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Review

Demystifying global climate models for use in the life sciences

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For each assessment cycle of the Intergovernmental Panel on Climate Change (IPCC), researchers in the life sciences are called upon to provide evidence to policymakers planning for a changing future. This research increasingly relies on highly technical and complex outputs from climate models. The strengths and weaknesses of these data may not be fully appreciated beyond the climate modelling community; therefore, uninformed use of raw or preprocessed climate data could lead to overconfident or spurious conclusions. We provide an accessible introduction to climate model outputs that is intended to empower the life science community to robustly address questions about human and natural systems in a changing world.

Informing our complex and changing future

We are living in the Anthropocene: our planet is warming, rainfall patterns are changing, oceans are acidifying, biodiversity is declining, and the distributions of plants, animals, and diseases are shifting poleward [1,2]. Scientists increasingly rely on outputs from global climate models to produce **projections** (see Glossary) of the most likely direction, magnitude, and timing of these changes. This research facilitates the management of natural and human systems, as well as planning for a dynamically changing future (Box 1). Climate models simulate physical, chemical, and sometimes biological processes and phenomena. They produce petabytes of output, comprising hundreds of variables across a range of temporal and spatial scales [3]. Although climate models provide invaluable information, their output can be difficult to access and use, and their associated terminology can be impenetrable to non-experts [4]. The applicability, interpretability, and use of these outputs in different contexts and at different scales is not always clear, posing a challenge for scientists wishing to use this information at a time when rigorous and informed action is critically needed for climate change adaptation and natural resource management [5,6].

Herein, we provide a concise, accessible review of climate models and their uses, building on earlier advice (e.g., [7]), in a way that is tailored to life scientists who are not themselves climate modellers. Much of the material provides valuable context for using preprocessed climate projections (e.g., WorldClim [8] and Bio-ORACLE [9]), although our emphasis is on empowering users who wish to directly use climate-model output.

What are climate models?

A climate model is a numerical representation of the physical, chemical, and biological processes that operate across the atmosphere, cryosphere, ocean, and land. Because the climate system is complex and challenging to observe over long temporal and large spatial scales, these models are invaluable tools for understanding how climate works (Box 1). They simulate how climate has changed in the recent and even distant past (e.g., [10]), and how it might evolve in the future,

Highlights

Confronted with the reality of climate change, the rigour of the science underpinning advice to policymakers worldwide is increasingly important.

Although life scientists often rely on preprocessed data repositories – which provide data that more closely match the spatial scales of the questions that life scientists ask – technical problems with underlying models persist and are not always evident.

Demystifying climate model outputs, and developing practical workflows for their use, empowers life scientists to use these data directly. Doing so makes caveats more explicit and places decisions regarding potential tradeoffs in the hands of the user.

Cross-disciplinary collaboration between life scientists and expert users of the output of Earth system models greatly enhances the likelihood of developing the robust evidence necessary to address the challenges posed by climate change to human and natural systems.

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subject to different plausible scenarios of future human development and greenhouse gas emission pathways (Box 2).

Conceptual models for understanding aspects of the climate system have existed for >100 years. In the late 19th century Arrhenius made one of the first climate projections using the existing understanding of the heat-trapping effect of CO_2 and a simple model describing the energy balance of the Earth [11]. His model suggested that a doubling of the atmospheric CO_2 concentration would warm global surface temperatures by 5–6°C – remarkably, only slightly more than modern estimates [1].

The early 20th century saw the development of the differential equations describing the conservation of energy, Newton's laws of motion, and other physical principles necessary to simulate fluid dynamics in the atmosphere and ocean [12]. However, the complexity of these equations meant they could be applied to only idealised problems. It was not until after World War II that the development of digital computers allowed scientists to apply these equations at a global scale, thus facilitating the evolution of modern climate models. The first numerical model to simulate global atmospheric processes in 3D was developed in the mid-1950s [13]. This was followed a decade later by the first global ocean model [14] and the first climate model that coupled ocean and atmosphere [15]; work for which Syukuro Manabe would later receive a share of the 2021 Nobel Prize in Physics. Model complexity, spatiotemporal resolution, and realism have been advancing ever since.

As model complexity increased to include chemical and biological processes, climate models (also called coupled atmosphere–ocean general circulation models: AOGCMs or GCMs) became known as **Earth system models (ESMs)**. In contrast to GCMs that do not simulate biogeochemical processes, ESMs typically include land vegetation dynamics that were previously run offline as dynamic global vegetation models [16]. ESMs also simulate ocean chemistry, marine plankton, and their associated biogeochemical cycles because of their importance in global carbon cycling [17,18]. ESMs thus typically simulate the 3D evolution of the ocean and its biogeochemical processes, dynamic sea ice, the atmosphere, and the land surface and vegetation. They also include the effects of multiple greenhouse gases, ozone, and anthropogenic and volcanic aerosols.

To solve the climate system equations, time and space must be discretised by dividing the ocean and atmosphere into 3D grid cells and by splitting time into discrete steps. The more grid cells, the higher the model resolution, and the better its ability to simulate finer-scale phenomena. Shifting to finer spatial resolution and shorter timesteps is analogous to upgrading to television with a higher resolution and faster refresh rate – fidelity improves, but at the cost of greatly increased computational requirements [19,20].

Based on existing computing capacity, ESMs used in the IPCC Sixth Assessment Report typically have horizontal spatial resolutions of 100 × 100 km (~1° × 1° at the equator) in the ocean and 250 × 250 km (~2.5° × 2.5° at the equator) in the atmosphere, although there is a growing number of models at higher resolution [20]. Both ocean and atmosphere also have multiple vertical layers. ESMs solve dozens or hundreds of equations for each grid cell at each timestep, producing petabytes of raw data [3]. Although model timesteps may be minutes or hours (with shorter steps in the atmosphere than in the ocean, and depending on the spatial resolution), data storage restrictions mean that model output is archived less frequently. Most ESM variables are archived as monthly means, although some variables are stored at daily or shorter timescales (Box 3 and Table 1), primarily for the examination of extreme events.

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ESMs are unlike the more familiar weather forecasting models in that they are not used to provide direct **predictions** of the future. Instead, they estimate a set of possible climate futures that are associated with multiple plausible climate scenarios (Box 2). Each climate scenario specifies future greenhouse gas, aerosol, and other anthropogenic emissions, as well as land-use changes that might be associated with different socioeconomic pathways, each of which describes different rates of population growth, demographic changes, and energy mixes [21,22]. For this reason, estimates from ESM outputs are correctly referred to as projections and not as predictions or forecasts.

