COMMENTARY:

Climate goals and computing the future of clouds

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How clouds respond to warming remains the greatest source of uncertainty in climate projections. Improved computational and observational tools can reduce this uncertainty. Here we discuss the need for research focusing on high-resolution atmosphere models and the representation of clouds and turbulence within them.

In the 2015 Paris Agreement[1], 193 countries agreed to holding "the increase in the global average temperature to well below 2 °C above pre-industrial levels … to reduce the risks and impacts of climate change". Currently, the carbon dioxide concentration in the atmosphere stands at 404 ppm. This is 120 ppm higher than in pre-industrial times, and Earth has already warmed 1 °C since then[2]. How much higher can the concentration of CO_2 and other greenhouse gases rise before the 2 °C threshold is crossed? The answer to this crucial question is uncertain. Depending on which, if any, climate model one trusts, CO_2 concentrations could reach between 470 and 600 ppm before the 2 °C warming threshold is crossed (Fig. 1a). Or, translated into time by assuming CO_2 concentrations continue to rise rapidly[3], the 2 °C threshold may be crossed by the late 2030s, or much later at around 2060 (Fig. 1a, right axis). Optimal emission pathways differ vastly between allowable CO_2 concentrations at the high or low end of this spectrum.

A number of factors contribute to the spread of projections, including uncertainties about how much heat oceans take up and how anthropogenic aerosols affect climate. But the bulk of the spread can be traced to the equilibrium climate sensitivity, ECS (Fig. 1a). ECS is the global surface temperature increase that results after CO_2 concentrations have doubled and the climate system has equilibrated to this one perturbation[4]. Because regional changes, for example in temperature or precipitation extremes, scale with global surface temperature[5], ECS also measures how strongly rising CO_2 concentrations impact regional climate. ECSs of current climate models are scattered between 2 and 5 K. This wide range of ECS has neither shifted nor narrowed substantially since the first comprehensive climate change assessment[4,6] by the US National Academy of Sciences in 1979.

What lies behind the recalcitrant ECS uncertainty are primarily uncertainties about how clouds respond to warming,

