

On the relationship between cloud feedbacks and circulation changes in the tropics



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Statement of Contributions

This thesis contains work that has been previously published and collaborative work that involved contributions from others.

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I designed the study in collaboration with my co-authors, carried out the data analysis, and drafted and revised the manuscript. My co-authors additionally provided feedback on the analysis and interpretation, and revised the manuscript in response to reviewer comments.

Chapters 3–5 use data from climate model simulations performed by (Huber, 2022). I designed the research questions and carried out the data analysis, interpretation, and integration into the thesis in collaboration with my supervisors. Aiko Voigt, group leader of the team that generated the simulations, provided support with data processing, analysis, and the development of research questions.

Unless otherwise stated, all remaining work presented in this thesis is my own.

Abstract

Clouds and their radiative effects are strongly coupled to the large-scale circulation, and this coupling plays a fundamental role in the climate response to CO₂ forcing. This thesis examines this interaction from two complementary perspectives: how circulation changes influence tropical cloud feedbacks inferred from observations, and how cloud-radiative changes drive circulation and hydrological responses in a warming climate.

Using top-of-atmosphere radiative flux observations and an atmospheric reanalysis, we estimate tropical cloud feedbacks based on trends from 1985 to 2020. Decomposing the feedbacks into dynamic and non-dynamic components reveals that regional dynamic feedbacks from narrowing and strengthening of ascent are large but, as in high- and low-resolution climate models, these dynamic feedbacks largely cancel in the tropical mean. This highlights the value of isolating non-dynamic feedback components when estimating feedbacks for individual cloud types. Feedbacks inferred from multi-decadal trends differ from those inferred from inter-annual variability, reflecting distinct physical drivers. As previous estimates of tropical cloud feedbacks relied on inter-annual variability, we provide a new trend-based estimate of the combined anvil area and albedo feedback.

Next, we use radiation-locking experiments with a global climate model to isolate how radiative changes in CO₂, water vapour, and clouds shape the tropical precipitation–minus–evaporation, $P-E$, response to increased CO₂. Cloud-radiative changes drive a robust wet-gets-drier, dry-gets-wetter pattern that offsets an opposing water vapour-driven response, leaving the overall $P-E$ response closely resembling the comparatively weak CO₂-driven pattern of drying in climatologically wet and dry regions. Comparing fixed-SST and slab-ocean simulations allows the separation of cloud-driven $P-E$ changes into those occurring via the atmospheric/land pathway versus via the SST-mediated pathway. The wet-gets-drier, dry-gets-wetter response occurs via the atmospheric/land pathway: upper-tropospheric heating from rising high clouds increases static stability, weakens the overturning circulation, and reduces precipitation in wet regions and evaporation in dry regions. In contrast, the SST-mediated pathway drives poleward precipitation shifts – most notably over the Indian and West Pacific Oceans – reflecting spatial gradients in cloud-driven SST changes.

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Hinksey, 2 Dec 2021

They paved up paradise and put up a parking lot.

— Joni Mitchell

1

Introduction

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Earth’s climate is powered by radiation from the sun. Absorbed solar energy flows through our planet’s atmosphere and the land, ocean, ice and ecosystems that populate its surface before being released to space. Approximating the Earth and the Sun as blackbodies provides a starting point for exploring this flow. A blackbody is an idealised object that emits the maximum possible radiation at each wavelength for a given temperature. Its emission spectrum is described by Planck’s law, and the spectral intensity peaks at wavelength λ_{peak} determined by Wien’s law:

$$\lambda_{peak} = \frac{b}{T_s}, \quad (1.1)$$

where T_s is the surface temperature and b is Wien’s displacement constant.

Radiation emitted by the sun originates from the photosphere, which has a temperature of ~ 5800 K (Liou, 2002). This means its wavelength lies in the ultraviolet, visible and near-infrared (or ‘shortwave’) regions of the electromagnetic spectrum.

At equilibrium, the radiation emitted by Earth must balance the solar radiation it absorbs. This suggests that, if Earth were a blackbody, it would have a surface temperature of 255 K (-18°C) and emit infrared radiation (Marshall & Plumb, 2008). In reality, however, the global mean surface temperature is 288 K (15°C), because Earth’s atmosphere strongly absorbs infrared radiation. As a result, it is not the surface that is constrained to be 255 K, but the region of the atmosphere from which radiation escapes to space. As the atmosphere emits infrared radiation both upward and downward, the surface receives additional longwave energy on top of the incoming solar flux, leading to a higher equilibrium temperature. This process is known as the greenhouse effect (e.g., Marshall & Plumb, 2008).

This simple discussion masks a wealth of complexity. Earth both reflects incoming shortwave radiation and emits outgoing longwave radiation, and the details of these processes depend on the characteristics of the planet’s intricate and interconnected climate system. The vertical flow of energy between the surface and the top of the atmosphere (TOA) is shaped by atmospheric composition and thermodynamics, as well as by the presence of aerosols and clouds, which cover roughly 70% of the planet at any given time (Trenberth et al., 2009). In addition,

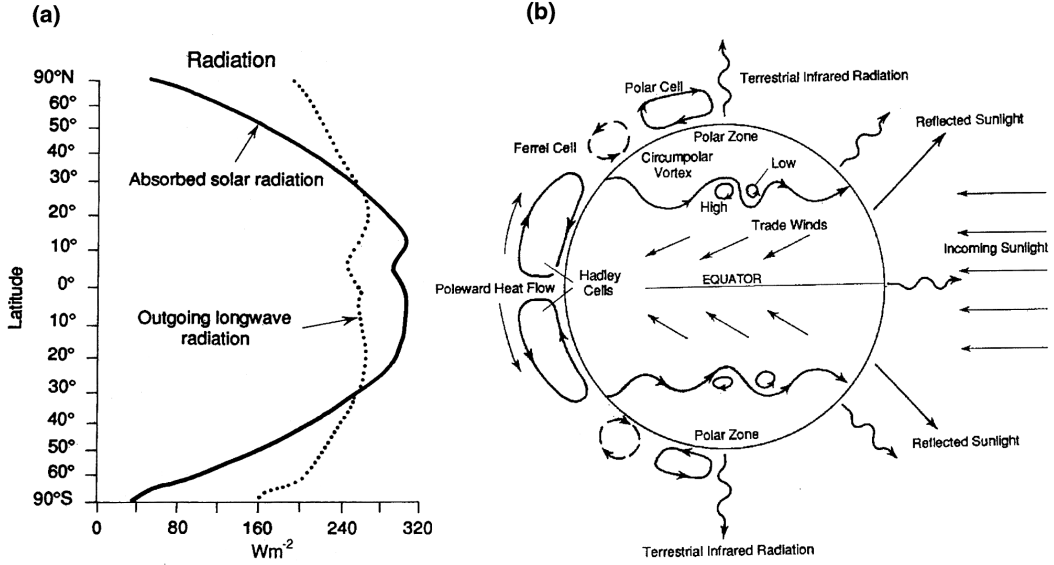


Figure 1.1: (a) The latitudinal dependence of absorbed solar radiation and outgoing longwave radiation and (b) a schematic of the dynamics and energetics of the Earth's climate system. Adapted from McGuffie and Henderson-Sellers (2001).

sensible heating and evaporation play essential roles in energy exchange between the surface and the atmosphere.

Spatio-temporal variability in these factors, as well as in the incoming radiative fluxes, also shapes energy flow. Notably, annual-mean absorbed solar radiation peaks around the equator while outgoing longwave radiation has a flatter distribution (e.g., Hartmann, 2016, Fig. 1.1). The resulting transition from net energy gain in the tropics and subtropics to net energy loss at the poles implies the existence of large-scale atmospheric and oceanic circulations transporting energy poleward (e.g., Holton & Hakim, 2012). In the tropical atmosphere, this large-scale meridional circulation comprises the Hadley cells: rising warm air near the equator flows poleward at upper levels before sinking in the subtropics and returning to the equator at the surface. When zonally averaged, the midlatitudes appear to be characterised by the thermally-indirect Ferrel cell, but this masks a mix of stationary and transient eddies driven by baroclinic instability (e.g., Schneider, 2006). Alongside transporting energy, these circulations redistribute angular momentum from the tropics towards higher latitudes (e.g., Holton & Hakim, 2012).

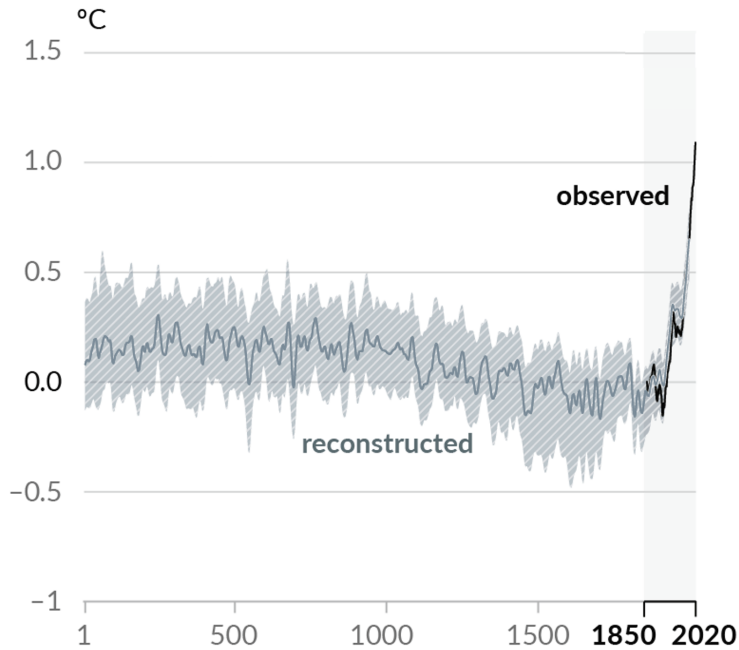


Figure 1.2: Changes in global mean surface temperature reconstructed from paleoclimate archives (solid grey line, years 1–2000) and from direct observations (solid black line, 1850–2020), both relative to 1850–1900 and decadal averaged. The grey shading with white diagonal lines shows the very likely ranges for the temperature reconstructions. Adapted from IPCC (2021b).

At geological timescales, the flow of energy through the climate system has been affected by changes in incoming solar radiation, variations in Earth’s orbit around the sun, and terrestrial processes, such as large volcanic eruptions. The evolution of life on Earth has also caused fluctuations in energy flow through the climate system. When microbes first evolved oxygenic photosynthesis, the oxygen they released reacted with atmospheric methane, reducing its concentration. This altered the greenhouse properties of the atmosphere and may have contributed to global glaciation during the Great Oxidation Event (Catling & Kasting, 2017).

Over the last ~12,000 years, Earth’s climate has been relatively stable, enabling the development of a resilient biosphere and the rise of human civilisation (Ruddiman, 2001). However, we have recently entered what is widely referred to as the ‘Anthropocene’, a geological epoch defined by the profound impact of human activities on the Earth system (Crutzen, 2002). Similar to the oxygenation of the atmosphere by early microbes, the emission of greenhouse gases and aerosols since the industrial revolution has fundamentally altered atmospheric composition (e.g., IPCC, 2021a). Consequently, over the last ~150 years, Earth has warmed rapidly (Fig. 1.2), in line with pioneering model predictions of the climatic effect of

increasing greenhouse gases by Manabe and Wetherald (1967).¹ The consequences of rising greenhouse gas concentrations are already evident (Eyring et al., 2021) and, if emissions remain unabated, they will compromise planetary habitability for centuries to millennia (e.g., Rockström et al., 2009).

The Intergovernmental Panel on Climate Change (IPCC) endeavours to collate and assess scientific knowledge on how the climate will change, the impacts of these changes, and potential mitigation pathways. Their most recent comprehensive assessment highlights large uncertainties in projections of future climate (IPCC, 2021a). This includes the overall sensitivity of global mean surface temperature changes to anthropogenic emissions (Forster et al., 2021) as well as many aspects of the response of regional temperature and rainfall patterns (Lee et al., 2021).

Much of this uncertainty arises from how models represent processes that regulate the flow of energy through the climate system, particularly those involving clouds and atmospheric circulation (Bony et al., 2013; Shepherd, 2014; Kent et al., 2015; Byrne et al., 2018; Sherwood et al., 2020; Zelinka et al., 2020). Although past efforts to understand clouds and convective processes often developed independently from studies of larger-scale circulation, it has become increasingly clear that these processes are tightly coupled (Hartmann & Larson, 2002; Bony et al., 2004; Feldl & Bordoni, 2016; Byrne & Schneider, 2018; Stevens et al., 2020; Voigt et al., 2021; Bloch-Johnson et al., 2024). Consequently, advancing our understanding of the interplay between clouds and circulation has been identified as a promising avenue for reducing uncertainties in climate change projections (Stevens & Bony, 2013; Bony et al., 2015).

Motivated by this perspective, this thesis investigates how interactions between cloud radiative effects and the large-scale circulation influence changes in the tropical climate. The remainder of this chapter provides the physical background and motivation for this work. We first introduce key aspects of the tropical circulation and summarise how it is expected to respond to anthropogenic forcing. We then discuss clouds and their radiative effects, and review how they contribute to radiative

¹The role of carbon dioxide in atmospheric warming was first demonstrated experimentally by Eunice Foote (1856) and later quantified by Arrhenius (1896).

feedbacks. Building on these discussions, we introduce the two-way coupling between clouds and circulation and the idea that uncertainties in cloud feedbacks and circulation changes may be linked. The chapter concludes by presenting the specific research questions that structure the remainder of the thesis and by outlining the observational and modelling approaches used to address them.

1.1 Tools for understanding Earth's climate

Our understanding of Earth's climate system relies on a combination of observations and models ranging from simple conceptual frameworks to comprehensive three-dimensional simulations. These models complement observations by providing detail on processes that are difficult to observe directly, as well as allowing exploration of climate states outside the historical record. Most importantly, they are the primary means through which we investigate how the climate system might respond to anthropogenic forcing.

1.1.1 Models and model hierarchies

The most widely used models are general circulation models (GCMs). In GCMs, the atmosphere, ocean, land, and cryosphere are divided into a three-dimensional grid of cells. The temporal evolution of the physical properties of each cell is calculated based on a set of governing equations. In the atmosphere, these properties typically include temperature, humidity, pressure, and wind. Processes occurring at spatial scales larger than an individual grid cell and at timescales longer than the model timestep are explicitly resolved by numerically solving the governing equations of fluid motion (Navier–Stokes) together with thermodynamic conservation laws.

However, computational constraints mean that climate models often operate at relatively coarse spatial and temporal resolutions. Typical GCMs have horizontal grid spacings of around 50–150 km, time steps of ~ 20 minutes, and vertical grid spacings ranging from ~ 50 meters near the surface to several kilometres in the upper atmosphere (Eyring et al., 2016). As a result, many small-scale processes – such as cloud microphysics, convection, radiation, and turbulence –

cannot be resolved explicitly. Instead, they are parametrised: theory, observations or empirical relationships are used to approximate their average impact at the grid-cell scale (Stensrud, 2007).

Parametrising sub-grid scale processes presents one of the central challenges in climate modelling (Arakawa, 2004). These processes can be highly complex and poorly understood, and so hard to develop an appropriate approximation for. As a result, parameterisations contribute significantly to the uncertainty in model projections of future climate (e.g., Schneider et al., 2017).

The Climate Model Intercomparison Project (CMIP) provides a framework for comparing climate models developed by different modelling centres (Eyring et al., 2016). Participating groups run a common set of experiments, enabling systematic comparisons across models. This helps to identify sources of disagreement and guide model development. Throughout this thesis, ‘AMIP’ refers to atmosphere-only simulations with prescribed sea surface temperatures and sea ice (Gates et al., 1999), while ‘CMIP’ refers to simulations from the coupled CMIP experiments (Taylor et al., 2012).

An alternative approach to improving model fidelity is increasing model resolution, thereby increasing the number of resolved processes and improving the realism of already resolved features through reduced numerical error and more accurate representation of multi-scale interactions (Iles et al., 2020; Schneider et al., 2024). Recent advances in computational power have enabled the development of global convection-permitting models with horizontal resolutions of ~ 5 km (e.g., Segura et al., 2025). However, these models are computationally expensive and are not yet used for long-term climate simulations.