To facilitate the use and intercomparison of climate-model data from the dozens of models developed by research groups around the world, the World Climate Research Programme developed the Coupled Model Intercomparison Project (CMIP), currently in its sixth phase (CMIP6) [1,23]. CMIP6 ESMs form the basis for projections detailed in the IPCC Sixth Assessment Report. All CMIP6 ESMs adhere to common standards for data and documentation, and they run a suite of common experiments to facilitate intercomparison and assessment of ESM performance [3,23]. Storage of, and access to, ESM outputs is managed by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the Earth System Grid Federation (ESGF) [3] (Table 1, and Table S1 in the supplemental information online).

Accounting for uncertainty in climate models

When using ESM outputs, the user should consider three interacting sources of uncertainty: structural uncertainty (i.e., differing representation of physical and biogeochemical processes), alternative emission scenarios, and internal variability in the climate simulation [24].

Accounting for structural uncertainty: the use of multimodel ensembles

Although ESMs are based on the same underlying physics, different models often produce divergent simulations of past, present, and future climates. This arises primarily from differences in model resolution, and **parameterisation** of unresolved processes such as clouds. These differences give rise to model or structural uncertainty. Attempts are sometimes made to select a single model, or subsets of the 'most-realistic' models, usually based on how well they simulate present-day climate. However, different models often perform well at simulating different aspects of the climate (e.g., [25–27]), making model selection difficult. It is therefore important to encompass the structural uncertainty in climate projections, which typically involves using multimodel **ensembles** to explore the range of projections from a diverse suite of ESMs such as CMIP6 [4] (e.g., the uncertainty ranges across CMIP6 models for each scenario illustrated in the IPCC Sixth Assessment Report [1]).

Accounting for alternative emission scenarios: the use of multiple scenarios

Different climate scenarios (Box 2) represent another key source of uncertainty in estimating the future climate. Although projections are sometimes made for individual policy-relevant scenarios, it is more common to account for scenario uncertainty by considering projections across multiple scenarios [4]. No projection has meaning without the context provided by its underlying scenario and timeframe.

Accounting for internal variability: averaging across time-slices or model ensembles

Even without changes in forcing from anthropogenic (e.g., greenhouse gas emissions) or natural (e.g., volcanic eruptions) sources, both real and simulated climates will vary naturally and chaotically across a range of timescales (e.g., related to weather systems, the El Niño/La Niña Southern Oscillation, or internal decadal variability) – this is termed 'internal variability'. Past and future projections can be distorted or swamped by internal variability, which becomes more prominent at finer spatial and temporal scales.

Glossary

Anomaly: the deviation of a variable from its long-term mean climatology.
Attribution: in relation to climate impacts, attribution is the process of evaluating the relative contributions of multiple causal factors (including anthropogenic greenhouse gas emissions) to a change in a variable.
Climate sensitivity: a feature of the climate system that describes the temperature change associated with a given perturbation to the climate system. Often used as shorthand for 'equilibrium climate sensitivity', which is the globally averaged surface warming after the climate system has reached a steady state (generally over thousands of years) in response to an instantaneous doubling in the concentration of atmospheric CO_2.
Climatology: a statistical description of the climate system. Examples include the long-term mean and the long-term mean annual cycle.
Downscaling: the process by which finer-resolution climate information is derived from coarse-resolution model output.
Earth system model (ESM): a model that simulates interactions between the physical, chemical, and biological processes of the global climate system.
Ensemble: a set of simulations from multiple climate models, or multiple simulations using the same model with different initial conditions, that are subject to the same external forcing. Individual simulations are called ensemble members.
Model Intercomparison Project (MIP): an international research effort that brings together multiple climate (or other) modelling groups from around the world to collaborate on a common research question using standardised approaches.
Model skill: the ability of model outputs to match observations. In the context of ESMs, assessments of model skill depend on comparisons of historical model runs against observational or reanalysis datasets.
Parameterisation: a simplified representation in climate models of processes that operate at scales too small for the model to resolve. These simplified representations rely on relationships between unresolved and resolved processes.

Two approaches are commonly used to isolate the anthropogenic component in projections. First, temporal averaging can reduce the effect of internal variability. This is the rationale behind, for example, the convention in the IPCC Sixth Assessment Report [1,2] to identify risks of impact in the near-term (2021–2040), mid-term (2041–2060), and long-term (2081–2100) using multidecadal means. Second, by averaging across multiple ensemble members of the same model (known as a single-model initial condition large ensemble [24,28]) or across different models, out-of-phase internal variability is damped, accentuating the common anthropogenic signal. It is important to remember that chaotic internal variability in a model will not covary across different ensemble members or correspond with variability in observations.

Using ESMs at local scales

ESM output is appropriate for use at global to regional scales but is often poorly suited to the local scale required for many applications in the life sciences. There are two broad approaches for deriving finer-scale detail from climate model output: interpolation and **downscaling**, both of which are often accompanied by bias correction. We next introduce the concepts, and then in the following section provide recommendations for best practice.

Interpolation

Interpolation (also called regridding or remapping) uses values from points on the original ESM grid to estimate finer-scale values between these points. The main strength of interpolation is its simplicity, but it cannot account for small-scale processes that contribute to local-scale differences in climate. For instance, the effects of a mountain on rainfall involve processes at scales finer than can be **resolved** by global ESMs, and these cannot be reintroduced via interpolation.

Downscaling

The second and more sophisticated approach to obtaining finer-scale data is statistical or dynamical downscaling. Statistical downscaling uses statistical relationships between the fine-scale variable of interest and regional-scale climate phenomena resolved by ESMs. Techniques for establishing these relationships range from simple regression-type models to more advanced machine-learning algorithms trained using corresponding ESM-derived and observational time-series (e.g., [29–31]). Statistical downscaling assumes that the relationships existing today will also hold in a warmer tomorrow, although this assumption could break down under different future climates.

