emissions trading market (started in July 2021), low-carbon pilot demonstrations and the preparation of local action plans [26]. In terms of volume, China's fossil-fuel CO_2 emissions are projected at about 11.4 $GtCO_2$ (about 3.1 GtC) for 2022, roughly 30% of the global total, so that the pace of its peaking has a decisive influence on the rate at which the global carbon budget is consumed [14].

4.4 Adaptation Capacity Building and Risk Management

Even if the 1.5 °C target were achieved, the warming already locked in would still bring perceptible climate risk, so adaptation constitutes a second pillar of equal weight with mitigation. IPCC WGII stresses that adaptation options fall into three classes—ecosystem-based (mangrove and wetland restoration), engineering-based (flood walls, seawall upgrading) and institutional (climate risk insurance, early warning systems)—but that all are subject to soft or hard adaptation limits, beyond which "residual risk" arises, so that adaptation cannot substitute for deep emission reduction [16]. China's institutional basis in the adaptation domain is relatively systematic: Qin et al., in the National Assessment Report on Extreme Weather and Climate Events and Disaster Risk Management and Adaptation in China, systematically assessed the evolution and risk patterns of hazards including high temperature, drought, rainstorm flooding and typhoons, recommending that climate risk management be incorporated into the comprehensive disaster prevention and reduction system [24]; the State Council Information Office white paper likewise lists "giving equal weight to mitigation and adaptation" as a basic principle and lays out adaptation actions in agriculture, water resources, oceans and coastal zones, and human health [25]. At the observational level, the rising high-temperature and drought risk indices, the accelerating rise of coastal sea level and the degradation of permafrost revealed by the Blue Book on Climate Change in China (2023) provide scientific target areas for prioritising adaptation investment [2].

It should be pointed out here that the priority ordering of adaptation investment benefits directly from the threshold analysis of Section 4.2: near a threshold the marginal damage per unit of warming is markedly higher and the marginal return on adaptation resources rises correspondingly, whereas in stretches remote from a threshold the same input yields a much lower marginal return. This ordering principle of "looking at marginal rather than average damage" is a key link in converting impact assessment into investment decisions, and is where the practical significance of threshold identification, emphasised in this review, actually lies.

4.5 International Cooperation and Governance Mechanisms

Climate change has the character of a global public good, so governance can only rest on multilateral mechanisms. The Paris Agreement established the long-term goal of "holding the increase in global average temperature to well below 2 °C and pursuing efforts to limit it to 1.5 °C", and replaced top-down mandatory allocation of emission reductions with a governance model of "nationally determined contributions (NDCs) plus global stocktake" [15]. IPCC assessment reports supply the scientific basis for successive Conferences of the Parties, and AR6 states explicitly that the sum of current NDCs is insufficient to reach the above temperature goals, so that effort must be stepped up before 2030 to close the emissions gap [1,16]. Along with submitting an enhanced NDC, China announced that it would no longer build new coal-fired power projects abroad, and supports capacity building in developing countries through channels including Green Belt and

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Road development and South–South cooperation on climate change [25]. The keys to future governance are three: converting the 1.5 °C carbon budget into accountable sectoral pathways (energy, industry, transport, buildings and land use); implementing loss-and-damage mechanisms in finance and technology; and using the global stocktake to push NDCs upward round by round [15,16].

4.6 Baseline Specification: Relative to What Are These Conclusions Stated

Every judgement of the form "increased by so much" or "decreased by so much" conceals a counterfactual baseline. Three classes of baseline appear in this review, and readers citing its conclusions should first establish which one applies.

The first is the trend baseline. "Accelerating" sea-level rise is relative to a linear trend ($dh/dt = b$); if the baseline is changed to a piecewise-linear form, or if a decadal oscillation term is added to the model, both the estimated value and the statistical significance of the acceleration change accordingly [5]. The second is the counterfactual-world baseline. P_0 in attribution conclusions—the probability of the event in a world without human influence—is constructed by climate models and is not itself observable, so the value of FAR depends on models rather than on pure observation [10,12]. The third is the no-climate-change baseline. The "−3.8% for maize, −5.5% for wheat" of Lobell et al. is relative to the yield that would have occurred without the observed climate trend [21]; the "about 23% lower per capita income in 2100" of Burke et al. is relative to a growth path without climate change [22].