Over time, GCMs have evolved into more comprehensive Earth System Models, incorporating additional processes such as atmospheric chemistry, ocean biogeochemistry, the carbon cycle, and dynamic vegetation (Stocker, 2011). While this can also increase model fidelity, the greater complexity can lead to challenges in understanding the drivers of model behaviour. For this reason, it is important to consider the intended purpose of a climate model experiment, as experiments

targeting hypotheses about specific phenomena or processes may benefit from a simpler set up. Reed et al. (2025) describe two key approaches to model idealisation: (1) simplifying internal model processes, such as parametrisations, and (2) simplifying external boundary forcings, including couplings between model components (Fig. 1.3). The use of models with varying levels of complexity to study Hadley cell dynamics, as discussed in Section 1.2, provides a compelling example of how a model hierarchy can be used to build physical understanding (Maher et al., 2019).

A related distinction is between climate models and numerical weather prediction (NWP) models, which aim to predict the evolving atmospheric state over short timescales. NWP systems solve the same governing equations and employ many of the same physical parameterisations, but are optimised for short-range forecasting. Rather than being integrated forward freely for long periods, they are run in short forecast cycles. Every so many hours, the previous forecast is combined with newly available observations (weighted by their respective uncertainties) to produce a new best estimate of the state of the atmosphere, called the analysis, which provides the starting point from which a new forecast is run (Kalnay, 2002).

1.1.2 Earth observations and reanalyses

Earth observations are collected using a variety of platforms including satellites as well as ground-based, airborne, and sub-surface instruments. Observational datasets encompass both long-running measurement records, which enable analysis of climate variability and trends (e.g., CERES EBAF; Loeb et al., 2018), and data gathered during targeted research campaigns designed to investigate specific scientific questions (e.g., EUREC4A; Stevens et al., 2021).

A complementary approach is to combine observations with a NWP system to produce a physically consistent, gridded estimate of the evolving atmospheric state known as a ‘reanalysis’. A reanalysis is generated by running a NWP model in short forecast cycles in which observations are assimilated in regular sub-daily windows to produce an analysis that initialises the next forecast; repeating this

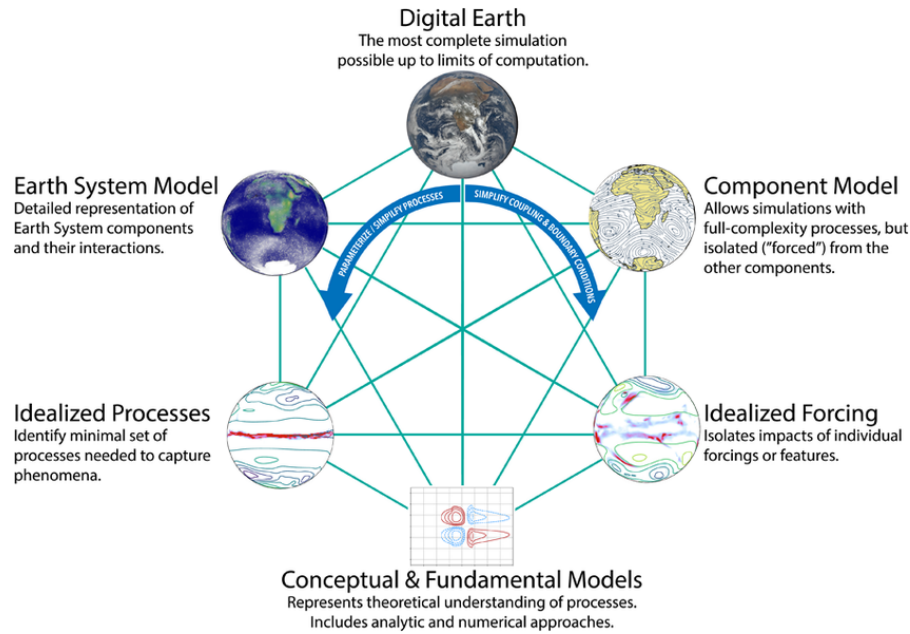


Figure 1.3: The climate model hierarchy, as envisioned by Reed et al. (2025). Nodes are representative of model variants while the approaches to model idealisation of simplifying internal model processes and simplifying external boundary forcings traverse the hierarchy roughly anticlockwise and clockwise, respectively. Adapted from Reed et al. (2025).

procedure sequentially yields a temporally continuous record. While reanalyses are powerful tools for studying climate variability and change, they inherit systematic errors from the forecast model and they can contain spurious variability associated with changes in data coverage and instrumentation over time (e.g., Kalnay, 2002; Fujiwara et al., 2017).

Observations and reanalyses provide an essential reference for understanding the historical climate system. However, interpreting these datasets requires careful consideration of the uncertainties and limitations of observations. These datasets may be affected by instrument errors, discontinuities due to changes in instrumentation or instrument location, and sparse coverage in remote or otherwise data-poor regions, leading to large uncertainties or spurious results (e.g., Evan et al., 2007; Liu et al., 2015; Chemke & Yuval, 2023). Insights from these datasets are also limited by the short observational record and by the complex mix of internal variability and external forcings influencing the climate system (Eyring et al., 2021). Finally, the dependence of the climate response to forcing on the base state and on the pattern of surface warming, which is affected by slow changes in ocean circulation,

means that the historical response to CO₂ forcing may not be representative of future changes (e.g., Sherwood et al., 2020).

1.2 Dynamics, thermodynamics and energetics of the tropical atmosphere

1.2.1 Basic characteristics of the tropics

The tropics spans approximately 30°N to 30°S. Incoming solar radiation peaks here and the region is characterised by consistently warm surface temperatures. The latitude of the insolation peak varies over the course of the year, reaching its northernmost and southernmost positions in June and December, respectively.

The tropical atmospheric circulation is characterised by large regions of weak subsidence punctuated by regions of convective ascent where warm humid air rises and cools leading to precipitation. At large spatial scales, this convection contributes to the ascending branches of the overturning cells known as the Hadley and Walker circulations. The rising branch of the Hadley circulation is the Intertropical Convergence Zone (ITCZ): a band of deep convection and heavy rainfall that forms a near-continuous band around the globe. The ITCZ migrates seasonally in response to the movement of the insolation peak and, over land, forms the monsoons (Trenberth et al., 2000; Geen et al., 2020). The Walker circulation is the zonal component of tropical overturning circulation, notably featuring ascent over the warm western Pacific and descent over the cooler eastern Pacific.

1.2.2 The convective quasi-equilibrium and weak temperature gradient approximations

The convective quasi-equilibrium (CQE; Betts 1982; Raymond 1995; Emanuel 2007) and weak temperature gradient (WTG; Bretherton and Smolarkiewicz 1989; Sobel et al. 2001) approximations provide a natural starting point for understanding the main features of the tropical atmosphere. Together, they describe how convection and large-scale dynamics adjust the atmosphere to maintain a balance between

radiative and surface energy fluxes, thereby constraining the vertical distributions of temperature, humidity, and moist static energy.

A central concept in both of these approximations is the moist static energy, h , the sum of the sensible heat, gravitational potential energy, and latent heat of an air parcel:

$$h = c_p T + L_v q + gz, \quad (1.2)$$

where c_p is the specific heat capacity of air, T is temperature, L_v the latent heat of vaporisation, q the specific humidity, g gravitational acceleration, and z altitude (e.g., Emanuel, 1994).

Convective quasi-equilibrium

To understand CQE, we first review the physical processes that govern the development of deep convection. Convection typically begins in the boundary layer, the lowest part of the troposphere, which is directly influenced by the surface. Boundary-layer air can be lifted by turbulent thermals and by low-level convergence associated with mesoscale and large-scale disturbances as well as by orographic lifting over land (e.g., Houze, 2014). The subsequent evolution can be understood in terms of buoyancy, which reflects the density difference between a parcel and its environment and is governed by temperature, water vapour concentration, and condensate loading. In many tropical environments the atmosphere is only conditionally unstable: a lifted parcel may be negatively buoyant over a finite depth before becoming positively buoyant above the level of free convection, allowing ascent to accelerate into deep convection (e.g., Emanuel, 1994; Houze, 2014). The transition to deep convection can occur either through strong dynamical lifting, or through thermodynamic changes in the boundary layer (surface warming and moistening). Once a parcel reaches the level of free convection, it ascends until it approaches the level of neutral buoyancy, typically in the upper troposphere.

The thermodynamics of convective ascent can be approximated as follows: while unsaturated, the parcel cools at the dry adiabatic lapse rate and approximately

conserves moist static energy. At the lifting condensation level, it becomes saturated; further ascent produces condensation and latent heat release. Assuming pseudoadiabatic ascent, in which condensate is immediately removed as precipitation, the parcel then follows a moist adiabat and approximately conserves its saturation moist static energy.² This idealised framework neglects entrainment of environmental air and assumes that condensate does not significantly affect the parcel buoyancy (e.g. through condensate loading or the re-evaporation of precipitation), processes which are important in nature (Emanuel, 1994). In particular, entrainment of drier free-tropospheric air can strongly reduce buoyancy through evaporative cooling and dilution.

CQE builds on this framework by assuming that, in the tropics, convection occurs frequently enough that it rapidly removes convective instability generated by slower processes such as radiative cooling and surface fluxes (Betts, 1982; Raymond, 1995; Emanuel, 2007). In practice, this means that convection continually adjusts the free-tropospheric temperature profile so that the boundary-layer moist static energy remains close to the saturation moist static energy aloft. Convection tends to occur when the boundary-layer moist static energy exceeds the saturation moist static energy of the free troposphere (Williams & Pierrehumbert, 2017). The resulting convective heating warms the free troposphere, increasing its saturation moist static energy and reducing the imbalance, thereby keeping the atmosphere close to equilibrium.

Weak temperature gradients

Whereas CQE emphasises the vertical structure of convection, WTG captures a complementary horizontal constraint. Near the equator the Coriolis force is weak, so pressure gradients are not balanced by rotation as in the midlatitudes; instead, air flows more directly from high to low pressure regions. Consequently, temperature anomalies are rapidly homogenised and the lapse rate across much of the tropical free troposphere is set by convecting regions (Emanuel et al., 1994; Sobel et al.,

²Saturation moist static energy is obtained by replacing q with the saturation specific humidity in Equation (1.2).

2001). On short timescales, gravity waves provide the main mechanism for damping horizontal temperature gradients (Bretherton & Smolarkiewicz, 1989), while changes in the large-scale circulation may also contribute to redistributing energy from more sustained heating perturbations (e.g., Gill, 1980).

Box models of the tropical atmosphere

Together, the WTG and CQE approximations idealise the tropical atmosphere as subject to strong constraints: horizontal temperature gradients remain weak, while the free-tropospheric profile is tied to boundary-layer moist static energy. These constraints motivate simplified models of the tropics that separate moist, convecting regions from dry, subsiding ones. Pierrehumbert (1995) formalised this two-box model, while later studies partitioned the atmosphere by buoyancy (Williams & Pierrehumbert, 2017) or vertical velocity (Bony et al., 2004) to capture a broader range of regimes. These approaches provide both a conceptual foundation and practical tools for interpreting observations and model output, and they form the basis for several analyses presented later in this thesis.

A practical advantage of the box-model framework is that it motivates simple diagnostics of the tropical circulation based directly on vertical motion. In this thesis we primarily characterise the tropical circulation using the vertical pressure velocity ω (hereafter ‘vertical velocity’). Alongside this, we make use of the mass continuity constraint: the mean vertical mass flux in ascending and subsiding regions must balance. Denoting the fractional areas of ascending and descending regions as $\alpha_{\uparrow}$ and $\alpha_{\downarrow}$, and the region-mean vertical velocities and atmospheric densities as $\omega_{\uparrow}$, $\omega_{\downarrow}$ and $\rho_{\uparrow}$, $\rho_{\downarrow}$, this can be written as

$$\alpha_{\uparrow}\rho_{\uparrow}\omega_{\uparrow} = -\alpha_{\downarrow}\rho_{\downarrow}\omega_{\downarrow}. \quad (1.3)$$

where we define $\omega_{\uparrow} > 0$ as the magnitude of ascent and $\omega_{\downarrow} > 0$ as the magnitude of subsidence.

To connect this ω -based description to the literature, note that many studies quantify circulation strength in terms of the convective mass flux in ascending

regions, $\rho_{\uparrow}\omega_{\uparrow}$ (e.g., Held & Soden, 2006). Changes in circulation strength are often discussed alongside changes in the fractional area of ascent to provide a more complete perspective on changes in the tropical circulation (e.g., Jenney et al., 2020).

Alternative characterisations of the tropical circulation are also widely used in the literature, including the zonal-mean meridional mass streamfunction for the Hadley circulation and analogous streamfunction-based measures of the Walker circulation. These diagnostics are employed in several of the studies referenced throughout this thesis (e.g., Held & Hou, 1980).

A further advantage of this regime-based framework is that it provides a simple energetic closure for the free troposphere in subsiding regions, linking radiative cooling directly to the strength of large-scale descent. Because these regions are relatively dry, moist processes can be neglected and their energy budget approximated in terms of dry static energy, $s = c_p T + gz$. In steady state, radiative cooling must be balanced by adiabatic warming from large-scale descent, directly linking diabatic processes to vertical motion (e.g., Knutson & Manabe, 1995; Bony et al., 2016). Put differently, subsidence strength adjusts so that adiabatic warming offsets radiative cooling. In pressure coordinates, this balance is expressed by the dry static energy budget:

$$\omega = \frac{-Q^R}{\partial s / \partial p}, \quad (1.4)$$

where Q^R is radiative cooling of the atmosphere. Note that $\partial s / \partial p$ is commonly referred to as the static stability.

In this thesis, we use this box-model framework as a starting point for linking large-scale circulation, thermodynamics, and energetics in the tropics. That said, idealised GCM studies have emphasised that the tropical circulation is also shaped by broader dynamical and energetic constraints. The remainder of this section therefore places our regime-based ideas in the context of these idealised GCM studies before noting the further complexities present in the real atmosphere, including shallow circulations, mesoscale convective organisation, and transient waves.

1.2.3 Insights from idealised models

Idealised GCMs have provided a complementary route to understanding the tropical circulation, with previous studies focusing on the Hadley circulation and its role in global energy and momentum transports (Held, 2005; Schneider, 2006; Maher et al., 2019). In this literature, the Hadley circulation is most commonly quantified using the zonal-mean meridional mass streamfunction. To explore the dynamical constraints on this key component of tropical energy transport, Held and Hou (1980) developed an axisymmetric, nearly inviscid model.³ Their results showed that because air parcels conserve angular momentum as they move poleward aloft, a Hadley cell extending too far from the equator would generate unrealistically strong subtropical jets. Based on this, they derived a theoretical prediction for the strength and meridional extent of the Hadley cell by assuming a steady-state thermal balance and combining this with angular momentum conservation and thermal wind balance — an approach now known as the Held–Hou model.

Moving up the model hierarchy to a dry three-dimensional GCM demonstrates why the real Hadley cells are not angular momentum conserving: midlatitude eddies penetrate into the tropics, extracting momentum through eddy fluxes and thereby controlling the circulation strength (Schneider, 2006; Walker & Schneider, 2006). However, when the peak in surface warming is displaced far from the equator, as in some regional monsoon systems, the circulation becomes more thermally driven and transitions into an approximately angular momentum conserving regime (Bordoni & Schneider, 2008; Schneider & Bordoni, 2008). In this regime, monsoon location is closely tied to the latitude of maximum sub-cloud moist static energy, consistent with the CQE framework (Plumb & Hou, 1992). Bordoni and Schneider (2008) and Schneider and Bordoni (2008) also showed that the transition from an eddy-driven to an angular momentum conserving regime occurs abruptly, driven by several dynamic feedbacks. Their aquaplanet simulations employed idealised

³Axisymmetric models are two-dimensional (latitude–height) and assume zonal symmetry. Held and Hou (1980) employed further simplifications, including steady-state assumptions and an inviscid atmosphere i.e. an atmosphere in which frictional and turbulent mixing of momentum is neglected so that momentum is transported only by the resolved large-scale flow.

moist physics with simplified convection and prescribed radiative forcing. Building on this work, Geen et al. (2019) re-examined monsoon onset and withdrawal in aquaplanet simulations with interactive moisture and precipitation. They found that the transition into an angular momentum conserving regime occurs once the convergence zone migrates poleward of about 7°N/S , a threshold that proved robust across variations in slab-ocean depth and seasonal forcing.