Dynamical downscaling avoids assumptions of stationary statistical relationships by using high-resolution climate models – similar in structure to a global ESM – to simulate climate in smaller regions. The regional model is nested within a global ESM, receiving information ('boundary conditions') from a 'parent' ESM to drive the finer-resolution model. Such dynamically downscaled models include (i) regional climate models (RCMs) that simulate the atmosphere and land surface regionally, (ii) high-resolution regional or global ocean models, and, more recently, (iii) regional coupled models. The finer grids of these dynamically downscaled models allow them to simulate regional processes that operate at smaller spatial scales (e.g., ocean eddies) and features, such as temperature variation with topography, in greater detail. However, RCMs can have biases, either internally or propagated from the parent ESM [31,32].

Bias correction

Interpolation and downscaling are often accompanied by bias correction, typically to remove mean state biases in the ESM [33]. In its simplest form, this involves adding interpolated **anomalies** representing the climate change signal from the ESM to a **climatology** derived from high-resolution observations [33,34] (an approach known as the delta change method; see Text S2 in the

Preindustrial: the time before anthropogenic activities had a major effect on the climate. This may be defined in different ways. From a climate modelling perspective, preindustrial model simulations cover the time before 1850. For practical reasons the IPCC Sixth Assessment Report refers to the preindustrial as a baseline period (1850–1900) against which recent and future climate states are compared, albeit recognising that the Industrial Revolution and the initiation of associated anthropogenic impacts on the climate pre-date this period.
Predictions: model outputs that rely on knowledge of the past and present to develop an expectation of future conditions (potentially including an estimate of uncertainty). A prediction is what we expect to happen. ESM outputs constitute projections not predictions.
Projections: model outputs that rely on prespecified assumptions about the future (potentially including an estimate of uncertainty). A projection is what we expect to happen under a given course of action (and/or other assumptions about the future). ESM outputs constitute projections not predictions.
Radiative forcing: the difference between the amount of energy entering and leaving the atmosphere ($W.m^{-2}$). Radiative forcing is caused by natural and anthropogenic factors, the latter including effects of changing greenhouse gas emissions. The greater the (positive) radiative forcing, the more climate warms.

supplemental information for more details). However, in practice there are many elaborations on this theme that adjust both the mean and variance of individual or multiple variables [35–37].

Preprocessed data

A fundamental problem for modelling natural systems is that ecological processes often operate at smaller scales than those commonly modelled by RCMs [9,38,39]. Finer-grain datasets of major bioclimatic variables have been developed (generally involving interpolation, statistical downscaling, and bias correction) to make it easier to access local-scale data. Prime among these data sources is WorldClim [8], but there are many others [9,39–41]. Although these readily available data have practical advantages, they all have underlying assumptions and limitations that are not always obvious, and care is therefore required in their interpretation and use [42] (Box 3).

A structured approach to working with climate-model outputs

Even with a sound understanding of ESM basics, working with their output can be a somewhat daunting task that is best approached systematically. Following the steps in Figure 1 should make it easier. We highlight later some key points in this workflow, provide additional detail, and emphasise caveats.

Solicit expert advice

We strongly encourage collaboration, whenever practical, with a climate scientist or user experienced in the application of climate model outputs pertinent to the question at hand. Doing so can make the process much easier and can greatly enhance the utility of results.

Define the problem

Carefully defining the problem includes identifying the underlying phenomena (e.g., warming-related range shifts), the variables driving these phenomena (e.g., surface air temperature), the processes that need to be resolved by a model to yield meaningful data related to the variable (e.g., altitudinal change in temperature), and the temporal scales at which the variable is needed (e.g., monthly).

Box 1. How are climate models commonly used?

A survey of the literature (Text S1 in the supplemental information for details) shows a rapid increase in the number of studies relying on climate model outputs across a wide range of disciplines, especially in the Earth and life sciences (Figure IA). Over the past 5 years the majority of these studies have focused on terrestrial systems (Figure IB), notably on aspects of climate that influence the resources that society depends upon. Prime among these are variables associated with precipitation (Figure IC), which influence water availability, streamflow, and soil erosion (e.g., [62,63]). Precipitation and temperature are frequently combined with other variables to explore the consequences of climate change for habitat suitability, productivity, and trends in the geographic distribution of biodiversity (e.g., [64–66]), including sources of food and fibre (e.g., [67,68]), in addition to vector-borne diseases that impact on humans, livestock, and crops (e.g., [69,70]). Extremes of temperature and precipitation are often studied in relation to risks of floods, droughts, wildfires, and human health (e.g., [71,72]).

Over the past 5 years global studies have been more common than those focusing on any specific region other than Asia (Figure IB). Fewer than 10% of studies focussed on outputs of ESMs relating to the ocean, and, of these, global studies were most common. Ocean studies have focussed on circulation [(e.g., [17]), biogeochemistry (including ocean acidification and deoxygenation), (e.g., [17])], the effects of coastal sea-level rise (e.g., [73]), and redistribution of biodiversity, including fish stocks (e.g., [74,75]).

Many studies failed to comply with our suggested best practice (discussed in the section on 'A structured approach to working with climate model outputs' in the main text). For example, the use of the extreme 'unrestrained emissions' scenario (RCP8.5; see Box 2 in the main text), in isolation, remains common (Figure ID). More often, however, best-practice guidelines have been followed by, for example, contrasting results from this extreme scenario with those from a scenario reflecting 'current policy' (RCP4.5) (e.g., [72,76]) and/or a 2°C future (RCP2.6) (e.g., [73]).

The community ecosystem model (CESM) [28] is by far the most-commonly used ESM (e.g., [71]). This model is often used alone because it provides many ensemble members for each individual climate scenario [28,43] (see Table 1 in the main text), which makes it useful in studies of the **attribution** of climate impacts. Some studies inadvisably rely on a single ensemble member from a single model, but multimodel ensembles of 2–10 ESMs (e.g., [64,65,67]) are more common, and multimodel ensembles of 11–20 or more ESMs (e.g., [76]) were also relatively common (Figure IE).