Stating the baseline matters because the same phenomenon can yield conclusions of different magnitude, or even opposite direction, under different baselines. If, for example, "full adaptation" is taken as the baseline instead of "no additional adaptation", the estimated economic loss becomes markedly smaller; if a high-emission pathway is taken as the baseline, the benefit of a moderate mitigation pathway is underestimated. This review therefore prefers to express estimates as "a value of Y relative to baseline X" rather than as an unconditional "Y".

4.7 Heterogeneity Across Periods, Regions and Anomalous Years

Differences in the estimate of the same variable across periods and regions are often larger than differences between models, a point easily overlooked when reading results.

Consider first heterogeneity across periods. The warming rate of mean surface air temperature over China is about 0.16 °C per decade over 1901–2022 but rises to about 0.26 °C per decade over 1951–2022 [2], a difference of more than 60%. The sources of the difference include real acceleration but also factors such as sparse early station coverage and the way urbanisation effects are handled. The rate of coastal sea-level rise in China is 3.5 mm yr^{-1} over 1980–2022 and 4.0 mm yr^{-1} over 1993–2022, both above the concurrent global average of 3.4 mm yr^{-1} [2]. This shows that a "rate" indicator is meaningful only given a time window, and that the window must be checked before comparing rates across studies, since otherwise the difference observed may come from window choice rather than from the physical process.

Consider next regional heterogeneity. Over 2011–2020, land warming (1.59 °C) was about 1.8 times ocean warming (0.88 °C) [1], the mechanism being the large thermal inertia of the ocean and the energy consumed by evaporation. This means that using global mean warming as a proxy for exposure underestimates the heat exposure actually experienced by land-dwelling populations. Similarly, Arctic amplification makes warming at high latitudes far exceed the global mean, and the cryosphere response to cumulative emissions (Equation (5)) is likewise concentrated in the Arctic. Global mean quantities are therefore appropriate for global budget accounting, but must be downscaled, with uncertainty stated, when used for regional risk assessment.

Consider also behaviour in anomalous years. Years with frequent extreme events are precisely the failure points of mean models. In 2022 China recorded 3501 station-days of extreme high temperature, and the high-temperature and drought risk indices were the highest since 1961 [2]; the 2003 European heatwave [10] and the 2016 global mass coral bleaching [19] belong to the same class. In these anomalous years the predictions of linear-trend or mean-response models deviate most from observation, and their value lies instead in signalling that the tails of the distribution have changed. Anomalous years should therefore not be discarded as "outliers" but treated as key samples for testing tail behaviour. If a model fails systematically in anomalous years, the defect lies in its structure (for example missing soil-moisture–temperature coupling, missing

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cumulative effects of heatwave duration, missing the tolerance window of symbiotic algae) and needs correcting at the level of mechanism rather than by simply adjusting parameters.

4.8 Robustness Checks and Interval Overlap

In the absence of a unified experimental platform, the following approaches were used to test whether the conclusions hold.

The first is convention robustness. After the carbon budget and emissions were unified in $GtCO_2$ and recomputed, the conclusions were unchanged; it was at this step that the "36.3 GtC" unit error noted earlier was found and corrected [14]. The second is baseline-period sensitivity. When the baseline period of the temperature anomaly is changed from 1850–1900 to 1961–1990, absolute anomaly values shift by about 0.2–0.4 °C, but the direction and significance of the warming rate and the warming trend are unchanged, so the conclusion of this review regarding "the fact of warming" is robust to the choice of baseline period; the specific anomaly values, however, are not robust, and the baseline period must be stated when citing them. The third is the interval-overlap test. For multiple estimates of the same parameter, this review does not compare point estimates but checks whether the uncertainty intervals overlap; once intervals overlap, no significant difference between the two can be established at the given confidence level. The fourth is single-source deletion. After each single study cited here was deleted in turn, the main conclusions (the fact of warming, anthropogenic dominance, nonlinear impacts, the carbon-budget constraint) were all unaffected, showing that the conclusions do not depend on any single paper; some secondary conclusions, however—specific attributable shares, the TCRE point estimate—do depend on individual studies, and this has been flagged at the corresponding places.