Further work has highlighted the role of radiative feedbacks: using radiation-locking techniques in an aquaplanet framework, Byrne and Zanna (2020) showed that seasonal variations in clouds and water vapour strongly modulate the monsoon system, reducing net precipitation by half and substantially influencing the timing of monsoon onset.

Aquaplanet simulations have also provided valuable insight into the role of the Hadley circulation in poleward energy transports. In the tropics, the meridional energy budget is balanced by a combination of atmospheric and oceanic heat transport (Marshall & Plumb, 2008). Within the atmosphere, the Hadley circulation transports energy poleward through its upper branch, while near-surface flow transports latent and sensible heat equatorward (Neelin & Held, 1987). The effectiveness of overturning circulations in exporting energy is often characterised by the gross moist stability, defined as the net export of moist static energy per unit upward mass flux in convective regions (e.g., Neelin & Held, 1987). In this framework, the relevant measure of circulation strength is therefore the upward mass flux in convecting regions, rather than the zonal-mean mass streamfunction.

Because poleward transport by the Hadley circulation dominates the tropical atmospheric energy budget, the latitude of the ITCZ is closely tied to hemispheric energy balance through the concept of the energy flux equator (EFE) – the latitude where the vertically-integrated meridional moist static energy flux vanishes (Kang et al., 2008). Under the assumptions that the EFE lies near the ITCZ and that weak temperature gradients prevail across the tropics, an interhemispheric energy imbalance is compensated by cross-equatorial atmospheric transport, shifting the ITCZ toward the hemisphere with the surplus. This mechanism helps explain why

the climatological ITCZ sits north of the equator: northward ocean heat transport leaves the Northern Hemisphere with an energy surplus, requiring compensating atmospheric transport into the Southern Hemisphere (Marshall et al., 2014). Further studies note that, in addition to interhemispheric energy contrasts, changes in the net energy input to the tropical atmosphere can drive shifts in ITCZ location (Bischoff & Schneider, 2014; Kang et al., 2018).

1.2.4 From idealised models to real-world complexities

Despite their insights, theories developed using idealised models can diverge from observed behaviour in the real atmosphere. For example, the EFE does not always align with the ITCZ latitude, particularly when the gross moist stability varies strongly or becomes negative, as occurs during monsoon retreat (e.g., Wei & Bordoni, 2018). In addition, dynamical theories do not explain why real-world monsoons often occupy intermediate regimes between angular momentum conserving and eddy-driven circulations (Schneider et al., 2010; Geen et al., 2020). Indeed, Baker et al. (2018) show that Hadley circulation strength is sensitive to diabatic heating throughout much of the tropical and extratropical atmosphere, indicating that processes beyond midlatitude eddies and near-surface moist static energy in the ascending branch of the circulation may play an important role.

More fundamentally, applying axisymmetric theories beyond the zonal mean remains challenging (e.g., Adam et al., 2016; Biasutti et al., 2018; Geen et al., 2020). This motivates exploration of how zonal asymmetries in surface boundary conditions influence mass and energy flows (e.g., Shaw, 2014; Boos & Korty, 2016; Voigt et al., 2016; Zhou & Xie, 2018). A canonical example is the linear analytical model of Gill (1980), which showed that localised tropical heating induces a zonally asymmetric overturning circulation – the theoretical foundation for understanding Walker circulations.

As this thesis focuses on the tropical overturning circulation and large-scale thermodynamics, many important aspects of tropical climate are beyond its scope. Notably, while the importance of ascent for precipitation motivates focus on the

divergent flow, rotational flow is three times stronger than divergent flow in the tropics (Wang et al., 2017). In addition, shallow overturning circulations make significant contributions to the divergent flow (Trenberth et al., 2000; Good et al., 2021), and smaller-scale disturbances, such as mesoscale convective systems, not only comprise but also influence the large-scale circulation (e.g., Biasutti et al., 2018). From a temporal perspective, we primarily emphasise the annual mean, but the timescale for atmospheric convection is on the order of minutes to hours (Emanuel, 1994). Transient waves are ubiquitous in the tropics (Geen et al., 2020) and stationary waves make important contributions to regional climate (e.g., Shaw, 2014). Finally, many modes of tropical variability exist, the most prominent of which is the El Niño–Southern Oscillation (ENSO).

1.3 Tropical clouds

1.3.1 Cloud formation, morphology and spatial distribution

Clouds form when air becomes slightly saturated with respect to water vapour. Supersaturation is most commonly produced by adiabatic cooling during ascent, although radiative cooling and turbulent mixing can also generate it. Once supersaturation is reached, water vapour condenses onto cloud condensation nuclei to form liquid droplets, while ice crystals form either by deposition onto ice-nucleating particles or by homogeneous freezing of supercooled droplets at sufficiently low temperatures (e.g., Pruppacher & Klett, 1997; Wallace & Hobbs, 2006). Newly formed droplets and crystals are initially small and grow by vapour diffusion; additional growth depends on phase, with growth mechanisms including collision–coalescence in warm clouds and the Bergeron–Findeisen process, riming, or aggregation in cold clouds. Cloud phase is therefore determined both by local temperature and the cloud’s past microphysical evolution: clouds are predominantly liquid above 0°C, mixed-phase is common at intermediate subfreezing temperatures, and clouds are almost exclusively ice below approximately -38°C (Koop et al., 2000). When hydrometeors become large enough that gravitational settling exceeds updraft support, they fall out as precipitation.

Cloud morphology varies widely in space and time. It reflects sensitivity to both the thermodynamic environment – temperature, humidity, and the availability of cloud condensation nuclei – and to atmospheric dynamics, ranging from turbulence and convection to waves and the large-scale circulation.

In the tropics, many clouds form through moist convection. Convective updrafts accelerate when buoyancy is strong, but weaken as buoyancy decreases and other decelerating forces become important. The depth of convection is therefore strongly influenced by stable layers in the troposphere, including the trade-wind inversion for shallow cumulus, the 0°C level for cumulus congestus, while deep cumulonimbus clouds peak near the tropopause (Johnson et al., 1999).

Cumulonimbus clouds are produced by the strongest convective updrafts. These clouds typically begin as buoyant convective towers that deepen rapidly, then enter a mature stage in which vigorous ascent coexists with heavy precipitation and precipitation-driven downdrafts. As the resulting cold pool spreads and disrupts low-level inflow, the updraft weakens and the system transitions into a dissipating stage (e.g., Emanuel, 1994). While this lifecycle is governed by convective dynamics and precipitation processes, the maximum depth reached by the convective towers and the level at which they detrain are strongly constrained by clear-sky processes. In particular, water vapour concentrations decrease around 220 K, reducing clear-sky radiative cooling and hence subsidence [from Eq. (1.4)], which leads to local mass convergence balanced by divergence in convective cores (Hartmann & Larson, 2002). This divergence causes cumulonimbus cloud tops to spread horizontally into anvils. These anvils are shaped by a combination of dynamical, radiative, and microphysical processes and can persist long after the parent convective towers decay (Gasparini et al., 2023).

Cumulus and cumulus congestus clouds are associated with weaker updrafts, whose vertical development is limited by lapse-rate variations lower in the atmosphere. Cumulus congestus clouds are typically capped near 0°C (Johnson et al., 1999), where latent heat release from freezing weakens the environmental lapse rate

and reduces convective instability. Shallower cumulus clouds are usually constrained by the trade-wind inversion,⁴ which inhibits further ascent.

These cloud types often coexist within deep convective regions, while shallow cumulus clouds become more prevalent in areas where weak ascent or subsidence dominate. The distribution of deep and shallow convective clouds is closely linked to mesoscale circulation features (e.g., Holloway et al., 2017; Stevens et al., 2020).

Over the eastern subtropical ocean basins, sea surface temperatures (SSTs) are kept cool by coastal upwelling associated with eastern boundary currents within the ocean. The resulting strong marine boundary-layer inversion suppresses deep convection, so shallow cumulus cloud fields gradually transition into extensive stratocumulus decks. Within these decks, radiative cooling at the cloud top strengthens the inversion, driving turbulent mixing in the boundary layer that transports moisture upward and helps sustain the clouds (Wood, 2012).

Thin cirrus clouds are widespread in the tropical upper troposphere. They form either from the outflow of dissipating convective systems or through local deposition (Gasparini et al., 2023). In-situ cirrus are particularly common at altitudes above the typical level of convective detrainment, where occasional overshooting convection delivers water vapour that can subsequently freeze into ice crystals through homogeneous or heterogeneous nucleation (Ueyama et al., 2018; Gasparini et al., 2023).

Our discussion so far highlights that cloud characteristics are shaped by local mixing and convection, and can also be influenced by the redistribution of heat and moisture by the circulation. Consequently, cloud distributions are closely tied to large-scale circulation regimes in the tropics. Figure 1.4a illustrates this: ascent regions are associated with cumuliform clouds, including deep convective cumulonimbus, while subsidence regions favour low clouds such as shallow cumulus and stratocumulus decks. This coupling is also striking from space, with the ITCZ, trade-wind regions, and subtropical subsidence zones all clearly demarcated by clouds in satellite images of Earth (Fig. 1.4b).

⁴In non-convective regions, warm, dry descending air overlies a moist marine boundary layer.

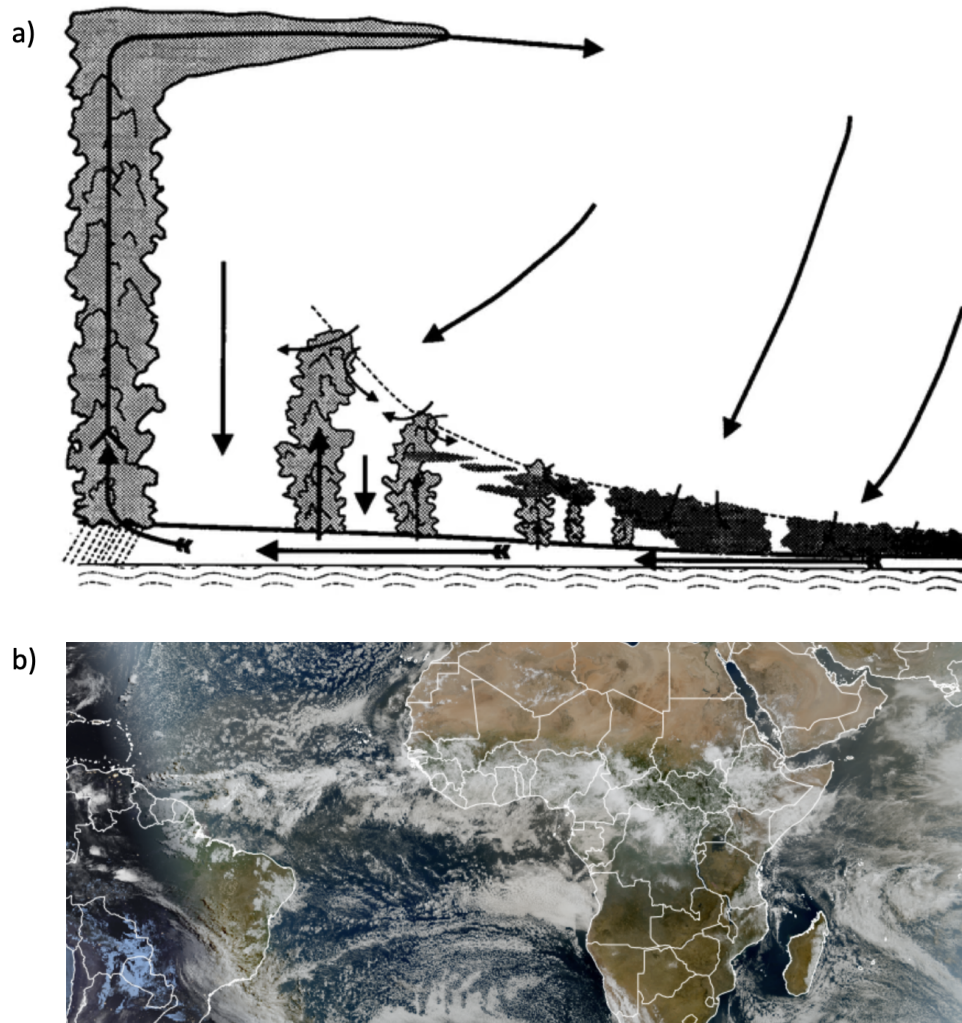


Figure 1.4: (a) Simplification of the structure of the tropical atmosphere showing the range of large-scale circulation regimes from mean ascent (left) to mean subsidence (right). Arrows denote wind direction and the dashed line represents the subsidence inversion. Adapted from Emanuel (1994). (b) Satellite image of Africa and the tropical Atlantic from 5th August 2025 (MTG GeoColour RGB with MSG IR10.8 in the background, EUMETSAT, 2025) Credit: EUMETSAT and NASA.

1.3.2 Cloud radiative effects

Tropical clouds exert a profound influence on Earth’s energy balance by modifying the flow of radiation. Before examining these cloud radiative effects in detail, we review how radiation interacts with the atmosphere in clear-sky conditions.

The absorption of radiation by the atmosphere depends on its constituent gases because each gas absorbs at specific wavelengths depending on its molecular structure (e.g., Liou, 2002). In the longwave region, absorption occurs primarily through transitions between rotational and vibrational energy levels. In the shortwave region, absorption is dominated by electronic transitions in the ultraviolet and by vibrational bands in the near-infrared. Once radiation is absorbed, its energy is redistributed within the atmosphere via collisions between gas molecules and is subsequently re-emitted at a rate determined by the local air temperature.

Earth’s atmosphere is opaque to many wavelengths in the longwave region of the electromagnetic spectrum. Although oxygen and nitrogen dominate atmospheric composition, they contribute little to absorption. Instead, longwave absorption is primarily controlled by water vapour and carbon dioxide (CO₂). The CO₂ concentration was 284 ppm in 1850 and this is typically taken to be the pre-industrial baseline (Meinshausen et al., 2017). Atmospheric water vapour is highly spatially variable, ranging from ~ 10 ppm in very cold air to $\sim 50,000$ ppm in warm tropical air (Wallace & Hobbs, 2006).

The atmosphere also absorbs shortwave radiation. In the ultraviolet, ozone and molecular oxygen remove much of the incoming solar radiation in the stratosphere (Brasseur & Solomon, 2005). In the near-infrared, water vapour and, to a lesser extent, CO₂ absorb part of the solar spectrum (Liou, 2002). As a result, the atmosphere is largely transparent in the visible band but absorbs a substantial fraction of solar radiation in the ultraviolet and near-infrared.

In addition to absorption and emission, radiation is also scattered by the clear-sky atmosphere. Rayleigh scattering redistributes incoming shortwave radiation in a strongly wavelength-dependent manner, while scattering of longwave radiation is negligible because infrared wavelengths are much larger than molecular dimensions.

The atmosphere is populated by aerosols such as sea salt, dust, and sulphate particles, whose radiative effects depend on their size, composition, and spatial distribution. Concentrations of individual species vary markedly in space, and aerosol particles scatter and absorb incident radiation to varying degrees, with the balance between scattering and absorption commonly characterised by the single-scattering albedo. Sea salt and sulphate aerosols are predominantly scattering in the shortwave, whereas carbonaceous aerosols, such as black carbon, have a much larger absorptive component, leading to local atmospheric heating.

Superimposed on this background, clouds strongly modify the radiative budget. First, cloud droplets and ice crystals scatter incoming shortwave radiation through Mie scattering. This scattering is characterised by a strongly forward-peaked phase function, so that many photons are scattered in the forward direction, while others are redirected backward, particularly after multiple scattering events within the cloud. As a result, the presence of clouds increases outgoing shortwave radiation at TOA, a process often referred to as cloud ‘reflection’, despite the term being something of a misnomer (e.g., Siebesma et al., 2020). Second, like water vapour, cloud droplets and ice crystals are highly efficient absorbers of longwave radiation. However, absorption occurs over a wider range of wavelengths because interactions between molecules in liquid water and ice broaden the spectral range of the absorption bands (e.g., Liou, 2002). The overall impact of these processes is quantified as the cloud radiative effect (CRE), defined as the difference in radiative fluxes between all-sky and clear-sky conditions. Here CRE is defined using net downward radiative fluxes, so that a negative TOA CRE corresponds to increased outgoing radiation to space (net cooling), while a positive TOA CRE corresponds to net warming. With this convention, shortwave CRE at TOA is typically negative (cooling), whereas longwave CRE is typically positive (warming). CRE can be evaluated at TOA and at the surface and decomposed into shortwave and longwave components. The difference in CRE between TOA and the surface yields the vertically integrated atmospheric CRE, while at individual atmospheric levels the cloud influence is often quantified in terms of cloud-radiative heating.