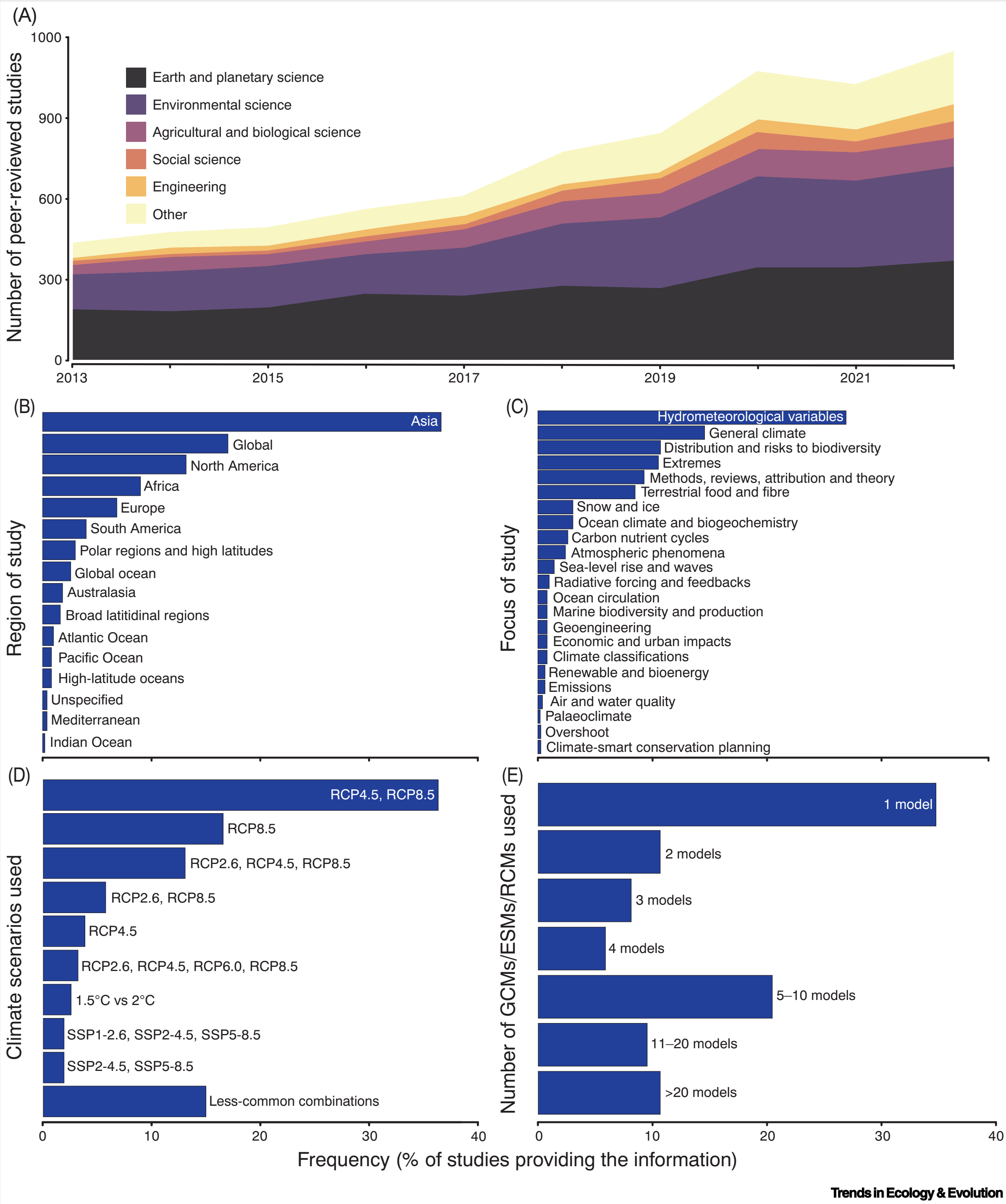

Figure I. Results from a literature survey. (A) Number of peer-reviewed studies per year over the past decade focusing on climate model outputs, classified by Scopus subject areas. Frequency of studies from the past 5 years by (B) region of study, (C) thematic focus, (D) climate scenarios used, and (E) the number of climate models considered. Abbreviations: ESMs, Earth system models; GCMs, general circulation models; RCMs, regional climate models; RCP, representative concentration pathway; SSP, shared socioeconomic pathway.

Box 2. What are climate scenarios?

Climate scenarios represent plausible storylines of future changes in population, demographics, and energy use. In CMIP5, scenarios were expressed as representative concentration pathways (RCPs) which describe greenhouse gas emission pathways (offset by other emissions) that result in specified levels of **radiative forcing** in 2100 [21] (Table I).

Table I. Descriptions of the common RCPs in CMIP5 and their associated warming levels [77].

Scenario	Pattern of radiative forcing	Warming in 2100 relative to preindustrial (90% confidence interval)
RCP2.6	Peaks at 3 $W.m^{-2}$ before declining to 2.6 $W.m^{-2}$ in 2100	1.6°C (0.9–2.3°C)
RCP4.5	Peaks at 4.5 $W.m^{-2}$ in 2100	2.4°C (1.7–3.2°C)
RCP6.0	Peaks at 6.0 $W.m^{-2}$ in 2100	2.8°C (2.0–3.7°C)
RCP8.5	Peaks at 12 $W.m^{-2}$ by 2200, having reached 8.5 $W.m^{-2}$ in 2100	4.3°C (3.2–5.4°C)

For CMIP6, these scenarios evolved to include narratives describing alternative shared socioeconomic pathways (SSPs) [20,22], as listed.

SSP1 Sustainability: the world shifts gradually toward a more sustainable path, emphasising more inclusive development that leads to lower levels of resource and energy use.

SSP2 Middle of the Road: historical patterns of social, economic, and technological change are maintained, leading to a slow decline in the intensity of resource and energy use.

SSP3 Regional Rivalry: an increasingly domestic focus leads to slow economic development with material-intensive consumption.

SSP4 Inequality: greater social inequality evolves among societies, with different countries employing a mixture of low- and high-carbon energy sources.

SSP5 Fossil-fuelled Development: the push for economic and social development is linked to the exploitation of fossil fuels and the adoption of resource- and energy-intensive lifestyles around the world, leading to rapid growth and rampant greenhouse gas emissions.

To accommodate these SSPs, the final climate scenarios used in CMIP6 and in the IPCC Sixth Assessment Report are reported using a combination of SSPs and RCPs (denoted SSP-RCP) (Table II and Figure I).