One qualification is needed: these checks can only show the stability of the conclusions under known sources of variation and cannot substitute for formal statistical testing. The original significance tests and confidence intervals of the empirical studies reviewed here are given in the source papers and are cited as they stand, without recomputation.

Table 9: Comparison of multi-source estimates of key parameters (interval-overlap test).

Parameter	Estimate source A	Estimate source B	Do intervals overlap	Implication for the conclusions
Equilibrium climate sensitivity (ECS)	AR6 best estimate 3.0 °C (likely range 2.5–4.0 °C) [1]	Sherwood et al. median 3.1 °C (66%: 2.6–3.9 °C) [9]	highly overlapping	evidence mutually supportive; no basis for preferring either at the given confidence level
Total anthropogenic ERF in 2019	AR6 +2.72 (1.96–3.48) W m^{-2} [1]	sum of independently estimated components (Table 4) [1,8]	consistent (components summed from the same source)	aerosol cooling −1.1 (−1.7 to −0.4) is the largest single source of uncertainty in total forcing
TCRE	AR6 0.45 (0.27–0.63) °C per 1000 $GtCO_2$ [1]	—	interval spans > 2×	the remaining carbon budget is highly sensitive to the TCRE value and should not be cited as a point value
Global rate of sea-level rise	satellite altimetry 3.1 ± 0.3 mm yr^{-1} (1993–2017) [5]	China's coast 4.0 mm yr^{-1} (1993–2022) [2]	regional value higher than global	regional rates cannot replace global rates, nor vice versa
Crop temperature threshold	maize $\tau \approx 29$ °C (US county level) [20]	—	single source	the threshold is region- and cultivar-dependent; extrapolation requires caution
Macroeconomic peak temperature	$T^* \approx 13$ °C (166-country panel, 1950–2010) [22]	—	single source	depends on a "no additional adaptation" scenario; should be read as a reference upper bound

Note: overlapping intervals mean that no significant difference between the two estimates can be established at the corresponding confidence level; entries marked "single source" indicate that no comparable independent estimate was found, so the strength of the conclusion is lower and it should be cited together with the data scale and scenario assumptions of the original study.

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4.9 Issues on Which This Review Makes No Claims

To avoid going beyond what the evidence supports, this review expressly refrains from the following claims.

First, the eight quantitative models are not ranked by predictive accuracy. They come from different studies, different datasets and different spatial and temporal scales; no common benchmark exists, and differences in accuracy could not be attributed to model structure.

Second, no single factor is claimed to be "the main influencing factor". Taking attribution as an example, AR6 gives a greenhouse-gas contribution of 1.0–2.0 °C and aerosol cooling of 0.0–0.8 °C; in the best-estimate sense the former dominates, but the intervals of the two overlap, so "dominates" here should be read as an ordering of best estimates rather than as a distinction in the sense of statistical significance.

Third, no deterministic prediction beyond the observational range is offered. The sea-level acceleration of Equation (4), the carbon–ice linear relation of Equation (5) and the response functions of Equations (6) and (7) are used only within their own calibration intervals; extrapolation beyond those intervals is treated in this review only as scenario discussion, flagged with the note that uncertainty grows with the time span.

Fourth, global-scale conclusions are not applied directly to a specific location or a single event. A high global attributable share (about 75% for high temperature) does not entail that a particular heatwave "was caused by climate change"; attribution of a single event requires a dedicated model ensemble and an explicit event definition [12].

Fifth, no point estimate is given for the future evolution of technological progress or adaptive capacity. The coefficients of Equations (6) and (7) themselves drift over time, and historical estimates do not constitute unbiased predictions of the future.

4.10 Limitations and Directions for Future Research

The limitations of this review are mainly threefold: it primarily surveys existing peer-reviewed literature and authoritative reports and does not develop original numerical simulations; the models come from different studies and lack a common benchmark and evaluation set; and some impact estimates do not incorporate full adaptation scenarios. When reading this review, the uncertainty intervals of the original literature should be consulted, and attention paid to the baseline settings and spatial and temporal scales on which each estimate depends.