Conditions within non-cloudy regions of an atmospheric column can be affected by the presence of clouds within the column (e.g., Stephens, 1994). Given the above definition, this difference in clear-sky conditions contributes a non-cloud component to the CRE. For example, some of the difference between all-sky and clear-sky longwave radiative fluxes at TOA is associated with spatial correlations in the presence of clouds and water vapour (Sohn et al., 2010).

Dependence of radiative effects on cloud properties

A cloud’s effectiveness in scattering incoming solar radiation is quantified by its albedo, which depends on a range of bulk and microphysical properties. Important factors include whether the cloud is composed of water droplets or ice crystals, its vertical extent, and the size, concentration, and shape of the droplets or crystals (Liou, 2002). The vertically integrated liquid water path and ice water path quantify the amount of liquid water or ice in the atmospheric column and provide a simple bulk measure of cloud condensate. They are used as predictors of cloud albedo, which generally increases with increasing water path, although the relationship saturates once water paths are large (e.g., Lohmann et al., 2016). Shortwave CREs also depend on the cloud fraction and on the magnitude of the incoming solar flux. Because clouds do not strongly absorb shortwave radiation, their shortwave interactions have little effect on atmospheric radiative fluxes, so shortwave CREs at the surface and TOA are typically similar (Voigt et al., 2021).

Absorption and emission of longwave radiation by a cloud depends on its temperature and emissivity. Emissivity describes a body’s effectiveness at absorbing and emitting longwave radiation compared with an idealised blackbody. Similarly to cloud albedo, the emissivity of a cloud depends on the nature and abundance of its water droplets and ice crystals (Liou, 2002). At TOA, longwave CREs depend on cloud fraction and on the difference between the temperature of the cloud-top and the effective emission temperature of the underlying atmosphere. Because cloud tops are generally cooler than the underlying emission level, clouds reduce outgoing longwave radiation. Within the atmosphere, cloud absorption

of longwave radiation leads to warming below the cloud base from absorption of upwelling clear-sky radiation, and cooling near the cloud top from emission of longwave radiation (Slingo & Slingo, 1988).

Spatial distribution of cloud radiative effects

Stratocumulus, cumulus, cumulus congestus and cumulonimbus clouds all have high albedos leading to large negative shortwave CREs at TOA (Ramanathan et al., 1989). Because the longwave CRE at TOA depends primarily on cloud-top temperature, it is closely tied to cloud-top height: low stratocumulus clouds have only a small impact on outgoing longwave radiation, whereas cumulonimbus clouds strongly reduce outgoing longwave radiation (Hartmann et al., 1992).

Overall, the shortwave cooling effect of stratocumulus, cumulus, and cumulus congestus clouds exceeds their weaker longwave warming effect (Ramanathan et al., 1989). The impact of cumulonimbus clouds on TOA radiative fluxes is more complex. While the average radiative effect of these clouds is approximately neutral, this results from cancellation between strong longwave and shortwave CREs (Hartmann et al., 2001). This balance varies between clouds and over the course of the cloud lifetime: In the thick, convective core of the cloud, shortwave CREs exceed longwave CREs but, as the core dissipates into an anvil, it optically thins until the balance is reversed (Gasparini et al., 2021). The radiative effect of an individual cumulonimbus cloud is also affected by the diurnal cycle because shortwave reflection does not occur during night time, meaning the lifetime radiative effect of individual clouds is often positive or negative (Jones et al., 2024). Cirrus clouds are generally optically thin and diffuse, resulting in relatively small shortwave and longwave radiative impacts. However, their high altitude means they are very cold and exert a net warming at TOA (Gasparini et al., 2023).

Figure 1.5a shows the spatial distribution of shortwave and longwave CREs at TOA. As discussed in Section 1.3.1, cloud type is closely tied to circulation regime, and consequently so are CREs. At TOA, both longwave and shortwave CREs peak in regions of ascent, while shortwave CREs are also strong in the subsidence

regions over the eastern subtropical oceans due to the prevalence of low clouds. Within the atmosphere and at the surface, longwave CREs depend strongly on cloud type. Clouds warm the atmosphere below their base by absorbing upwelling longwave radiation and cool near their top through longwave emission, with the magnitude of this cooling set by cloud-top temperature and therefore by height. High, cold-topped clouds substantially reduce radiative cooling of the atmospheric column and thus have a net warming effect, whereas low, warm-topped clouds have little impact on longwave cooling and therefore exert a net cooling effect (Slingo & Slingo, 1988; Allan, 2011; Voigt et al., 2021). As a result, atmospheric CREs are typically positive in convective regions of ascent and negative in subsidence regions (Fig. 1.5b). At the surface, shortwave CREs mirror those at TOA, while in the tropics longwave CREs are strongest in subsidence regions (Fig. 1.5c).

1.4 The forcing-feedback framework

Before turning to the responses of tropical clouds and the tropical atmosphere to anthropogenic forcing, it is useful to outline a framework for how radiative perturbations influence the climate system and how the system equilibrates.

We begin by defining the instantaneous radiative forcing as the change in net TOA radiative flux caused by an external perturbation, such as increased atmospheric CO₂ or aerosol emissions, prior to any climate response. The system then undergoes adjustments which are independent of changes in global-mean surface temperature and typically occur over timescales of days to weeks (Ramaswamy et al., 2018). Together, the instantaneous forcing and the adjustments comprise the effective radiative forcing (ERF; Sherwood et al., 2015; Smith et al., 2020). As the surface begins to warm (or cool), additional changes in the TOA energy budget arise known as climate feedbacks. Both adjustments and feedbacks alter the TOA energy budget and, depending on the process, they may amplify or dampen the initial radiative perturbation.

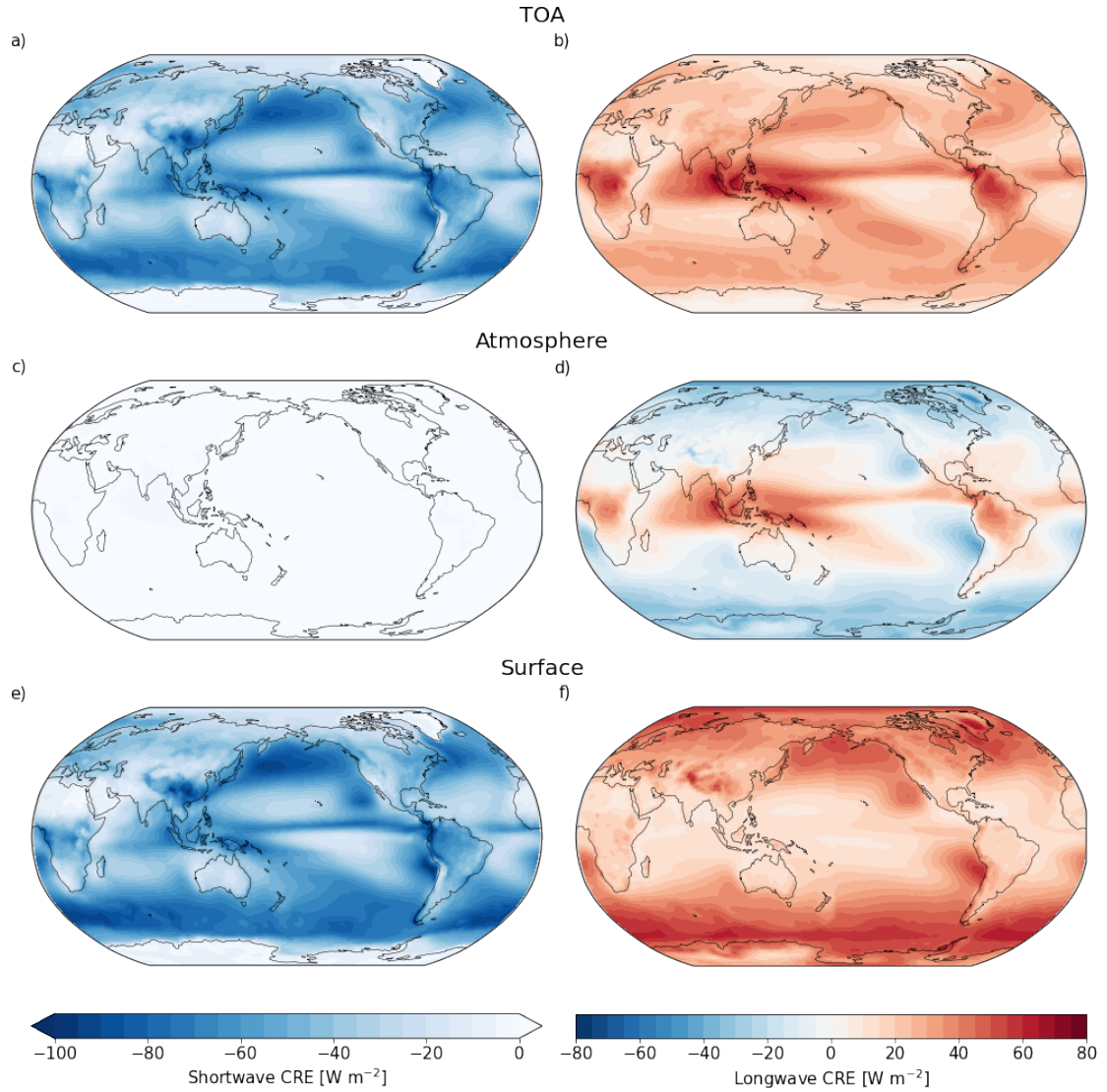


Figure 1.5: Longwave and shortwave CREs (a,b) at TOA; (c,d) within the atmosphere; and (e,f) at the surface evaluated using CERES EBAF Ed4.1 (2001 – 2020; Loeb et al., 2018).

This framework allows us to express the global-mean TOA radiative imbalance, ΔN , as:

$$\Delta N = \Delta F + \lambda \Delta T_s + V, \quad (1.5)$$

where ΔF is the global-mean ERF, λ is the climate feedback parameter, ΔT_s is the global-mean surface temperature change and V denotes variability in global TOA radiative fluxes unrelated to forcing or feedback (Hansen et al., 1997; Sherwood et al., 2015). As the climate system approaches equilibrium, $\Delta N \rightarrow 0$ and, over

long timescales, $V \rightarrow 0$.

The feedback parameter λ can be further decomposed into a sum of contributions from changes in individual system properties, x_i :

$$\lambda = \sum_i \lambda_i = \sum_i \frac{\partial N}{\partial x_i} \frac{\partial x_i}{\partial T_s}, \quad (1.6)$$

where the choice of system properties depends on the specific feedback framework employed.

Note that recent work shows that λ can vary significantly across scenarios due to its dependence on (1) the base climate, (2) the spatial pattern of surface warming, and (3) timescale (e.g., Armour et al., 2013; Caballero & Huber, 2013; Sherwood et al., 2020; Bloch-Johnson et al., 2021; Bloch-Johnson et al., 2024).

1.4.1 Radiative forcings and adjustments

The instantaneous radiative forcing caused by rising atmospheric CO₂ concentrations arises primarily from reduced outgoing longwave radiation. Associated T_s -independent adjustments include stratospheric cooling, physiological effects at the land surface, and tropospheric warming which modifies water vapour and cloud distributions. While the spatial pattern of these tropospheric adjustments varies substantially across models, a common feature is a reduction in mid-tropospheric cloud cover, which produces shortwave-driven warming (Smith et al., 2020; Wang & Huang, 2020). Potential mechanisms underlying the cloud adjustments associated with CO₂ forcing are reviewed in Sherwood et al. (2020, Section 3.2.1).

The aerosol radiative forcing comprises contributions from aerosol-radiation interactions and aerosol-cloud interactions (Forster et al., 2021). The instantaneous impact of aerosol-radiation interactions is dominated by the scattering of incoming solar radiation by aerosols, although some species, such as black carbon, absorb solar radiation and partially offset this cooling. The instantaneous impact of aerosol-cloud interactions arises from aerosol-induced changes in cloud particle number and size at fixed cloud liquid or cloud ice content. Surface temperature-independent adjustments to aerosol-cloud interactions are substantial, encompassing

changes in cloud liquid and ice water path, cloud fraction, and cloud lifetime (Forster et al., 2021). These adjustments are also highly uncertain, reflecting observational limitations and substantial differences in the representation of cloud microphysical and macrophysical processes among climate models (Smith et al., 2021). Adjustments associated with aerosol-radiation interactions are smaller at the global scale, but absorbing aerosols such as black carbon can locally heat the atmosphere and induce changes in cloud cover and circulation patterns (Ramanathan & Carmichael, 2008; Williams et al., 2022).

Over recent decades, anthropogenic emissions have driven a substantial positive effective radiative forcing (Fig. 1.6, thick black line; Forster et al., 2023). CO_2 has been the dominant contributor (positive ERF), partly offset by the negative ERF from aerosols (purple and grey lines). Whereas CO_2 forcing has strengthened steadily since the mid-20th century, aerosol forcing increased until the 1980s and has since gradually declined. The contribution to the ERF from natural processes is comparatively small, although volcanic eruptions cause large, short-term negative perturbations (dark green line).

Future CO_2 and aerosol emissions depend on global economics, policy and technological development. To explore the range of possible trajectories, standardised scenarios such as the Shared Socioeconomic Pathways (SSPs) are used (O'Neill et al., 2014). In addition, process-oriented modelling studies often employ idealised forcings, such as an abrupt quadrupling of CO_2 .

1.4.2 Radiative feedbacks

Radiative feedbacks quantify how the response of the climate system to increasing surface temperatures modifies Earth's TOA energy balance. These radiative changes are central to determining the climate system's sensitivity to external forcing and are associated with changes in atmospheric temperature and moisture as well as in clouds and surface albedo. We define radiative feedbacks as positive if they amplify surface warming and negative if they dampen warming.

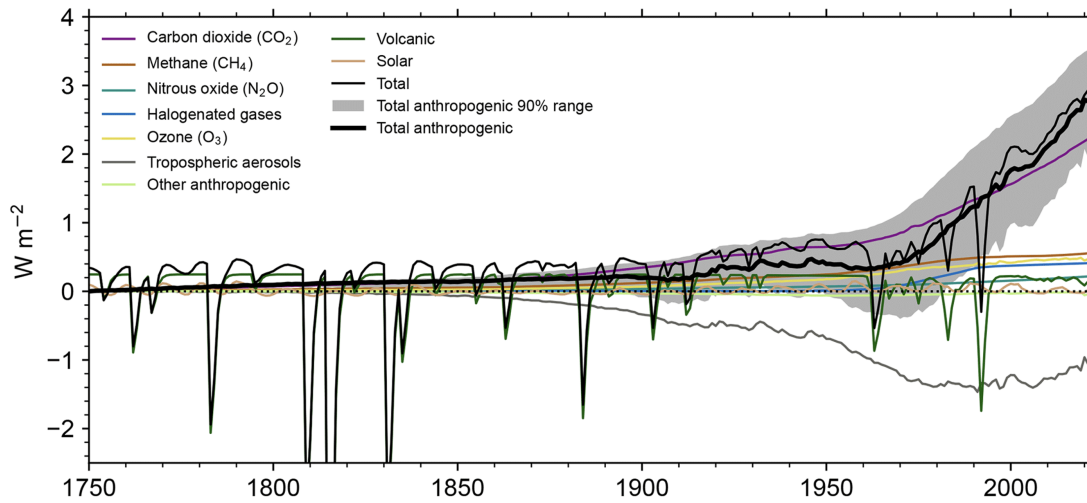


Figure 1.6: Time evolution of effective radiative forcing over 1950–2022. Adapted from Forster et al. (2023).