Table II. Descriptions of the five most common SSPs in CMIP6 and their associated warming levels [20,78]

Scenario	Description	Warming relative to preindustrial (90% confidence interval)
SSP1-1.9	Net zero CO_2 emissions achieved by mid-century; avoids exceeding 1.5°C of warming, in line with the ambition of the Paris Agreement	Stabilises at 1.4°C (1.0–1.8°C), with minimal overshoot beyond 1.5 °C
SSP1-2.6	Net zero CO_2 emissions achieved in the latter part of this century; achieves the goals of the Paris Agreement by avoiding 2°C of warming	Stabilises at 1.8°C (1.3–2.4°C)
SSP2-4.5	Approximates current climate policy, although this will change with commitments at each successive Conference of the Parties	2.7°C (2.1–3.5°C) by 2100
SSP3-7.0	Approximates a situation under which no new climate policy is implemented, resulting in a doubling of CO_2 by 2100	3.6°C (2.8–4.6°C) by 2100
SSP5-8.5	An extreme counterfactual scenario under which CO_2 emissions double by mid-century and increase thereafter	4.4°C (3.3–5.7°C) by 2100

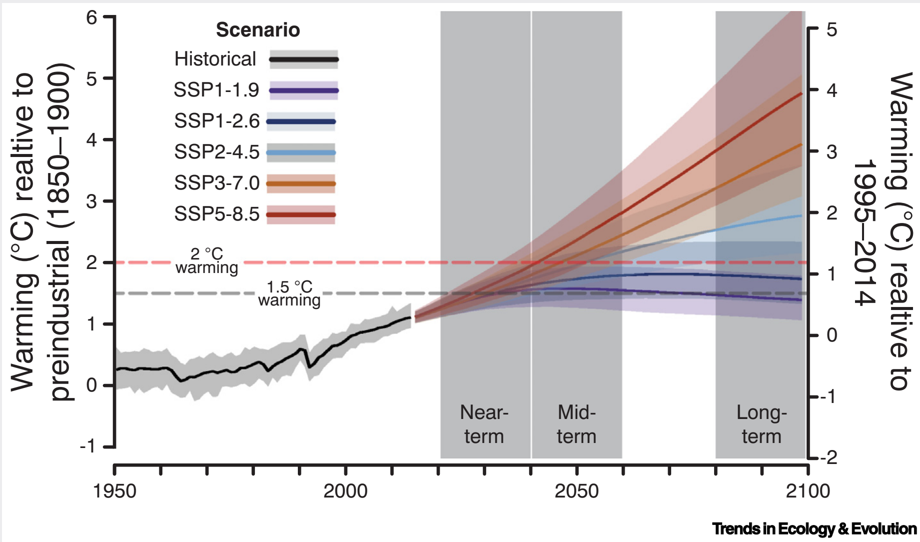

Figure I. Future temperatures under different scenarios. Global temperature change relative to preindustrial under different climate scenarios and periods considered in CMIP6, with 90% confidence intervals (as assessed in the IPCC Sixth Assessment Report [79]). Data from [80]. Abbreviations: CMIP, Coupled Model Intercomparison Project; IPCC, Intergovernmental Panel on Climate Change; SSP, socioeconomic pathway.

Another part of defining the problem is to decide upon the climate scenarios (Box 2) that are central to answering the question at hand. Note that each scenario has policy relevance (see Table II in Box 2), but individual scenarios should be used only where the problem is specific to that scenario. In all other instances, using multiple scenarios is more likely to encompass the range of plausible future outcomes.

Identify appropriate data sources and models

CMIP6 provides relatively coarse-scale (≥100 km resolution) global data, but if higher-resolution data are required the Coordinated Regional Downscaling Experiment (CORDEX) may provide more credible output at local scales than simple interpolation of ESMs. These data are available only for certain regions and primarily over land. Because each CORDEX RCM is typically driven by a single or a few ESMs, assessment of structural uncertainty is limited, and biases in the ESM will be present in the RCM (e.g., [31,35]). For this reason, different RCMs driven by the same ESM or one RCM driven by multiple ESMs can produce strongly divergent projections, so there are benefits of applying multi-model ensembles and bias correction.

Where addressing the problem requires data at spatial scales of 1–10 km, archives of preprocessed products may be considered, including WorldClim [8] and Bio-ORACLE [9]. However, the associated limitations should be carefully considered (Box 3).

Once the data source is identified, the initial selection of models will be dictated by data availability. The variables archived can vary considerably depending on the scenario, temporal frequency, and model (Table 1 and Box 3).

Box 3. Frequently asked questions

Our answers to questions that are frequently posed by our students and colleagues who wish to use ESM outputs, and that are not directly addressed elsewhere in the text.

When is it appropriate to use pre-prepared fine-scale datasets and when is it better to use custom interpolation or downscaling?

Off-the-shelf preprocessed data products [8,9,39–41] generally provide output that has been interpolated to a high resolution and bias corrected such that statistical properties of the historical model output more closely match those of the corresponding observed climate. Adjustments could include corrections to account for small-scale features that are not resolved in the climate models, such as cooler surface temperatures on mountains. Preprocessed data thus appear to provide the local information necessary for many applications in the life sciences. However, this apparent improvement in realism may provide a false sense of added value, and uncritical use of such datasets can be problematic [42,81–83]. For example, despite enhanced spatial resolution in off-the-shelf data, physical processes absent in the climate model from which the data are derived are not reintroduced by bias correction. Preprocessed products also typically archive only a selection of variables, and sometimes omit the variable of interest. A frequent major limitation is that preprocessed data tend to be archived as a climatology over multidecadal periods (e.g., a mean over the period 2081–2100) rather than as a time-series. Although climatologies can be useful when modelling processes for a set period (e.g., the long term), they do not facilitate understanding of how conditions evolve, and therefore cannot inform climate connectivity (e.g., [84,85]), the attainment of set warming levels (e.g., 1.5°C), or climate extremes. Processing raw climate data can often circumvent these issues, albeit at the cost of time and effort.

Why do scientists use reanalysis products (models constrained by observations) in preference to 'historical' runs from ESMs when assessing the skill of ecological models based on ESM outputs?

When assessing the skill of ecological models, the most desirable outcome is that they reproduce changes observed in nature. Because 'historical' ESM scenarios are 'free-running' (i.e., they do not assimilate observations), their natural variability (e.g., the timing of El Niño/La Niña Southern Oscillation events) will be out of phase with observations. Ecologists may therefore prefer to use reanalysis products to inform models for skill assessments. Ideally, these same reanalysis products would have been used to bias-correct the ESM outputs in the first place such that the statistical properties of the ESM outputs will be related to those from the reanalysis.