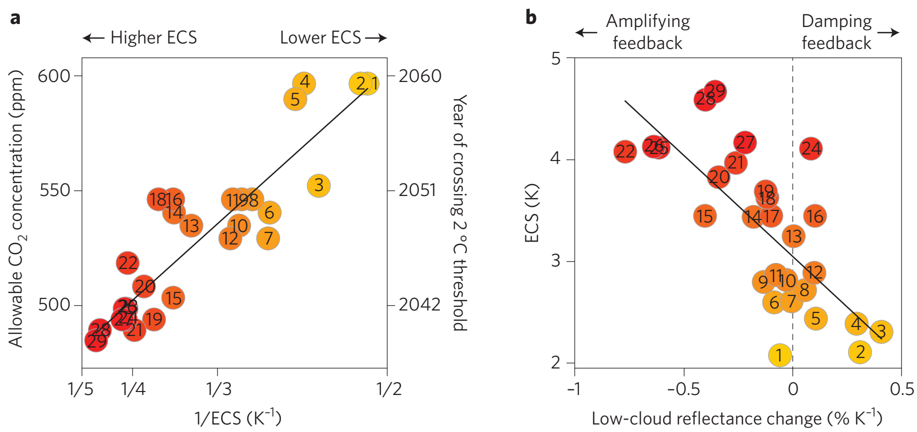

Figure 1 | Dependence of climate goals on equilibrium climate sensitivity (ECS) and of ECS on low-cloud feedback. **a**, Allowable CO_2 concentration before 2 °C warming threshold is crossed versus ECS. The bottom axes displays 1/ECS, the left axes the allowable CO_2 concentration, and the right axes the year when the 2 °C threshold is crossed (correlation coefficient $r = 0.89$). Each circle represents a climate model, numbered and coloured in order of increasing ECS (ref. 9). The horizontal axis is expressed as 1/ECS because temperature changes ΔT and concentration changes ΔCO_2 are to first order related by $\Delta T \propto \mathrm{ECS} \times \Delta CO_2$, so one expects $\Delta CO_2 \propto 1/\mathrm{ECS}$ for fixed ΔT. The allowable CO_2 concentration for each model is determined from a high-emission scenario simulation[3] as the concentration when the 5-year low-pass filtered global mean surface temperature rises 1.19 °C above the model's average for 2006–2015 (ref. 4). The 1.19 °C represents what remains of the 2 °C target because global mean surface temperatures[2] have increased by 0.81 °C from 1861–1880 to 2006–2015. Allowable CO_2 concentrations depend only weakly on the emission scenario considered (provided the 2 °C threshold is crossed in a scenario); however, the corresponding time when the 2 °C threshold is crossed (right axis) does depend on the emission scenario. Additional uncertainties would arise when one tries to convert allowable CO_2 concentrations into allowable emissions because it is uncertain how much of the emitted carbon dioxide will remain airborne. **b**, ECS versus changes in the amount of sunlight reflected by low clouds over tropical oceans[9] ($r = 0.73$). A reduced reflection under warming (negative values) implies an amplifying feedback by tropical low clouds on the warming; an increased reflectance implies a damping feedback by tropical low clouds.

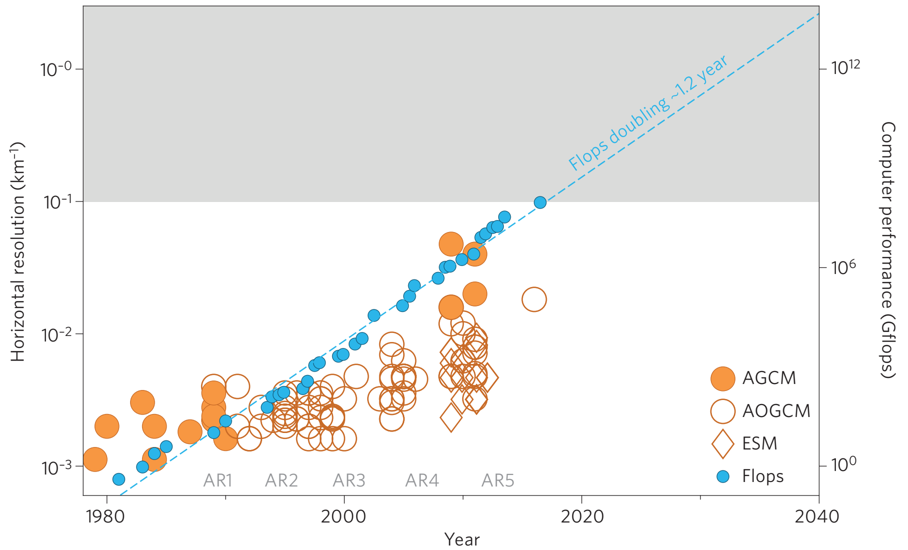

Figure 2 | Evolution of horizontal resolution of climate models and maximum computer performance since 1979. Left axis: atmospheric horizontal resolution (inverse horizontal grid spacing) of atmosphere general circulation models (AGCMs), coupled atmosphere–ocean general circulation models (AOGCMs), and Earth system models (ESMs). The model vintage for the climate models is the date of the first peer-reviewed publication describing the model (from the scientific literature and assessment reports of the IPCC). AR1–AR5 mark the dates of appearance of IPCC assessment reports. The gray shading indicates the resolution range at which deep convective clouds begin to be resolved. Right axis: maximum performance (number of floating point operations, flops) of the world's fastest computers (from www.top500.org since 1993, and from Wikipedia before then). The performance evolution of supercomputers used for climate modelling roughly parallels the performance evolution of the world's fastest computer[8]. The axes are scaled such that a factor 10 resolution increase on the left axis corresponds to a factor 10^4 performance increase on the right axis, because a resolution increase by a factor N in each of the three space directions in a global model requires a factor N^4 increase in computer performance. Resolution increases would be parallel to computer performance increases if all performance increases went into increasing resolution.