Changes in the atmospheric temperature profile are commonly divided into two components: the Planck feedback and the lapse rate feedback (Hansen et al., 1984; Sherwood et al., 2020). The Planck feedback refers to the increase in outgoing longwave radiation associated with vertically uniform warming. This response is stabilising: as the Earth warms, it emits more radiation to space, acting to dampen the initial surface warming (Fig. 1.7). The lapse rate feedback captures the impact of non-uniform vertical temperature changes on TOA radiative fluxes. Tropical lapse rate changes comprise enhanced warming aloft. This can be qualitatively explained via changes in the moist adiabatic lapse rate in convective regions driven surface warming (Payne et al., 2015). However lapse rate changes are controlled by a mixture of convective, dynamical and radiative processes including cloud changes (e.g., Flannaghan et al., 2014; Li et al., 2019; Miyawaki et al., 2020).

Increasing atmospheric temperatures allow the atmosphere to hold more water vapour, as described by the Clausius–Clapeyron relationship. As water vapour is a greenhouse gas, this is a positive radiative feedback. The magnitude of the feedback depends on relative humidity changes, but these are projected to be small, except over land (Held & Soden, 2000; Byrne & O’Gorman, 2016). Because the water vapour and lapse rate feedbacks are physically coupled and strongly

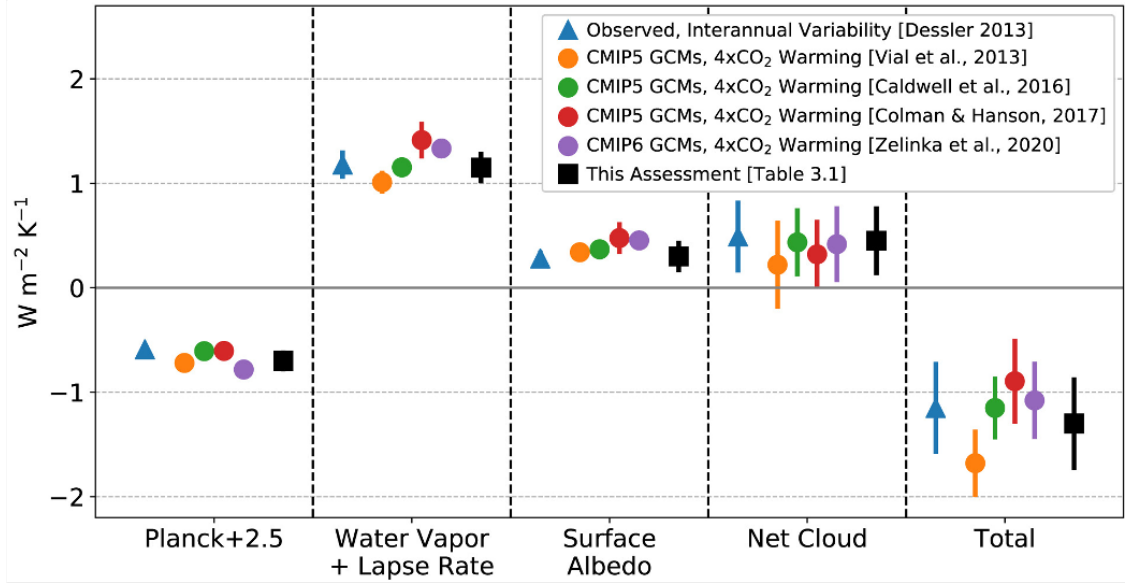


Figure 1.7: Estimates of global mean climate feedbacks from observations of interannual variability (Dessler, 2013) and CMIP5 and CMIP6 simulations of the climate system response to an abrupt quadrupling of CO₂ (Vial et al., 2013; Caldwell et al., 2016; Colman & Hanson, 2017; Zelinka et al., 2020) and from the Sherwood et al. (2020) assessment, which combines multiple lines of evidence including expert judgement. Error bars represent one standard deviation. Adapted from Sherwood et al. (2020).

anti-correlated across models, they are often reported together (Fig. 1.7; Colman, 2003; Soden & Held, 2006).

Changes in surface albedo also induce a positive radiative feedback. Surface warming leads to the melting of snow and sea ice, particularly at high latitudes, which reduces surface reflectivity and allows for greater absorption of solar radiation.

Cloud feedbacks are by far the largest source of uncertainty in the overall climate feedback (Fig. 1.7; Sherwood et al., 2020; Forster et al., 2021). As discussed, clouds are ubiquitous and have varying properties governed by processes operating over scales of micrometers to kilometres. This complexity makes their response to anthropogenic forcing particularly challenging to constrain.

Recently, Sherwood et al. (2020) combined a review of existing evidence from observations, climate models and theory with expert judgement to estimate cloud feedbacks. Building on this foundation, Zelinka et al. (2022) and Chao et al. (2024) developed more comprehensive frameworks for classifying cloud feedback processes

and provided new estimates of individual cloud feedback components strengths using CMIP6 model outputs and inter-annual variability, respectively.

The following sections introduce cloud feedbacks identified as potentially important in the tropics. Following Sherwood et al. (2020), Zelinka et al. (2022), and Chao et al. (2024), we categorise cloud feedbacks by changes in cloud amount, altitude, and albedo associated with individual cloud types. Existing studies have largely focused on cloud feedbacks at TOA, so we begin with this literature before turning to the influence of cloud changes on radiative fluxes within the atmosphere and at the surface.

From Section 1.3.2, we recall that, if CREs are calculated as the difference between all-sky and clear-sky TOA radiative fluxes, there is a non-cloud contribution to this. Depending on the nature of the study, changes in the non-cloud contribution may be removed from cloud feedback estimates using radiative kernels (Shell et al., 2008). Alternatively, cloud-radiative changes may be calculated directly from changes in cloud properties using the partial radiative perturbation method (Wetherald & Manabe, 1988).

High cloud altitude feedback

Surface warming is expected to drive an upward extension of the troposphere (Singh & O’Gorman, 2012). Evidence from GCMs (e.g., Zelinka et al., 2022), cloud-resolving models (e.g., Harrop & Hartmann, 2012), interannual variability (e.g., Vaillant de Guélis et al., 2018), and long-term trends between 2005 and 2022 (Ham et al., 2025) suggest that this leads to rising high clouds. This constitutes a positive radiative feedback: the upward shift means that cloud-top temperatures increase more slowly than the surface temperature and so the efficiency of longwave radiative cooling to space is reduced. Sherwood et al. (2020) estimate that this feedback contributes approximately $+0.20 \pm 0.10 \text{ W m}^{-2} \text{ K}^{-1}$ to the global-mean TOA feedback, where the uncertainty is one standard deviation (σ).

To explain this behaviour, Hartmann and Larson (2002) proposed the fixed anvil temperature (FAT) hypothesis, a theoretical framework grounded in the control

of anvil altitude by water vapour-driven radiative cooling in clear-sky regions (introduced in Section 1.3.1). Crucially, the capacity of an air parcel to hold water vapour depends on atmospheric temperature. Consequently, the decline in water vapour radiative cooling still occurs around the 220 K isotherm even if surface temperatures (and thus atmospheric temperatures) increase. However the isotherm, and thus the altitude of convective detrainment, shifts upwards (Hartmann & Larson, 2002). Zelinka and Hartmann (2010) extended this framework, showing that cloud-top temperatures do in fact increase slightly with surface warming. This arises because convection maintains the tropospheric temperature profile close to a moist adiabat and as surface temperatures rise, the lapse rate decreases (i.e. the troposphere becomes more stable). Note, however, that the increase in cloud top temperature is much smaller than the surface warming itself, so longwave heat loss to space is still reduced relative to a scenario without high clouds.

Recently, the robustness of the high-cloud altitude feedback has come under scrutiny. Seeley et al. (2019b) challenged the physical basis of the FAT hypothesis, arguing that the temperature of the tropopause, not convective detrainment, is independent of surface warming. In parallel, model-based analyses have highlighted considerable spread in high-cloud altitude feedback estimates. For instance, Zelinka et al. (2022) showed that the magnitude of this feedback varies widely across fully coupled CMIP5 and CMIP6 models subjected to abrupt CO₂ quadrupling, with 7 model estimates lying outside the Sherwood et al. (2020) $\pm 1\sigma$ confidence interval. Furthermore, Chao et al. (2024) found that the short-term high-cloud altitude feedback inferred from interannual variability in AMIP6 simulations is biased low relative to observational estimates in 12 of 17 models (at 90% confidence), with several models even suggesting that the feedback is negative at these timescales.

Tropical anvil area feedback

Despite the neutral net impact on TOA radiative fluxes of cumulonimbus clouds, the large individual magnitudes of these clouds' longwave and shortwave CREs

means that even small changes in cloud properties could produce substantial radiative feedbacks.

Several mechanisms have been proposed through which surface temperature changes might influence tropical anvil area. Increases in precipitation efficiency and convective aggregation have both been suggested as potential drivers of anvil shrinkage, but there is currently no evidence that surface warming affects these processes (Lindzen et al., 2001; Wing, 2019). Bony et al. (2016) instead proposed a ‘stability iris’ mechanism based on the clear-sky energy budget. In this view, amplified upper-tropospheric warming with surface warming increases static stability, so less cloudy-sky mass divergence is required to balance radiative cooling [Eq. (1.4)]. Consequently, the detrainment area—and thus the anvil extent—should shrink.

Unfortunately, challenges in parametrising convection and cloud microphysics mean that GCMs are of limited use in exploring anvil-area changes and their drivers, while convection-resolving simulations have produced varying results (see Sherwood et al., 2020, and references therein). Observational evidence supports the occurrence of the stability iris mechanism at inter-annual timescales (Saint-Lu et al., 2020), but does not connect this to cloud-radiative changes.

Given these uncertainties, Sherwood et al. (2020) based their estimate of the anvil area feedback on observations of inter-annual variability of CREs in ascending regions (Williams & Pierrehumbert, 2017), from which they subtracted an estimate of the high cloud altitude feedback, leading to an estimate of $-0.20 \pm 0.20 \text{ W m}^{-2}\text{K}^{-1}$ (Sherwood et al., 2020). This decision, alongside their allocation of a large uncertainty to the estimate based on the lack of evidence, has spurred renewed focus on constraining this feedback.

McKim et al. (2024) developed a quantitative model which connects the anvil area radiative feedback to the fractional change in anvil area with warming and climatological anvil properties. Based on observations of these climatological properties, their model suggests that the lower bound of the Sherwood et al. (2020) feedback would necessitate an implausibly strong anvil area sensitivity to warming of $\sim 50\% \text{ K}^{-1}$ and that the anvil area feedback is likely small.

Tropical anvil albedo feedback

Our discussion of anvil area feedbacks has thus far neglected a fundamental property of tropical anvil clouds: their radiative effect varies over the course of their lifetime (see Section 1.3.2). Thus, if cloud area changes vary over the cloud lifetime, this may induce an albedo feedback. The McKim et al. (2024) model assumes that the surface temperature impact on cloud area is invariant over cloud lifetime, while the approach of Sherwood et al. (2020) implicitly includes albedo changes in the area feedback.

Sokol et al. (2024) investigate this further by analysing cloud-radiative properties as a function of ice water path in convection-permitting models in radiative-convective equilibrium (RCE).⁵ They find that the area of thick, cooling anvils consistently decreases across models and associate this with the Bony et al. (2016) ‘stability iris’ mechanism. In contrast, changes in the area of thin, warming anvils show greater inter-model spread. Sokol et al. (2024) suggest that, during later stages of the anvil lifetime, anvil area may be less closely tied to convective detrainment and instead depend more on uncertain microphysical processes. It should be noted that anvil albedo feedbacks can also occur independently of area changes, for example, as a result of changing cloud microphysics (e.g., Gasparini et al., 2023).

Tropical low cloud feedback

Over recent decades, research on the response of tropical low clouds to surface warming has focused on low cloud changes in oceanic subsidence regions, which are populated by trade cumulus clouds and stratocumulus cloud decks. GCMs suggest that CO₂ forcing will increase SSTs in these regions and large eddy simulations show that local surface warming drives reduced cloud amount and thus reduced shortwave reflection, i.e., a positive feedback (Bony & Dufresne, 2005; Bretherton, 2015). The contribution from changes in altitude and albedo to low cloud feedbacks is likely small (Sherwood et al., 2020) but recent studies have explored the relationship between low cloud morphology and albedo (McCoy et al., 2023). Cloud controlling

⁵Radiative–convective equilibrium is an idealised representation of the tropical atmosphere with uniform surface conditions in which radiative cooling is balanced by convective and surface fluxes (Wing et al., 2018).

factor studies⁶ have used observed variability to constrain the radiative impact of changes in low clouds in subsidence regions (Klein et al., 2018), leading Sherwood et al. (2020) to estimate the feedback to be $+0.25 \pm 0.16 \text{ W m}^{-2}\text{K}^{-1}$. However, recent studies point towards a weak trade cumulus feedback (e.g., Vogel et al., 2022), suggesting the feedback estimate could be revised down.

An important source of uncertainty in low cloud amount feedbacks in subsidence regions arises from uncertainty in future SST pattern changes. While GCMs project that SSTs will increase in the tropical East Pacific, they fail to simulate the SST trend over the historical period, suggesting they might inadequately represent mechanisms controlling future SST pattern changes (Wills et al., 2022). Observations over recent decades indicate relatively little warming in the eastern Pacific compared to stronger warming in the west. Warming west Pacific SSTs strengthen local convection and thus tropics-wide static stability, leading to increases in low cloud amount (Zhou et al., 2016). This is an important example of the ‘pattern effect’: the dependence of feedbacks on the spatial distribution of warming, mentioned in Section 1.4.

Low clouds are also present in regions of climatological ascent in the tropics but the response of these clouds to warming has received less attention. Zelinka et al. (2022) show that the CMIP5 and CMIP6 multimodel mean albedo and area feedback of these clouds is neutral and that inter-model spread is limited.

Land cloud feedback

Greater surface warming over land compared to ocean is expected to reduce relative humidity over land, particularly in regions where climatological temperatures are high (Joshi et al., 2008; Byrne & O’Gorman, 2013; Byrne & O’Gorman, 2016). In response, GCMs simulate a robust reduction in cloudiness in these regions (Bretherton et al., 2014; Kamae et al., 2016). Although this reduction occurs across all vertical levels, the dominant contribution to the cloud feedback comes from reductions in low cloud, which drive a positive shortwave feedback. This finding is

⁶Cloud-controlling factor studies relate short-term CRE variability to large-scale environmental conditions (or ‘controlling factors’) and use projected changes in these factors under external forcing to infer long-term cloud feedbacks.

consistent with observations at a site in central USA (e.g., Zhang & Klein, 2013). Sherwood et al. (2020) assign the feedback a value of $+0.08 \pm 0.08 \text{ W m}^{-2}\text{K}^{-1}$, based on the mean feedback across the CMIP3 and CMIP5 models assessed by Zelinka et al. (2016). They assign a feedback uncertainty higher than the standard deviation across models to reflect limited confidence in model fidelity over land. In addition, the role of other over-land climate changes in driving cloud feedbacks has received relatively little attention. For example, multi-decadal satellite observations have shown a cooling of upper-tropospheric cloud temperatures over land (McGarraugh et al., 2018), which could be associated with changing convective processes.

Spatial distribution of cloud feedbacks

The latitudinal distribution of cloud feedbacks simulated by CMIP5 models in response to CO_2 quadrupling is shown in Figure 1.8a. To interpret this figure, recall that radiative feedbacks are positive if they amplify surface warming and negative if they dampen warming. Note also that at TOA shortwave CRE is typically negative, whereas longwave CRE is typically positive. Although there is substantial inter-model spread in the net cloud feedback, the multi-model mean shows an overall positive feedback throughout the tropics driven by weakening shortwave CREs in the region $10^\circ - 30^\circ\text{N/S}$ and strengthening longwave CREs at the equator (opposed by a weaker increase of shortwave CREs).

Similarly to the CRE climatology, cloud feedbacks at TOA can be separated into components associated with radiative changes within the atmosphere and at the surface (Fig. 1.8b,c). Given shortwave cloud feedbacks involve changes in reflection (which does not affect energy absorbed by the atmospheric column), shortwave feedbacks at the surface are almost identical to those at TOA. In contrast, changes in longwave absorption and emission by clouds modify the radiative balance in the atmosphere as well as at the surface.