Who decides which ESMs are available, and what scenarios are run?

The experimental design of CMIP ESMs is defined by the World Climate Research Programme, and any model contributing to CMIP must perform a set of core baseline experiments and historical simulations (referred to as the DECK – diagnosis, evaluation, and characterization of klima), including a long preindustrial control run [23]. In addition, most climate modelling groups run several projections based on some or all of the SSP (RCP) scenarios. Modelling groups may provide one or more ensemble members for the historical, projection, and other experiments. Some groups may contribute additional standardised experiments [**Model Intercomparison Projects (MIPs)**], including HighResMIP and GeoMIP, which are used to answer specific questions (see Table 1 in the main text). Output from any model that performs the compulsory experiments can be included in CMIP. There is no requirement for realism – model validation is the responsibility of the user.

Why is my variable of interest not available at the temporal frequency I need?

Climate modelling groups participating in CMIP6 produce copious outputs across experiments (scenarios), ensemble members (model variants), variables, and frequencies. To allow some flexibility and to reduce the burden of delivery and storage of data, each variable is assigned a priority from 1 (high) to 3 (low) by the World Climate Research Programme, and these might be different for different MIPs. Modelling groups must supply all priority 1 variables specified for the MIPs but can choose whether to supply priority 2 and priority 3 variables. Further information is given in Juckes *et al.* [86].

Why are all experiments not available for all models?

As for variables above, experiments within each MIP are organised into tiers based on their importance in answering the scientific questions posed by the MIP. Only tier 1 experiments within a MIP must be provided by all contributing modelling groups.

Which variables are most 'uncertain', which are more 'certain', and how do I tell?

In general, variables affected by large-scale processes will be simulated better than those influenced by small-scale processes. For instance, because temperature is affected by large-scale circulation patterns, distribution, and insolation, it is usually similar across large spatial scales, and therefore modelled with relatively low uncertainty. Rainfall, by contrast, is affected by processes at scales finer than the resolution of ESMs, and projections of precipitation therefore have greater uncertainty. Uncertainty also increases at finer spatial and temporal scales and with depth in the ocean [1]. In general, physical variables are more reliable than chemical variables, which in turn are more reliable than biological variables [5,44,87]. Importantly, all assessments of model skill depend on comparisons of historical model runs against observational or reanalysis datasets; because we do not know the future, we cannot assess projection skill.

I have heard about CMIP6 ESMs 'running too hot' – what does this mean and what should I do about it?

Some CMIP6 models project temperatures that are probably too warm because of a higher effective climate sensitivity that is seemingly related to the representation of clouds [88]. It remains to be established whether this phenomenon represents an error in these current ESMs or a previously unidentified misspecification of cloud-related feedbacks in earlier ESMs from CMIP5. Nevertheless, the existence of the 'too-hot' models has led to the suggestion that models with transient climate response beyond the likely range 1.4–2.2°C assessed by IPCC Sixth Assessment Report [20] should be disregarded [46]. Of course, warming is not the only process of interest; other ESMs will have issues beyond temperature, and even the 'too-hot' ESMs might robustly represent processes unrelated to temperature. Users should therefore maintain currency in the literature and carefully consider how to select models based on recommendations that might arise.

It is generally inappropriate to report on outputs of a single realisation from a single model. However, when the question at hand involves discerning the signal of anthropogenic climate change from natural (internal) variability, it may be useful to use a large ensemble comprising many realisations from a single model [43]. In most other cases, we recommend building ensembles comprising multiple distinct ESMs so that structural uncertainty can be accounted for.

Access the data

The space required to store output from climate models depends on the required scale (e.g., global or regional), temporal averaging (e.g., daily, monthly, annual), duration (e.g., 20 year time-slice versus centennial time-series), resolution (horizontally and vertically), the number of variables, the number of scenarios, and the number of ensembles/models selected. For example, daily sea surface temperature data across the 21st century interpolated to a 0.25° grid at global scale for 10 models and four scenarios requires several terabytes of disk space to store and process. Careful advance planning of resources and workflows is therefore essential. A variety of tools are available that facilitate the downloading and processing model outputs (Table S1).

Evaluate the models selected

The performance of ESMs is typically improving with successive generations of models. For example, **model skill** in relation to most ocean biogeochemical variables compared with observations has improved from CMIP5 to CMIP6 [44,45]. However, to develop credible projections it is important to evaluate the performance of the models used. This assessment can involve examining the features of the chosen variables that are important for the problem at hand, including mean state, seasonal cycle, interannual variability, or long-term trends. For example, for credible global warming-driven range shifts, a model should adequately simulate latitudinal temperature gradients and have **climate sensitivity** within acceptable ranges (some CMIP6 models have climate sensitivities that are outside most credible ranges, [46] and Box 3). In some cases, model evaluation can be facilitated by online benchmarking tools and/or expert opinion [44,46–50].

Assuming that models which perform poorly in simulating current climate (by comparing the 'historical' scenario with corresponding observations) are less credible, 'bad' models may be discarded. However, when multiple variables are projected, or multiple areas are studied, models that are poor in one respect (e.g., rainfall) might be good in others (e.g., temperature). In general, the more ESMs included in an ensemble, the more insight that can be gained [51,52]. We therefore recommend deliberately eliminating ESMs only when they are demonstrably problematic for the question at hand. However, working with ensembles of >10 ESMs can become onerous. Although there is some evidence that an ensemble of as few as six ESMs can capture much of the structural uncertainty in the full CMIP ensemble for some variables (e.g., [53]), this does not hold for all variables. Consequently, model selection remains an issue that requires thought and care.