Future research could deepen the work in the following directions: narrowing the uncertainty of climate sensitivity and regional feedbacks (the likely ECS range still spans 2.5–4.0 °C) so as to raise the credibility of carbon-budget and impact estimates [1,9]; developing rapid attribution services for individual extreme events to serve disaster response and judicial and insurance applications [10,12]; coupling ecological, agricultural and economic response models into integrated assessment frameworks so as to quantify "loss and damage" and evaluate the marginal benefit of adaptation investment [16,22]; and combining big data and artificial intelligence to improve the resolution and timeliness of Earth-system models and climate services.

More importantly, if future research is to move from review to original quantitative comparison, three things must be supplied. First, the prediction task and the prediction horizon must be specified (short-horizon prediction at $h = 1$ year and long-horizon prediction at $h = 10$ years should be evaluated separately), and a rolling-origin rather than fixed-origin evaluation scheme adopted. Second, models must be compared under fully identical conditions—same data source, same time window, same variable set, same evaluation set, same loss function—so as to avoid unfair comparisons arising from "model A used more variables". Third, reporting must go beyond point estimates such as MAE and RMSE to include confidence or prediction intervals, decomposed errors by period (season, decade) and by state (normal, anomalous years), and at least one simple benchmark (climatological mean, random walk, linear trend) as a reference. Only under such a setting does the assertion that "model X is better" have testable meaning.

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5. Conclusions

Along the framework "scientific facts—impact assessment—response pathways", this review has combined observational records with quantitative models to survey the key advances in climate change research. With baselines and uncertainties made explicit, three conclusions can be drawn.

First, the warming of the climate system is firmly established, and the available evidence consistently points to a dominant role for human activity: the world was already 1.09 °C warmer than pre-industrial in 2011–2020 (likely range 0.95–1.20 °C); indicators including ocean heat content, sea level, ice sheets and sea ice agree in direction; the probability of extreme high-temperature events is significantly higher in a "world with warming"; and the attribution evidence chain is corroborated across several independent methods [1,4–7,10–12]. It should be noted that the periods, spatial coverage and uncertainties of the various indicators differ, so this consistency should be read as consistency in direction rather than as consistency in the sense of a contemporaneous joint estimate.

Second, impacts are nonlinear and asymmetric, but the conditions of application of the individual estimates differ considerably: ecosystem responses show a directionally consistent signal across studies; crop yields show threshold-type damage above about 29 °C (based on a US county-level panel [20]); and the macroeconomy shifts from gain to damage above about 13 °C mean annual temperature (based on a national panel under no additional adaptation [22]). These values should be cited together with the data scale and scenario assumptions of the original studies and should not be lifted out and treated as universal thresholds.

Third, the response window is narrowing, and carbon-budget values depend heavily on convention: at the current emission rate of about 40 $GtCO_2\ yr^{-1}$, the AR6 remaining carbon budget for 1.5 °C (about 500 $GtCO_2$, 50% probability, counted from 2020) corresponds to little more than a decade of emissions; global CO_2 emissions must reach net zero around the middle of this century. China's "dual carbon" goals and its framework of giving equal weight to mitigation and adaptation are both a substantive contribution to the global carbon budget and an intrinsic requirement of its own high-quality development [1,14,15,25]. It should be stressed that this budget is highly sensitive to the starting year, the target probability and the treatment of non-CO_2 forcing, and that the convention must be stated when citing it.

In interpreting this review, the limitations set out in Section 4.10 should be borne in mind: it is a synthesis of published peer-reviewed literature and authoritative reports rather than an original modelling exercise; the models surveyed originate in different studies and lack a common benchmark; and some impact estimates do not incorporate full adaptation scenarios.

Abbreviations

AR6	Sixth Assessment Report of the IPCC
ECS	Equilibrium climate sensitivity
ERF	Effective radiative forcing
FAR	Fraction of attributable risk
GtC	Gigatonnes of carbon
$GtCO_2$	Gigatonnes of carbon dioxide
GDD	Growing degree days
IAM	Integrated assessment model
IPCC	Intergovernmental Panel on Climate Change
NDC	Nationally determined contribution
PR	Probability ratio
TCRE	Transient climate response to cumulative carbon emissions
TCR	Transient climate response

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VPD Vapour-pressure deficit

WGI / WGII Working Group I / Working Group II

ZEC Zero emissions commitment

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Conflicts of Interest

The author declares no conflicts of interest.

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