The FAT hypothesis for surface warming-driven changes in cloud altitude provides a useful starting point for understanding changes in cloud-radiative heating of the atmosphere. Because cloud-top temperatures remain approximately invariant,

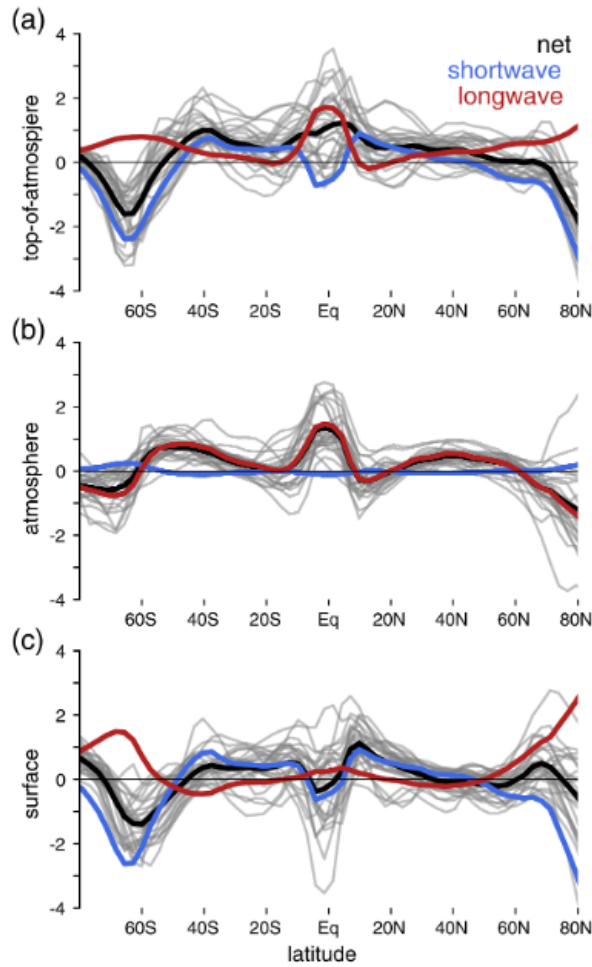


Figure 1.8: Cloud-driven radiative flux changes (a) at TOA; (b) within the atmosphere (vertically integrated); and (c) at the surface simulated by CMIP5 coupled models following an abrupt quadrupling of CO_2 . Heating is normalised by the global-mean surface warming and has units $\text{W m}^{-2}\text{K}^{-1}$. Gray lines show net changes for individual models while the multi-model mean is shown for the net (black), shortwave (blue), and longwave (red) radiative flux changes separately. From Voigt et al. (2021).

warming leads to an upward shift of the present-day heating profile (Voigt et al., 2024). This vertical shift is a robust feature of GCM simulations, including the CMIP6 ensemble (Voigt et al., 2019, 2024). This result is also evident in cloud-resolving models, although isothermal cloud altitude increases additionally drive an increase in cloud-radiative heating because air density decreases with altitude (Gasparini et al., 2024).

Although this theoretical basis for understanding changes in cloud-radiative heating is valuable, McGraw et al. (2025) showed that there is significant spread in the cloud-radiative heating response to a uniform +4 K SST increase among CMIP6 models, and this is also clear from the results of Voigt et al. (2019, 2024). This spread partly results from differing climatological cloud distributions leading to different heating changes associated with an isothermal upward shift (Fig. (1.9, second row; Voigt et al., 2019; McGraw et al., 2025). However, McGraw et al. (2025)

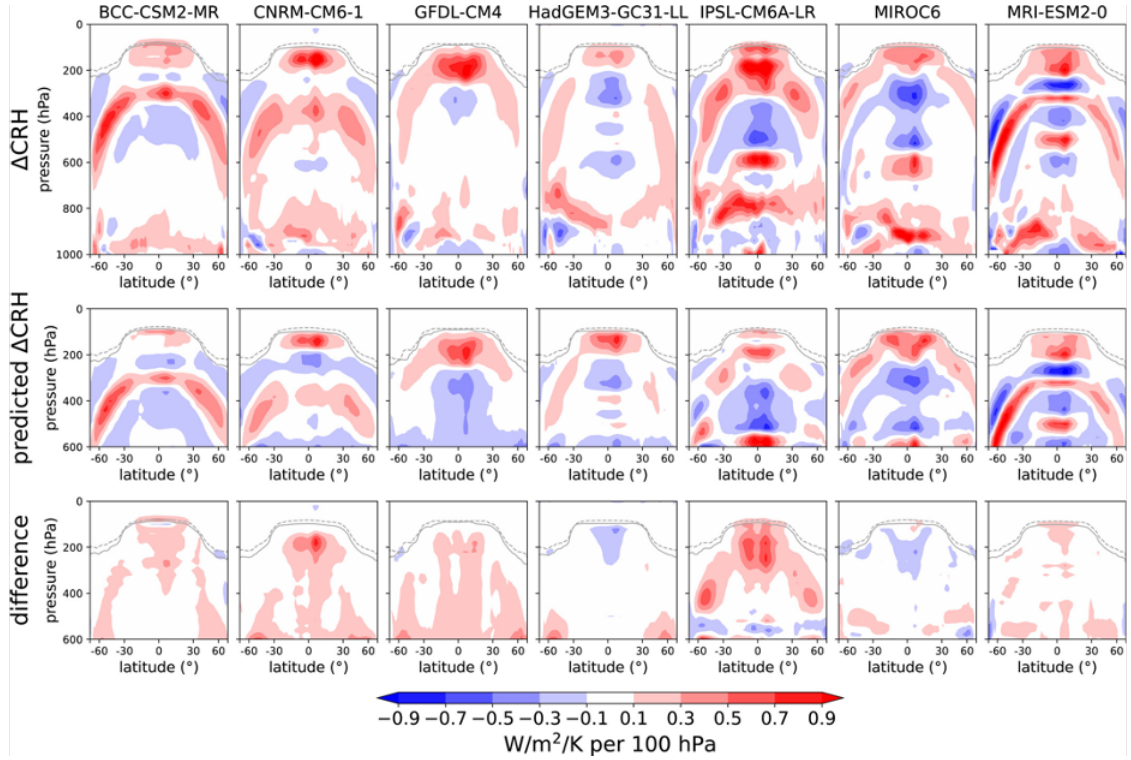


Figure 1.9: Cloud-radiative responses simulated by AMIP6 models following a uniform +4 K SST warming. Responses in the upper troposphere (above 600 hPa) are compared to what would occur if each cloud-radiative heating profile in the control simulation simply rose to maintain constant isotherms following the perturbation. Gray solid and dashed lines denote the tropopause in the control and uniformly warmed simulations, respectively. From McGraw et al. (2025).

also demonstrate that a significant contribution to cloud-radiative heating changes cannot be attributed to an isothermal shift, and which also exhibits substantial inter-model spread (Fig. 1.9, third row). This contribution may result from cloud altitude changes which do not conform to the FAT hypothesis, or from changes in cloud area and emissivity.

It is worth noting that there is some variation among these studies regarding the treatment of the non-cloud contribution to the change in cloud-radiative heating. While it is removed in Figure 1.8 and in Voigt et al. (2019), the multi-model studies of Voigt et al. (2024) and McGraw et al. (2025) do not remove it.

The spatial distribution of cloud feedbacks at the surface (Fig. 1.8c) has received less attention. The positive shortwave feedback in the subtropics is likely associated with reductions in low cloud amount, while high clouds will have a

larger impact near the equator. There is also a contribution to surface feedbacks from longwave cloud changes.

1.5 Tropical circulation response to forcing

1.5.1 Changes in circulation strength

We first discuss the circulation response to warming surface temperatures, before turning to how this response depends on the forcing agent through rapid adjustments and forcing-dependent patterns of surface warming.

The strength of the atmospheric overturning circulation is projected to decrease in response to warming surface temperatures (e.g., Held & Soden, 2006; Vecchi & Soden, 2007; Chadwick et al., 2013). This weakening encompasses both the Hadley and Walker circulations (Vecchi et al., 2006; Vecchi & Soden, 2007; D’Agostino et al., 2017; Duffy & O’Gorman, 2023) although there is spread among GCMs regarding the magnitude of the response (Bony et al., 2013; Feldl & Bordoni, 2016; Xia & Huang, 2017; Chemke & Polvani, 2021; Duffy & O’Gorman, 2023).

Several relationships have been proposed to understand this projected weakening. The most prominent argument is based on the energetic constraint on global-mean precipitation (Held & Soden, 2006). Because global precipitation is constrained by the atmospheric energy budget, it is projected to increase only weakly with warming (around 1–3% K⁻¹ in coupled models) (Stephens & Ellis, 2008; Jeevanjee & Romps, 2018). In contrast, boundary-layer specific humidity increases approximately at the Clausius–Clapeyron rate (around 7% K⁻¹). Taken together, these scalings imply that the upward convective mass flux (introduced in Section 1.2.2) must decrease with warming, typically by order −5% K⁻¹ (Held & Soden, 2006).

Additional insight into tropical circulation changes can be gained by also considering how ascent fraction changes. Jenney et al. (2020) found that, in RCE simulations, enhanced non-radiative heating (i.e., latent heating, detrainment, or dry static energy transport due to turbulence) in convective regions reduces ascent fraction with warming. This acts alongside weakening vertical velocities to reduce the tropical-mean convective mass transport.

While the previous discussion focuses on moist, convecting regions, further insight can be gained by considering the energy budget in dry, subsiding regions [Eq. (1.4)]. This approach shows that descent weakens because the fractional increase in static stability associated with increasing surface temperatures exceeds the fractional increase in radiative cooling (Knutson & Manabe, 1995; Bony et al., 2016).

More generally, circulation changes can be interpreted through the lens of large-scale energy transport. Spatial variations in the net energy received by the atmosphere create energetic imbalances which the large-scale tropical circulation may respond to (Held & Hou, 1980; Neelin & Held, 1987). Vertically, the efficiency of energy transport by the circulation is quantified by the gross moist stability, which is shaped by the vertical moist static energy gradient and the vertical structure of ascent (Neelin & Held, 1987). This can be affected by processes including lapse rate changes, near-surface moistening and changes in the altitude of convective outflow (Chou & Neelin, 2004; Chou et al., 2013). Horizontal energy transport is similarly affected by changes in horizontal moist static energy gradients and in the nature of the horizontal flow (Held & Hou, 1980; Neelin & Held, 1987; Duffy & O’Gorman, 2023). Viewed this way, changes in circulation can be linked to changes in TOA radiative fluxes, offering a useful framework for studying cloud-circulation coupling under forcing (e.g., Bony et al., 2016).

Finally, a dynamical explanation for warming-driven tropical circulation slowdown, known as the mean advection of stratification change mechanism, has been proposed (Ma et al., 2012). It posits that vertical advection of changes in the tropical lapse rate will reduce horizontal temperature and pressure gradients between regions of ascent and descent, thereby weakening the large-scale circulation.

Changes in circulation strength depend not only on surface temperature changes but also on the radiative forcing agent, through rapid adjustments and forcing-dependent patterns of surface warming. Increasing atmospheric CO₂ concentrations directly weaken the large-scale overturning circulation (Bony et al., 2013; Merlis, 2015), while absorbing aerosols induce in-atmosphere diabatic heating perturbations

and reflecting aerosols modify the pattern of surface temperature change (e.g., Kang et al., 2020; Stier et al., 2024).

The drivers of observed circulation trends are difficult to disentangle given the confounding influences of anthropogenic greenhouse gas and aerosol forcing, multi-decadal variability and potential biases in reanalysis products (e.g. Chung et al., 2019; Zplotnik et al., 2022). While Shrestha and Soden (2023) found that global-mean convective mass fluxes have weakened, the Walker circulation has strengthened in recent decades (e.g., Chung et al., 2019, and references therein), and reanalyses disagree on historical changes in the Hadley circulation (Nguyen et al., 2013; Pikovnik et al., 2022).

1.5.2 Shifts in the location of circulation features

In addition to changes in circulation strength, the atmospheric overturning circulation can undergo meridional or zonal displacements in response to external forcing. Large-scale energetic arguments provide a first-order explanation for meridional shifts: when external perturbations disrupt the cross-equatorial atmospheric energy balance, the zonal-mean ITCZ tends to migrate toward the hemisphere receiving greater net energy input (Kang et al., 2008; Bischoff & Schneider, 2014). This energetic perspective has been applied to interpret ITCZ migrations caused by changes in aerosol emissions, Arctic sea-ice loss, glacial melt, and ocean heat transport anomalies (Hwang et al., 2013; Marshall et al., 2014; Tomas et al., 2016; McFarlane & Frierson, 2017).

From a more regional perspective, spatial variations in SST warming patterns play a central role in reorganising convection. The ‘warmer-gets-wetter’ framework posits that, because upper-tropospheric temperature changes are relatively uniform, regional convective instability and precipitation changes primarily follow spatial variations in SST warming (Xie et al., 2010; Ma et al., 2012). Mechanisms of coupled ocean-atmosphere variability (such as the Bjerknes and wind-evaporation-SST feedbacks) can further amplify or dampen these SST-driven changes, influencing the structure of tropical convergence zones (Xie et al., 2010). Additional processes,

including land-sea temperature contrasts, land surface changes, and local circulation adjustments, also contribute to regional convergence shifts (Chadwick et al., 2013).

Recent work has combined these energetic and SST-based frameworks to explain zonally varying ITCZ responses to anthropogenic forcing. Mamalakis et al. (2021) analysed CMIP6 simulations under the SSP3-7.0 scenario and identified a robust sectoral pattern: a northward ITCZ shift over eastern Africa and the Indian Ocean, and a southward shift over the eastern Pacific and Atlantic. In their analysis, hemispheric energy asymmetries – driven by changes in ocean heat transport, surface albedo, and radiative feedbacks – set the large-scale direction of migration, while basin-scale SST gradients, maintained by coupled ocean-atmosphere feedbacks, shaped the regional ITCZ response.

The nature of tropical circulation shifts depends on the type of radiative forcing and on the resulting magnitude and pattern of surface temperature change. Aerosols tend to produce asymmetric, regionally varying forcing patterns, whereas greenhouse gases generate comparatively uniform forcings (Hwang et al., 2013; Williams et al., 2023b; Stier et al., 2024). Aerosol-driven energetic asymmetries may help explain observed trends: because anthropogenic aerosol emissions are concentrated in the Northern Hemisphere, they preferentially reduce shortwave energy input there, generating an interhemispheric energetic contrast (see Section 1.2.3) that several studies suggest has contributed to a northward displacement of the ITCZ and associated changes in Sahelian rainfall over recent decades (e.g., Hwang et al., 2013; Zhang et al., 2021). However, despite advances in theory and modelling, projections of regional circulation shifts still show substantial inter-model spread (Kent et al., 2015; Good et al., 2021; Mamalakis et al., 2021), reflecting differences in the representation of cloud and convective processes, ocean heat transport, land surface processes, and coupled ocean-atmosphere interactions.

1.5.3 Linking changes in circulation and $P-E$ patterns

The precipitation-minus-evaporation, $P-E$, response to CO_2 forcing is often explored using the moisture budget, sometimes in conjunction with the moist static energy

budget (e.g., Chou & Neelin, 2004; Seager et al., 2010; Bony et al., 2013).

The moisture budget links changes in $P-E$ to changes in atmospheric moisture and circulation, providing a framework for interpreting dynamically and thermodynamically driven responses. Held and Soden (2006) proposed that, on large spatial scales, increasing atmospheric water vapour with rising surface temperatures enhances moisture transport from dry to wet regions, strengthening the climatological $P-E$ distribution. This thermodynamic effect is partly offset by the weakening of the tropical overturning circulation described above (Held & Soden, 2006; Seager et al., 2010). Using an alternative decomposition, Chadwick et al. (2013) showed that, in CMIP5 models, the interplay between dynamic and thermodynamic changes produces rainfall anomalies that are primarily associated with changes in the location of convective regions.

1.6 Cloud-circulation interactions

In the present-day climate, cloud–circulation coupling is evident in the strong dependence of cloud type and cloud radiative effects (CREs) on large-scale dynamics. As shown in Section 1.3.1, regions of climatological ascent are associated with deep convective clouds, while regions of subsidence favour low clouds such as trade cumulus and stratocumulus decks (Section 1.3.2; Bony et al., 2004). At the same time, idealised theories and model hierarchies emphasise that the tropical overturning circulation is fundamentally constrained by the atmospheric energy balance (Section 1.2.3). Given that clouds exert spatially variable radiative effects, they directly affect influence circulation (e.g., Pierrehumbert, 1995; Kang et al., 2008; Bony et al., 2016).