Table 1. Components of CMIP6 Earth system models archived by the Earth System Grid Federation (ESGF)[a]

Component name	Description	Details (examples in single quotes)
Activity ID	Describes the MIP to which the model output belongs. The 21 endorsed MIPs are managed independently [23] but follow the same technical requirements for all models.	MIPs most pertinent to the life sciences are 'CMIP' (historical and diagnostic simulations) and 'ScenarioMIP' (projections under different IPCC scenarios described in Box 2 in the main text). There are many others, including 'GeoMIP' (geoengineering scenarios) and 'HighResMIP' (high-resolution model outputs for assessing fine-scale phenomena such as cyclones).
Source ID	The name of the ESM.	CMIP6 currently hosts 122 models from >50 modelling centres. There are 72 ESMs in CMIP, 56 ESMs in ScenarioMIP, 8 ESMs in GeoMIP, and 40 models in HighResMIP. There are 9 ESMs that each currently provide >25 000 datasets on ScenarioMIP: (in order of decreasing number of datasets archived) 'MPI-ESM1-2-LR', 'CanESM5', 'ACCESS-ESM1-5', 'EC-Earth3', 'IPSL-CM6A-LR', 'UKESM1-0-LL', 'MIROC-ES2L', 'GISS-E2-1-G', and 'MIROC6'.
Experiment ID	The climate scenario under which the model simulations are run (see Box 2 in the main text). In CMIP6, future scenarios are denoted as SSP-RCP. The SSP prefix describes assumptions associated with socioeconomic development [22]. The RCP suffix describes greenhouse gas emissions pathways that result in specified levels of radiative forcing ($W.m^{-2}$) in 2100. All future scenarios cover 2015–2100, but in some cases extend longer (to 2300 or beyond).	Under CMIP, 'historical' simulations cover the period 1850–2014. These simulations are free-running, which means that natural variability (e.g., the El Niño/La Niña Southern Oscillation) will be out of phase with observed variability. The five most commonly used future scenarios under ScenarioMIP are [20,78]: SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and 'SSP5-8.5' (see Box 2 in the main text).
Model variant label	Realisation (r)	Identifies the model run, also known as the ensemble member. Different realisations ('r' numbers) denote small (and random) differences in the initial conditions for the run.
	Initialisation method (i)	Many models use a range of initialisation schemes. For example, in one scheme, different ensemble members ('r' numbers) might involve initialising from different years from the 'Control' experiment. In another, different ensemble members might be initialised from the same point of the 'Control' experiment but with a small random change added to one or more variables.
	Physics (p)	Different 'p' values indicate that some different physical processes are used in the model. For example, 'p1' and 'p2' might employ different approaches to determine when convective rainfall occurs.
	Forcing (f)	Different 'f' values indicate different forcing datasets. For example, there might be multiple different datasets available that specify anthropogenic aerosol emissions.
	Model variant numbers ('r-i-p-f' combinations) are consistent among scenarios within models, but not among models. Where specific values of any model variant descriptor are required, these details would need to be extracted from model documentation. Commonly, an ensemble from a single model across a range of variants is used to explore model sensitivity to different configurations. For example, an ensemble of realisations from a single model is useful to separate the forced signal from internal (natural) variability.	
Grid label	Each ESM is constructed around a system of grid cells that define the spatial resolution of the model on a spherical surface.	The two most common grid labels are 'gn' (outputs on the ESM natural spatial grid), and 'gr' (ESM outputs regridded onto a regular 1° grid).
Frequency	The temporal frequency at which model outputs are archived.	Not all variables are archived at all frequencies, but most are archived at monthly ('mon') intervals. Other common frequencies (in order of decreasing number of datasets archived) include annual ('yr'), daily ('day'), six-hourly ('6hr') and three-hourly ('3hr') (see also Box 3 in the main text).
Realm	The realm(s) within which the variables occur. This is important for distinguishing among variables in multiple realms.	Includes 'aerosol' (aerosol), 'atmos' (atmosphere), 'atmosChem' (atmospheric chemistry), 'land' (land surface), 'landIce' (land-based ice), 'ocean' (ocean), 'ocnBgchem' (ocean biogeochemistry) and 'seaIce' (sea ice). Despite standardised terminology, capitalisation occasionally differs among ESMs for some realms.

(continued on next page)

Table 1. (continued)

Component name	Description	Details (examples in single quotes)
Variable	There is a huge range of variables in ESM outputs, and not all are archived at all frequencies (see Box 3 in the main text).	Within ESGF, variables are listed alphabetically. A full list is available at https://pcmdi.llnl.gov/mips/cmip3/variableList.html, but common examples include: 'tas' ('air_temperature'; near-surface air temperature in K), 'tos' ('sea_surface_temperature'; sea-surface temperature in K) and 'pr' ('precipitation_flux'; precipitation in both liquid and solid phases in kg.$m^{-2}s^{-1}$).

[a]Abbreviations: MIP, Model Intercomparison Project; RCP, representative concentration pathway; SSP, shared socioeconomic pathway.

Preprocess the data

Because individual ESMs have different grid structures, interpolation to a common spatial resolution is often necessary to facilitate intercomparison or averaging of models. The target resolution, and the interpolation method used, depends on the application (https://climatedataguide.ucar.edu/climate-tools/regridding-overview). In general, bilinear interpolation can be used with smoothly varying fields (e.g., temperature), but using it on highly heterogeneous fields (e.g., rainfall) can lead to spurious results (e.g., rainfall totals are not conserved). In this case, conservative interpolation, which conserves grid totals, would be preferable. Where possible, interpolation of derived variables (e.g., wind stress curl or divergence) that are sensitive to gradients in the underlying fields should be calculated on the original grid prior to interpolation. Finally, for categorical variables (e.g., land cover type), nearest-neighbour interpolation can be used if regridding is required.

The target resolution also matters. For example, if the aim is to compare the variability in a particular variable across models, one must be aware that variability is typically higher at smaller spatial scales [54]. Therefore, when comparing models of different resolution, it may be appropriate to interpolate to the lowest common resolution, otherwise model outputs will have greater variability simply by virtue of their higher resolution rather than reflecting the simulated physical processes.

Bias correction methods are highly technical and have been widely critiqued [33,54,55], but they remain central to the development of unbiased projections. We therefore recommend that, in most circumstances, at least a basic bias correction should be implemented in the form of adding climate anomalies to a reliable estimate of the climate mean state (Text S2 for details). More complex bias correction might be best attempted in collaboration with a subject specialist.

We also recommend that best practice for researchers using preprocessed projections such as those from WorldClim is to report the downscaling and bias correction methods employed in developing these products and take cognisance of their potential caveats.

Construct a climate projection, taking care to represent uncertainty

The last step in the workflow is to compute and present a robust projection. In the simplest cases, when a single variable is projected, the median of an ensemble is often more appropriate than the mean, especially when the frequency distribution of the variable is skewed or where outliers are expected. The most extreme projections might be important for disaster risk management, for example, for storms, extreme heat, or heavy precipitation [56–58].