especially cumulus and stratocumulus clouds over tropical oceans[4,7–9]. These low clouds cool the underlying surface by reflecting sunlight. If they reflect more sunlight as the climate warms — for example, by covering larger areas — they reduce the warming and lower ECS. If they reflect less sunlight, they amplify the warming and raise ECS. Current climate models produce tropical low-cloud responses to warming with either sign and widely differing magnitudes. Most of the spread in ECS across models arises from this spread in the response of tropical low clouds (Fig. 1b). Why is modelling low clouds difficult?

Computing clouds

Although clouds cover 70% of the sky, they contain very little water. If one took all condensed water in clouds (cloud droplets and ice crystals) and spread it as a liquid layer on Earth's surface, one would get a film 0.1 mm thin — the thickness of a human hair. The amount of water vapour in the atmosphere is about 250 times greater, corresponding to a liquid layer 2.5 cm thick. To predict how clouds respond to warming, we need to predict changes in the minuscule residual of water vapour that condenses when air ascends and cools in turbulent updrafts. Currently we do so with climate models that are not made for the task: their atmosphere models have a horizontal grid spacing around 50–100 km and a vertical grid spacing in the lower atmosphere of around 200 m. This is much too coarse to resolve the 10–100 m wide turbulent updrafts that originate in the planetary boundary layer and generate low clouds. Instead, climate models predict where clouds form with physically motivated parameterizations that relate the small-scale turbulence of clouds and the planetary boundary layer to the large-scale dynamics resolved on the models' grids.

Advances in computing will eventually enable climate models to resolve the turbulence controlling clouds, although uncertainties about the microphysics of droplet and ice crystal formation may remain. But to resolve low clouds, including the numerically challenging stratocumulus[10], climate models need grid spacings on the order of 10 m in the lower atmosphere. To achieve that, the number of atmospheric grid cells in climate models — currently around 10^6 — needs to increase 10^8-fold. This will be possible once computer performance has increased 10^{11}-fold (Fig. 2). If we assume optimistically that computer performance continues to double every 1.2 years, as it has over the past decades, and that all added performance goes to increase model resolution, global climate models will resolve low clouds by the 2060s (Fig. 2). Computing advances may eventually deliver answers — but not before Earth's climate system itself has revealed its sensitivity in the experiment we are currently performing on it[11].

Since the 1970s, the atmospheric grid spacing of climate models has been refined by a factor of 5–10. A factor of 100 refinement would have been possible had much of the 10^8-fold increase in computer performance over that period been invested in increasing atmospheric resolution (Fig. 2). Instead, much of the added computer performance was used to broaden scope from atmosphere-only models, to coupled atmosphere-ocean models, to Earth system models that include the biosphere. The increased complexity has improved our understanding of the oceans' role in the climate system and of climate changes on timescales of centuries and longer. But because the bulk of the spread in allowable CO_2 concentrations is traceable to the ECS uncertainty (Fig. 1a), ocean dynamics and other processes that do not affect ECS contribute little to this spread. To reduce the uncertainty in climate projections for the next decades, we need to focus on the atmosphere. Computer performance increases could make atmosphere models with kilometer-scale resolution routine within a decade (Fig. 2). This will improve projections of monsoons, precipitation, and tropical cyclones[12–14] among other phenomena. But even in kilometer-scale models, low clouds must be parameterized. A convergence of what is feasible computationally on small and large scales, paired with unprecedented observational capabilities, can now enable rapid progress in parameterizing low clouds.

Cloud and climate simulations

While global models resolving low clouds are not feasible, limited-area models resolving their dynamics do exist[15–17]. Such large-eddy simulation (LES) models compute approximate solutions to the equations of fluid dynamics and thermodynamics, while using simplified representations for still unresolvable processes such as droplet and ice crystal formation. With LES, we can now simulate the clouds and the planetary boundary layer within a climate model grid column: enhanced computer performance has enabled both larger domains in limited-area LES, and smaller horizontal grid spacing in global climate simulations (Fig. 3).