This coupling implies that cloud and circulation responses to forcing cannot be interpreted independently. Changes in the strength and spatial structure of the circulation can contribute to cloud feedbacks by reorganising cloud regimes. For example, changes in the frequency of occurrence of different ascent and descent strengths, changes in the relative area of ascending versus descending regions, and shifts in the location of circulation features can all alter the distribution of cloud types and therefore CREs (e.g., Bony et al., 2004; Byrne & Schneider, 2018; Voigt

et al., 2021). CREs can also depend on the circulation indirectly via the relationship between circulation and other atmospheric properties and constituents. For example, changes in convection can affect stability throughout the tropics, which, in turn, can affect clouds in subsidence regions. Conversely, cloud-radiative changes alter atmospheric heating and the surface energy balance and can therefore modify circulation and hydrological-cycle responses (e.g., Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Voigt & Shaw, 2016; Voigt et al., 2021). While not the focus of this thesis, smaller-scale interactions between clouds and circulation, including the mesoscale organisation of deep and shallow convection and cloud-scale dynamical feedbacks within stratocumulus and convective anvils, may also influence their response to forcing (e.g., Muller & Held, 2012; Wood, 2012; Gasparini et al., 2023).

Untangling the mechanisms that link changes in CREs and circulation presents a significant challenge because the coupled cloud–circulation system spans a vast range of spatial scales. CREs depend on processes ranging from cloud microphysics and turbulence to mesoscale organisation, while the circulation spans scales from convective and regional circulations to planetary-scale Hadley and Walker circulations (Sections 1.2 and 1.2.3). Furthermore, both cloud feedbacks (Section 1.4.2) and circulation responses (Section 1.5) depend on the forcing agent and on the spatial pattern of surface warming. Because no single observational or modelling tool spans this full range of scales and forcing regimes, isolating mechanisms is difficult. Climate models enable targeted experiments and causal attribution, but GCMs represent key cloud and convective processes via parameterisations, while higher-resolution models resolve more cloud processes but cannot easily capture the full coupled climate response due to high computational costs. Satellite observations allow analysis of the present-day cloud and radiation climatology, including variability and trends, but are limited by retrieval uncertainties, incomplete sampling, and the short length of the observational record (Section 1.1). Circulation, and vertical motion in particular, is far harder to observe globally than cloud and radiation fields. In this case, reanalyses provide an important resource, offering physically

consistent, gridded estimates of the atmospheric state, but they remain model-based and inherit systematic errors (Section 1.1).

Before turning to the big questions motivated by these considerations, we note that interactions between clouds and circulation are not limited to interactions between cloud *radiative effects* and the circulation. Cloud formation and dissipation are associated with condensation and evaporation of water vapour, driving latent heating and cooling of the atmosphere and thereby affecting the circulation (e.g., Schneider et al., 2010). Similarly, small-scale turbulent motions within clouds interact with larger-scale atmospheric dynamics (e.g. Arakawa, 2004). Here, we focus specifically on interactions between CREs and the circulation.

1.7 Outstanding questions

Together, the discussions above motivate several outstanding questions regarding how cloud–circulation interactions shape the tropical climate response to anthropogenic forcing.

First, to what extent do interactions between clouds and circulation influence the tropical temperature and hydrological-cycle response to anthropogenic forcing? Changes in the circulation can affect cloud feedbacks and therefore the magnitude and spatial structure of warming (e.g., Bony et al., 2004, 2015; Williams & Pierrehumbert, 2017; Byrne & Schneider, 2018). Conversely, cloud-radiative changes can influence the circulation response by modifying atmospheric heating and the surface energy balance, with implications for the strength and spatial structure of the atmospheric circulation (e.g., Ceppi & Hartmann, 2016; Byrne & Schneider, 2018; Voigt et al., 2021). Changes in both temperature and circulation then affect the hydrological cycle, shaping $P-E$ responses through energetic and dynamical constraints (e.g., Held & Soden, 2006; Seager et al., 2010; Chadwick et al., 2013).

Second, through what mechanisms do cloud–circulation interactions influence the tropical climate response? Progress on this question requires frameworks that connect changes in cloud radiative effects to both the energetic constraints governing

the tropical atmosphere and the circulation changes that reorganise convection and subsidence (e.g., Bony et al., 2004; Held & Soden, 2006; Bony et al., 2016).

Third, to what extent do cloud–circulation interactions contribute to uncertainty in projections of tropical temperature and hydrological change? Cloud feedbacks are the dominant source of uncertainty in climate sensitivity (Section 1.4.2), while projections of tropical circulation and rainfall changes also show substantial spread (Section 1.5). A key open question is whether these uncertainties are linked — that is, whether differences in cloud responses across models systematically drive differences in circulation and hydrological responses, and vice versa (e.g., Bony et al., 2013; Feldl & Bordoni, 2016; Xia & Huang, 2017; Sherwood et al., 2020; Zelinka et al., 2020).

Fourth, how can we best use the tools at our disposal to address these questions? Progress requires drawing on complementary lines of evidence: observations, reanalyses and a hierarchy of models spanning from ‘pen and paper’ to idealised GCMs to high-resolution simulations (e.g., Stevens & Bony, 2013; Bony et al., 2015; Reed et al., 2025; Segura et al., 2025).

These outstanding questions motivate the more specific research questions addressed in this thesis. We first use observations to examine how circulation changes contribute to estimates of tropical cloud feedbacks, drawing on a novel observational dataset that allows cloud–circulation relationships to be analysed over multi-decadal records. We then use targeted GCM experiments to isolate the radiative impact of changes in clouds and test how this shapes circulation and hydrological responses to anthropogenic forcing. Throughout, we use simplified box-model representations of the tropics as a tool for understanding the large-scale relationship between CREs and vertical motion.

1.7.1 Influence of the tropical circulation on observed cloud feedbacks

Bony et al. (2004) proposed a method to identify dynamically driven changes in CRE based on the tight coupling between cloud properties and vertical velocity. In this method, the vertical velocity at 500 hPa, ω_{500} , is used as an imperfect

proxy for tropospheric dynamics. The tropics is separated into dynamical regimes based on ω_{500} intervals, and the mean CRE is calculated for each regime. Then dynamically driven changes in CRE can be quantified using changes in the frequency of occurrence of the different dynamical regimes. It is important to note that this method only identifies changes in CRE which are *directly* circulation driven. This regime-based decomposition provides the methodological starting point for the observational analysis in the first part of this thesis.

Byrne and Schneider (2018) used this method to show that, in CMIP5 models, changes in dynamics can contribute large local cloud feedbacks but the global-mean dynamically driven feedback is small. They showed that this is a consequence of (1) the steady-state atmospheric mass budget and (2) the approximately linear relationship between ω_{500} and CRE. Mackie and Byrne (2023) found similar results for cloud resolving models run in RCE, although nonlinearity in the relationship between clouds and circulation led to a substantial dynamic component for some models. Mackie and Byrne (2023) further showed that spread in the dynamic component can be related to inter-model differences in ascent fraction changes, which they linked to differences in non-radiative diabatic heating in ascending regions. Together, these studies highlight both the potential importance of circulation changes for cloud feedbacks and the need to test whether similar behaviour is evident in observations.

Beyond quantifying feedback contributions, the CRE- ω relationship has also been used as a process-oriented benchmark for models. The observed climatological relationship between CREs and circulation regime has also been used to evaluate climate models (Wyant et al., 2006; Yuan et al., 2008; Voigt et al., 2014a). More recently, observational estimates of this climatological relationship have been used to constrain GCM feedback estimates (Hill et al., 2023; Hill et al., 2025). For example, Hill et al. (2023) highlighted that GCMs fail to accurately capture the difference in shortwave CRE between shallow cumulus versus stratocumulus clouds, leading to an underestimation of the dynamical cloud feedback.

The same framework can also be applied using observations alone, providing a more direct link to the real climate system. Williams and Pierrehumbert (2017) used the Bony et al. (2004) decomposition to produce entirely observational estimates of tropical cloud feedbacks, and to estimate the contribution to these feedbacks from circulation changes, based on inter-annual co-variability between CRE and surface temperature. Referencing the substantial uncertainty in modelled anvil-area changes, Sherwood et al. (2020) used results from this study to estimate the anvil area feedback (Section 1.4.2). These results inspired the first research question of my thesis:

Q1. How do circulation changes contribute to tropical cloud feedbacks estimated from observed trends?

Addressing Q1 using observations requires careful interpretation of trends. As discussed in Section 1.1, the short observational record can lead to underlying trends being obscured by short-term variability. However, as datasets begin to extend over longer periods, it is intriguing to explore whether long-term trends are emerging. Of course, it is crucial to note that trends should not be misconstrued as being CO₂-forced, with important roles likely played by long-term modes of variability as well as other forcings. Even so, such trends offer a valuable lens for probing the behaviour of the real climate system – particularly for clouds, where difficulties in parametrising small-scale processes limit the realism of climate models.

To explore Q1, we use the DEEP-C all-sky radiative flux dataset combined with clear-sky fluxes from ERA5 to calculate CREs over 1985–2020 (Hersbach et al., 2020; Liu & Allan, 2022). Alongside estimating the dynamic and non-dynamic components of the cloud feedback following Bony et al. (2004), we explore the physical origins of the feedbacks. In particular, we aim to identify the circulation changes driving the dynamic component. We are also interested in whether, as for Byrne and Schneider (2018) and Mackie and Byrne (2023), the overall dynamic

component is small. Finally, we compare feedback estimates based on long-term trends to estimates based on inter-annual variability.

1.7.2 Influence of cloud-radiative changes on the tropical circulation and hydrological cycle

The influence of CREs on circulation is often explored using ‘mechanism denial’ experiments. These are experiments in which cloud-radiative properties are artificially removed or altered within climate models to test their role in a particular physical mechanism. The ‘cloud-locking’ method is typically used to explore the role of the cloud-radiative changes in climate change simulations (Wetherald & Manabe, 1988; Voigt et al., 2021). For example, one might prescribe CREs from a simulation in which CO₂ was quadrupled in a present-day simulation to estimate the impact of cloud-radiative changes on the circulation response. In cloud-locking studies, the term ‘cloud feedback’ is typically avoided, instead the focus is on changes in radiative fluxes or radiative heating of the atmosphere. This is because the method essentially involves applying radiative responses as forcings. Alternative strategies have been applied to understand how CREs influence the climatology. These include making clouds transparent to radiation (Hunt, 1978; Slingo & Slingo, 1988; Stevens et al., 2012) and spatially smoothing CREs (Tompkins & Craig, 1998; Bretherton et al., 2005; Muller & Held, 2012). These methods provide a practical route to isolating the radiative influence of clouds within models, and they form the basis of the modelling strategy used in the latter part of this thesis.

Early cloud-locking studies used aquaplanet simulations to investigate how clouds shape the circulation response to forcing in simplified settings (Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Voigt & Shaw, 2016). These studies revealed that cloud-radiative changes strengthen the equator-to-pole energy gradient in the atmosphere, driving a poleward shift of the extratropical jets, storm tracks and Hadley cell edges (Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Voigt & Shaw, 2016). Clouds strengthen the energy gradient through two key mechanisms: (1) increased optical depth of high-latitude mixed-phase clouds, which cools local SSTs, and (2) increased

upper-tropospheric heating from rising high clouds in the tropics and midlatitudes (Ceppi & Hartmann, 2016; Voigt & Shaw, 2016; Albern et al., 2020). Identification of these mechanisms was aided by separation of the cloud-radiative influence into that occurring via the ‘atmospheric pathway’ versus the ‘surface pathway’, i.e., that occurring in the absence of SST changes versus via SST changes (Voigt et al., 2021).

Ceppi and Shepherd (2017) and Voigt et al. (2019) showed that similar changes occur in simulations with realistic surface boundary conditions. As poleward circulation expansion is a robust projection of GCMs (Yin, 2005; Barnes & Polvani, 2013; Shaw, 2019; Grise & Davis, 2020), Ceppi and Shepherd (2017) and Voigt et al. (2019) also sought to understand the relative contribution to the expansion of cloud-radiative changes versus the original CO₂ forcing or changes in water vapour radiative effects or surface albedo. They achieved this using ‘radiation locking’, a method in which each of these radiative changes is locked individually, in a similar manner to cloud locking. Their studies showed that without cloud-radiative changes, the poleward circulation shift is significantly diminished in three GCMs (Ceppi & Shepherd, 2017; Voigt et al., 2019).

Analyses of future changes in the tropical hydrological cycle and tropical circulation have highlighted cloud-radiative changes as a potential driver of inter-model spread (Feldl & Bordoni, 2016; Xia & Huang, 2017), motivating exploration of how clouds influence tropical climate changes. Voigt and Shaw (2015) used radiation locking to demonstrate that cloud-radiative changes substantially influence vertical velocity and $P - E$ in two aquaplanet models, with the magnitudes of cloud-driven changes comparable to those of isolated SST changes. Notably, the two models diverged sharply in their cloud-driven responses: one simulated a narrowing and strengthening of the ITCZ, while the other simulated a widening and weakening. These opposing cloud effects explained roughly half of the difference between the models’ overall $P - E$ changes.

Advancing this line of inquiry, Ceppi and Hartmann (2016) employed an aquaplanet model with a slab ocean (rather than fixed SSTs) and found that the shortwave cloud response to CO₂ quadrupling strengthened the Hadley circulation

and the longwave response weakened it. While the tropics was not their focus, they hypothesised that these opposing influences arose because the shortwave changes drove enhanced meridional SST gradients in the tropics while the longwave changes stabilised the tropical atmosphere. Using a similar set up but with seasonally varying insolation and a different model, Byrne and Zanna (2020) found that both longwave and shortwave cloud-radiative changes increased $P-E$ within the monsoon region via their impact on atmospheric dynamics.

Clouds also influence annual-mean ITCZ location in aquaplanet slab-ocean studies. When an energetic perturbation is applied to a single hemisphere, cloud-radiative changes modulate the ITCZ shift that occurs in response (Kang et al., 2008; Voigt et al., 2014b, 2014a). Furthermore, Byrne and Zanna (2020) found that longwave CREs shift the aquaplanet monsoon circulation equatorward while shortwave CREs shift it poleward, although these effects approximately cancelled one another out.

Thus far, radiation-locking studies have shown that cloud-radiative changes can substantially alter the tropical circulation and hydrological cycle in aquaplanet simulations. However, the mechanisms driving these changes remain uncertain, as does the extent to which insights from idealised aquaplanets translate to the real climate system. The latter chapters of this thesis contribute to addressing these gaps by examining how cloud-radiative changes influence the tropical hydrological cycle and circulation in simulations with realistic boundary conditions. We use simulations performed by Huber (2022) using the ICON GCM (Giorgetta et al., 2018) in which radiation locking isolates the roles of cloud, water vapour, and CO_2 radiative effects in the climate response to CO_2 quadrupling. To structure our analysis, we employ a similar set of research questions to that used to understand the cloud influence on the poleward circulation expansion. We use the moisture and moist static energy budgets to gain understanding of the mechanisms driving these changes, which provide an intuitive means of connecting atmospheric dynamics and thermodynamics.

Q2. How do radiative changes in clouds, water vapour and CO₂ contribute to changes in tropical $P-E$?

Q3. How do cloud-radiative changes affect tropical $P-E$ via the atmospheric/land pathway?

Q4. How do cloud-radiative changes affect tropical $P-E$ via the oceanic pathway?

The remainder of the thesis is structured such that a chapter is dedicated to each of Q1–4. After this, a final chapter outlines the overall conclusions and outlook.



Folly Bridge, 11 Aug 2023

2

Tropical cloud feedbacks estimated from observed multi-decadal trends

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2.1 Introduction

Cloud feedbacks are the largest source of uncertainty in estimates of equilibrium climate sensitivity (Zelinka et al., 2020). Longstanding difficulties in modelling clouds, caused by the wide range of impactful processes and scales, have resulted in observational studies becoming an important line of evidence for estimating their feedbacks (Sherwood et al., 2020).