We recommend that uncertainty across an ensemble should be represented by reporting appropriate statistics to summarise the variability (e.g., range, standard deviation, or percentile range). When outputs are mapped, an alternative is to emphasise areas (e.g., cross-hatching) where projections from a predetermined proportion of models in the ensemble agree in the sign of change

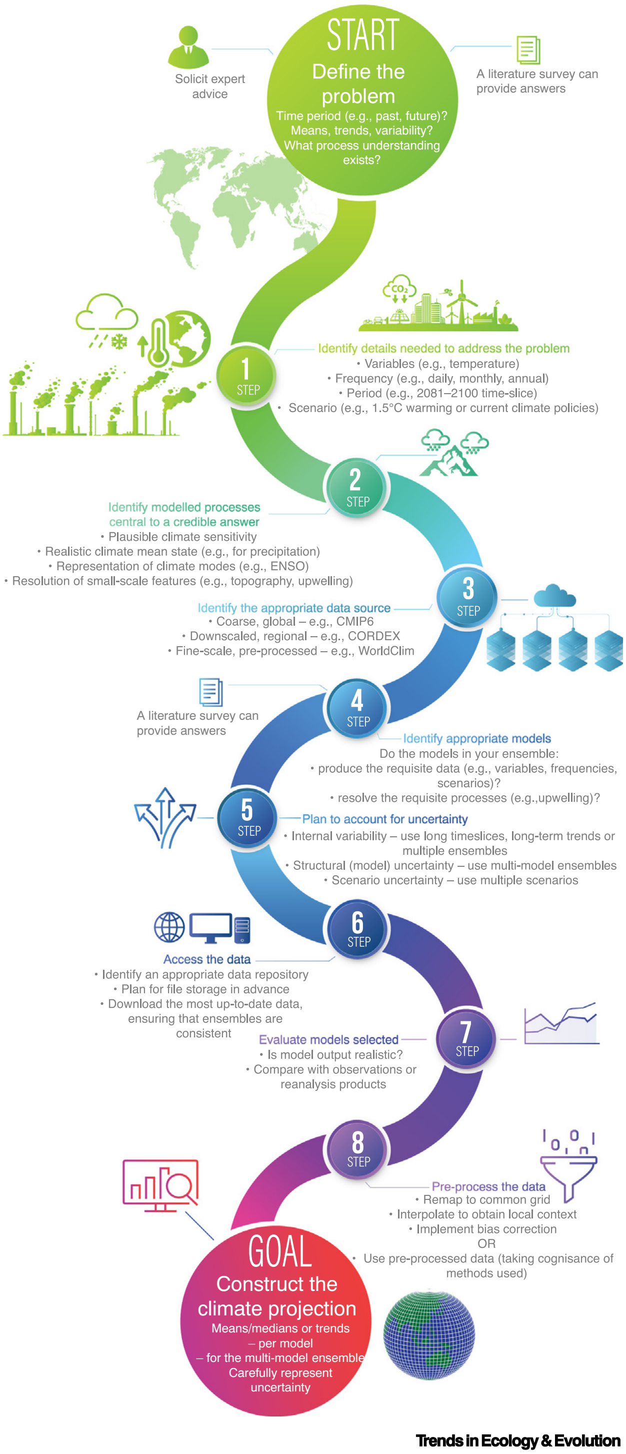

Figure 1. Synopsis of a workflow for using climate model outputs. Key decision points are highlighted, with brief examples of issues to be considered. Abbreviations: CMIP, coupled Model Intercomparison Project; ENSO, El Niño Southern Oscillation.

or where they exceed a predetermined range of estimates (e.g., [1,2]). A final option is to present projections from each ESM in the ensemble (e.g., [56]). When fitting subsequent models (e.g., species distribution models) to projections, best practice involves fitting these models to each member of the ensemble to preserve uncertainty (e.g., [59,60]) rather than fitting them only to the ensemble mean or median. This approach is particularly relevant when two or more variables are projected (e.g., temperature and precipitation) because it preserves relationships between variables within individual ESMs that might influence biological processes (e.g., [42]).

Concluding remarks

Warming by 1.5°C since **preindustrial** times is now more likely than not to be reached before 2040, irrespective of the emissions pathway [1]. Further, given current nationally determined contributions by 2030, the 2°C target of the Paris Agreement will be difficult to achieve in 2100 without overshoot [61]. Therefore, a strong, concerted, and coordinated effort is required from the scientific community to provide analyses that can inform robust advice regarding the urgent action that will be necessary to adapt to effects of climate change.

Although initial studies on impact and adaptation have been facilitated by the many preprocessed data products available [8,9,39–41], the often unacknowledged caveats associated with these data risk communicating a false sense of precision and credibility (Box 3). Working directly with climate model outputs to develop bespoke data products with which to address specific questions in the life sciences (Figure 1) makes the caveats more explicit and places decisions regarding potential tradeoffs in the hands of the user. Simultaneously, rapid improvements in the performance of computers and the falling price of data storage, coupled with ever-increasing access to high-performance computing resources and near-ubiquitous access to high-speed internet connections, mean that most researchers now have the required hardware to download, process, and analyse ESM outputs. These tasks are further facilitated by open-source tools for manipulating ESM outputs (Table S1). Although challenges remain (see Outstanding questions), we hope that this review will empower life scientists to overcome any misgivings they might harbour and develop data products tailored to addressing their specific questions about our changing future.

Outstanding questions

What is the best approach to bias correction? Selecting among available bias correction techniques requires time and skill, but machine learning and artificial intelligence may offer solutions that reliably correct both the mean and variance across a range of variables.

What is the best approach to selecting individual ESMs for inclusion in ensembles with which to address questions about the future?

How best can scientists assess climate change impacts in regions that are challenging for current ESMs to resolve, such as those with complex orography or land–sea interfaces?

How can life scientists address future scenarios that are not already considered by mainstream MIPs?

How best can life scientists use data at temporal frequencies shorter than annual, and how can they use variables beyond the often-used temperature and precipitation on land, and sea surface temperature in the ocean?

Given that the climate modelling community is relatively small and busy, how best can life-scientists collaborate with them in processing and interpreting raw ESM output? The answer could lie in the user community developing their own forums to learn from each other.

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Declaration of interests

The authors declare no conflicts of interest.

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