This convergence of LES and climate simulations creates fresh opportunities for understanding low clouds[18] and for building better parameterizations. We can embed LES in grid columns of global models. The large-scale weather systems resolved in a global model drive the LES, and if desired, the LES can feed back into the large scale models. Embedding an LES in each grid column of a global model is computationally feasible if the LES covers a fraction of the footprint of each grid column[19]. Alternatively, LES that fully resolve a grid column of a global model can be embedded in a subset of columns. Numerical experimentation in such 'supercolumns' can anchor the development of new approaches to parameterizing cloud dynamics, for example, through physically informed machine learning. New parameterizations and LES driven by weather hindcasts[20–22] can be evaluated against a wealth of new observations, be they local *in situ* measurements or global satellite data of the three-dimensional structure of clouds, which have become available in the past decade[23].

The prevalent frameworks for the parameterization of cloud dynamics were developed between the 1960s and 1980s[24]. They were a breakthrough at the time, commensurate in complexity with the available computational and observational resources. The exponential increase in computer performance and observing capabilities calls for new breakthroughs now.

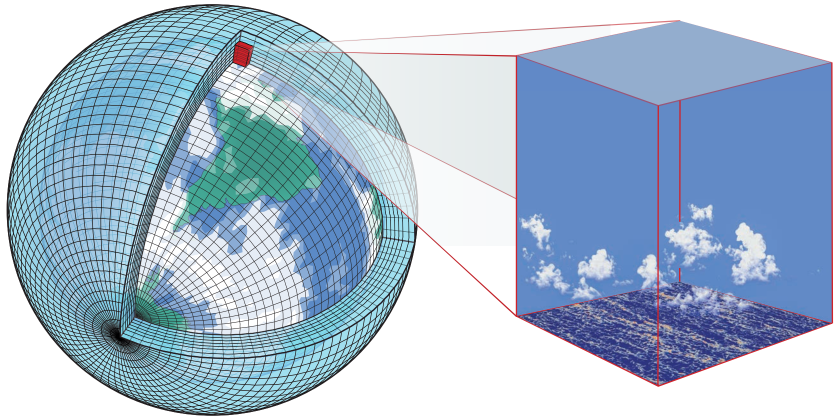

Figure 3 | Grid cells in a global climate model and a large-eddy simulation of shallow cumulus clouds at 5 m resolution[15]. The colours at the bottom of the LES domain indicate the buoyancy of near-surface air. The horizontal grid spacing of global climate models is approaching the feasible domain size in limited-area cloud simulations. This creates fresh opportunities for developing parameterizations of the turbulent dynamics of low clouds, such as the shallow cumulus clouds here, for climate models with grid spacings of order kilometers and larger.

Paths forward

A concerted program that capitalizes on today's computational and observational resources is needed to build a framework for the parameterization of clouds and turbulent dynamics at scales below the 1–10 km grid spacing that the next generation of climate models will achieve. Such a framework can rest on the three pillars of observations, global climate simulations, and limited-area LES, whose linkages can be continuously probed in a development cycle that simultaneously improves climate models and parameterizations and identifies additional observations needed to further constrain unresolvable processes.

Given the societal importance of climate projections and fresh opportunities to improve them, it may come as a surprise that the factor limiting progress in climate modelling is human. It has been estimated that reducing uncertainties in climate projections has an economic value of trillions of dollars if accomplished in the next decade[25]. Yet the number of scientists working in the area that is central to reducing uncertainties — developing representations of turbulence and low clouds — is low, only dozens worldwide. There is ample room for growth, and the area is primed for advances. It is a societal imperative for the climate sciences to provide accurate projections, including an accurate answer to the question of how much CO_2 can accumulate in the atmosphere before the 2 °C Paris threshold is crossed. This is achievable now. ❒

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