Observational cloud feedback estimates often rely on the CERES dataset (Loeb et al., 2018) for top-of-atmosphere (TOA) fluxes. However, data collection only began in 2000, so CERES-based feedback estimates have largely focused on inter-monthly or inter-annual co-variability between cloud radiative effect (CRE) and surface temperature. In an early study of this kind, Dessler (2010) found a global-mean short-term feedback of $+0.50 \pm 0.75 \text{ W m}^{-2}\text{K}^{-1}$ and, in a follow up paper, assessed that dataset choice led to variations of $0.2\text{--}0.3 \text{ W m}^{-2}\text{K}^{-1}$ in this estimate (Dessler & Loeb, 2013). More recent global studies have produced similar estimates (e.g., Chao et al., 2024), while estimates of the equivalent tropical-mean cloud feedback include $-0.06 \pm 0.73 \text{ W m}^{-2}\text{K}^{-1}$ (Williams & Pierrehumbert, 2017) and $+0.23 \pm 0.40 \text{ W m}^{-2}\text{K}^{-1}$ (Raghuraman et al., 2024). Recently, Raghuraman et al. (2023) used CERES to estimate the global-mean cloud feedback based on trends (rather than variability) in CRE and surface temperature and found a global-mean feedback close to zero ($+0.20 \pm 0.34 \text{ W m}^{-2}\text{K}^{-1}$).

In this study we use all-sky top-of-atmosphere (TOA) radiative fluxes from the DEEP-C dataset (Liu & Allan, 2022) which spans 1985–2020. Combining DEEP-C all-sky fluxes with clear-sky fluxes from the ERA5 atmospheric reanalysis (Hersbach et al., 2020) allows estimation of cloud feedbacks from trends over a period almost double the length of the CERES observational period. Although several other long-term products such as ISCCP (Young et al., 2018) and Cloud_cci

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AVHRR-PM (Stengel et al., 2020) include TOA radiative fluxes, trends in those datasets are likely influenced by variations in the contributing array of satellites, satellite drift and calibration changes (Norris & Evan, 2015; Hollmann & Pinnock, 2020). DEEP-C carefully combines CERES (Loeb et al., 2018) with the well-characterised and bias-corrected ERBS WFOV dataset (B. A. Wielicki et al., 2002; Wong et al., 2006), and was originally created to estimate the global TOA radiative flux imbalance (Liu et al., 2015).

Interpretation of observational estimates of cloud feedbacks is hindered by the complexity of the climate system. It is well known that trends in TOA fluxes are driven by a range of radiative forcings alongside CO₂ (notably anthropogenic aerosols) and also by internal variability. Additionally, TOA flux anomalies reflect not only the surface temperature-driven response of the climate system, but also the instantaneous radiative response to these forcings and the associated surface temperature-independent adjustments (Raghuraman et al., 2021). However, increased understanding of the drivers of changes in CREs over recent decades may help constrain future cloud feedbacks.

In this study, we focus on interactions between clouds and the large-scale atmospheric circulation, which remains a persistent source of uncertainty in cloud feedbacks (Bony et al., 2015; Byrne & Schneider, 2018; Bloch-Johnson et al., 2024). Furthermore, we compare feedbacks estimated from trends versus variability to learn about the extent to which contributing processes are similar on the two timescales. To isolate the influence of the large-scale circulation, we decompose cloud feedbacks by vertical velocity regime following Bony et al. (2004). This method has previously been used to investigate the contribution of circulation changes to cloud feedbacks in the CMIP5 ensemble (Byrne & Schneider, 2018) and in cloud resolving models (Mackie & Byrne, 2023), and to place observational constraints on dynamic cloud feedbacks from the CMIP6 ensemble (Hill et al., 2023).

Motivated by where the largest uncertainties in cloud feedbacks lie (Sherwood et al., 2020), we limit our analysis to the tropics. Understanding and quantifying the changes in clouds associated with deep convection is particularly important as

these clouds strongly reflect incoming shortwave radiation while also having high, cold cloud-tops that generate a local greenhouse effect. Small changes in the balance of these effects could result in sizeable changes in TOA fluxes. The associated feedbacks are often related to changes in cloud altitude, albedo and area. Sherwood et al. (2020) cited changes in the area of tropical anvils as the most uncertain cloud feedback, but recent studies have shown this feedback is likely small (McKim et al., 2024) and highlighted the albedo feedback as potentially playing an important role (Sokol et al., 2024). Importantly global climate models (GCMs) and cloud resolving models are not considered trustworthy for simulating changes in anvil area and albedo because of the sensitivity of results to sub-gridscale convection, turbulence and microphysics (Sherwood et al., 2020).

The remainder of the chapter is structured as follows. We begin by introducing the data and methods used. We then present feedback estimates using observed trends in CRE and surface temperature, including the decomposition into dynamic and non-dynamic components. Following this we discuss some implications of these results, including a new estimate of the combined anvil area and albedo feedback, and conclude with a summary and discussion.

2.2 Data

The analysis uses all-sky top-of-atmosphere (TOA) radiative fluxes from two sources: DEEP-C v5.0 (Liu & Allan, 2022) and the ERA5 reanalysis (Hersbach et al., 2020). DEEP-C combines CERES EBAF and ERBS WFOV observations over the period January 1985 to July 2020 to produce a continuous time series of TOA fluxes. Clear-sky TOA fluxes, surface (‘skin’) temperature, and all other fields used are from ERA5. Cloud radiative effect (CRE) is calculated as the difference between all-sky and clear-sky TOA radiative fluxes, with an additional adjustment for non-cloud effects using observation-based radiative kernels derived from CloudSat/CALIPSO (Kramer et al., 2019). Monthly-mean data over 30°S to 30°N are used, conservatively re-mapped to a standard 1°×1° grid. Following Williams and Pierrehumbert (2017),

the years 1991 – 1992 are excluded due to the strong aerosol forcing associated with the Pinatubo eruption.

Using multiple all-sky TOA flux datasets enables evaluation of their agreement and provides a measure of uncertainty in our results. However, the datasets are not fully independent because ERA5 is used in the DEEP-C reconstruction process. Furthermore, although ERA5 does not explicitly assimilate CERES flux products, some overlap may exist through the radiances used. In later sections of the chapter, we refer to the case using DEEP-C all-sky fluxes as ‘DEEP-C’ and the case using ERA5 all-sky fluxes as ‘ERA5’, despite both cases using ERA5 clear-sky fluxes. Below, we provide a description of each data source used.

2.2.1 CERES EBAF

CERES (Clouds and the Earth’s Radiant Energy System) is a series of broadband scanning radiometers flown on NASA satellites (Wielicki et al., 1996; Loeb et al., 2018). The instruments measure outgoing radiance in the total and shortwave channels, from which longwave radiance is inferred as the difference between the two. These measured radiances are then converted to top-of-atmosphere (TOA) radiative fluxes using angular distribution models that account for viewing-geometry effects. The primary CERES record is provided by instruments on the Terra and Aqua platforms, which are in sun-synchronous polar orbits and therefore achieve near-global sampling through repeated overpasses that are accumulated into gridded monthly-mean products (Loeb et al., 2018). However, because Terra and Aqua observe at fixed local times (approximately 10:30/22:30 and 13:30/01:30, respectively), they do not fully sample the diurnal cycle. As a result, gridded CERES products additionally rely on geostationary satellite observations and modelling assumptions to represent diurnal variability. The CERES product used in DEEP-C is CERES EBAF Edition 4.1, where EBAF (Energy Balanced and Filled) denotes a processing approach in which gridded TOA fluxes are adjusted to improve consistency with independent constraints on the Earth’s energy budget,

particularly estimates of the global mean energy imbalance from Earth heat uptake (Loeb et al., 2018; Liu & Allan, 2022).

2.2.2 ERBS WFOV

ERBS WFOV (Earth Radiation Budget Satellite Wide Field of View) provides near-global observations of TOA radiative fluxes from a single satellite instrument (B. A. Wielicki et al., 2002). Similar to CERES, the WFOV instrument measures broadband radiances in the shortwave and total channels, from which longwave radiance is inferred, and gridded TOA fluxes are produced by converting radiances to fluxes using angular distribution models and averaging over time and space (Liu et al., 2020). The ERBS WFOV record has been corrected for known instrument and orbit drifts (Wong et al., 2006).

2.2.3 ERA5

ERA5 is the fifth-generation global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It is generated using the Integrated Forecasting System (IFS) together with a 4D-Var data assimilation scheme, producing a dynamically consistent estimate of the atmospheric state constrained by a wide range of in situ and satellite observations. ERA5 provides hourly fields on a ~ 31 km horizontal grid with 137 vertical levels, and includes a broad set of surface and atmospheric variables as well as radiative fluxes (Hersbach et al., 2020).

2.2.4 DEEP-C

DEEP-C v5.0 is an observation-based reconstruction of all-sky TOA radiative fluxes designed for climate applications (Liu & Allan, 2022). It provides a temporally continuous record spanning January 1985 to July 2020 by combining satellite flux products with information from the ERA5 reanalysis. From March 2000 onwards, DEEP-C uses CERES EBAF v4.1 TOA fluxes (Loeb et al., 2018). Prior to March 2000, radiative fluxes are reconstructed using the CERES EBAF v4.1 seasonal cycle together with de-seasonalised spatial anomalies from ERA5 (Allan et al., 2014).

The reconstructed variability is additionally constrained using ERBS WFOV (v3.0) TOA fluxes at $10^\circ \times 10^\circ$ resolution (Liu et al., 2020). Two gaps in the satellite record (1993 and 1999–2000) are filled using ERA5 flux anomalies, with adjustments applied such that global-mean flux changes across the gaps are consistent with a set of AMIP6 simulations (Allan et al., 2014; Liu et al., 2020). Because ERA5 is used in the reconstruction procedure, DEEP-C is not fully independent of ERA5, but it provides an observation-constrained alternative estimate of TOA flux variability and trends (Liu & Allan, 2022).

2.2.5 CloudSat/CALIPSO radiative kernels

Radiative kernels provide a linearised framework for diagnosing how changes in atmospheric state variables influence TOA radiative fluxes. In this chapter they are used to quantify the contribution of non-cloud variables (e.g., temperature, water vapour, and surface properties) to changes in cloud radiative effect (CRE). This contribution arises because the radiative impact of non-cloud changes can differ between cloudy and clear-sky conditions.

The radiative kernels used in this study are observation-based kernels derived using CloudSat and CALIPSO measurements from the A-Train satellite constellation (Kramer et al., 2019). CloudSat provides vertically resolved cloud structure from cloud-profiling radar, while CALIPSO provides complementary information on cloud and aerosol vertical distributions from lidar. Together, these observations are used to construct realistic vertical profiles of clouds and the atmospheric state, which serve as the base state for radiative transfer calculations. Radiative kernels are then computed by perturbing individual non-cloud variables within the radiative transfer model and diagnosing the resulting change in TOA radiative fluxes. The kernels therefore represent the local linear sensitivity of TOA radiative flux to each variable (Shell et al., 2008; Kramer et al., 2019). This procedure is performed both for all-sky conditions and for an equivalent clear-sky atmosphere in which clouds are removed.

To estimate the radiative contribution of non-cloud changes, the kernels are combined with observed anomalies in each variable to reconstruct the corresponding

TOA flux change. Comparing the reconstructed all-sky and clear-sky contributions isolates the component of CRE change that is driven by non-cloud variables, sometimes referred to as “cloud masking” (e.g., Shell et al., 2008). In this way, the CloudSat/CALIPSO kernels allow changes in CRE to be decomposed into contributions from cloud changes themselves and from non-cloud changes acting in the presence of clouds.

2.3 Methods

2.3.1 Decomposing cloud feedbacks into dynamic and non-dynamic components

Framework

A method introduced by Bony et al. (2004) is used to isolate the component of the cloud feedback driven by circulation changes. The vertical pressure velocity (hereafter ‘vertical velocity’) at 500 hPa, ω , is used as a proxy for the large-scale circulation. Discretising ω into dynamic regimes allows the circulation to be characterised by a normalised probability density function, $P(\omega)$, describing the relative occurrence of each vertical velocity regime. The tropical-mean CRE, denoted $\overline{\text{CRE}}$, can then be written as:

$$\overline{\text{CRE}} = \int P(\omega)\text{CRE}(\omega) d\omega \approx \sum_{\omega} P(\omega)\text{CRE}(\omega), \quad (2.1)$$

where $\text{CRE}(\omega)$ describes the tropics-wide relationship between CRE and ω . In this study, each dynamic regime covers an interval of 10 hPa day⁻¹.

Bony et al. (2004) used this decomposition to study the CRE response to a discrete change in the climate system from a base state to a perturbed state (denoted using the prime symbol). Assuming the perturbed state can be described using a Taylor expansion about the base state, the sensitivity of $\overline{\text{CRE}}$ to a change in mean surface temperature, $\overline{T}$, can be expressed as:

$$\frac{d\overline{\text{CRE}}}{d\overline{T}} \approx \sum_{\omega} \left(\text{CRE}(\omega) \frac{P'(\omega) - P(\omega)}{\overline{T}' - \overline{T}} + P(\omega) \frac{\text{CRE}'(\omega) - \text{CRE}(\omega)}{\overline{T}' - \overline{T}} + \frac{[P'(\omega) - P(\omega)][\text{CRE}'(\omega) - \text{CRE}(\omega)]}{\overline{T}' - \overline{T}} \right). \quad (2.2)$$

The first term on the right hand side of the equation is the circulation-driven, or ‘dynamic’, component of the cloud feedback, and the second term is the ‘non-dynamic’ component. The final term is a nonlinear component resulting from interactions between dynamic and non-dynamic changes.

In this study, we estimate (kernel-adjusted) tropical cloud feedbacks using timeseries of monthly-mean CRE and surface temperature over the DEEP-C period. For each calendar month, we consider individual instances of that month to be perturbations relative to the monthly climatology and assume that these perturbations can be described using a Taylor expansion about the monthly climatology. We then estimate feedbacks for each calendar month – using all instances of that month over the complete time period – before averaging over calendar months to estimate the annual-mean feedback. This method can be written as:

$$\frac{d\overline{\text{CRE}}}{d\overline{T}} \approx \sum_{\omega} \left\langle \text{CRE}_{CLIM}(\omega, m) \frac{dP(\omega, m, y)}{d\overline{T}(m, y)} + P_{CLIM}(\omega, m) \frac{d\text{CRE}(\omega, m, y)}{d\overline{T}(m, y)} + \frac{dP(\omega, m, y) d\text{CRE}(\omega, m, y)}{d\overline{T}(m, y)} \right\rangle, \quad (2.3)$$

where m and y denote month and year, respectively, $P_{CLIM}(\omega, m)$ and $\text{CRE}_{CLIM}(\omega, m)$ are monthly climatologies, $P(\omega, m, y)$, $\text{CRE}(\omega, m, y)$ and $\overline{T}(m, y)$ are the data for individual months within the timeseries, and $\langle \cdot \rangle$ denotes a weighted average over months. For each calendar month, $dP(\omega, m, y)/d\overline{T}(m, y)$, $d\text{CRE}(\omega, m, y)/d\overline{T}(m, y)$ and $[d\text{CRE}(\omega, m, y)dP(\omega, m, y)]/d\overline{T}(m, y)$ are calculated by linear regression over all years.

To estimate cloud feedbacks from trends in CRE and surface temperature, we rewrite

$$\frac{d}{d\overline{T}} = \frac{d}{dy} \left(\frac{d\overline{T}}{dy} \right)^{-1}, \quad (2.4)$$

in Equation (2.3). In other words, for each calendar month we compute the multi-decadal linear trends in e.g., $P(\omega, m, y)$, and divide by the trends in $\bar{T}(m, y)$. To compare behaviours on long and short timescales, we also use Equation (2.3) to calculate cloud feedbacks based on year-to-year co-variability of CRE and surface temperature.

We are presented with a choice as to which change in surface temperature is used to define the cloud feedback (Feldl & Roe, 2013). Here, we use the tropical-mean surface temperature because this allows circulation changes to be viewed as part of the adjustment of the tropical atmosphere to the temperature perturbation. Sometimes the local surface temperature is considered to be the natural process-based choice but, because the flow of air between regions is by definition non-local, insight into the coupling between clouds and circulation is lost with this approach.

Note that in previous literature the non-dynamic component is typically referred to as the ‘thermodynamic’ component. However, there are many influences on cloud behaviour beyond ω and local surface temperature, as has been demonstrated by recent work on cloud-controlling factors (e.g., Klein et al., 2018; Datseris et al., 2022; Wall et al., 2022), thus we use a more neutral term.

Estimating the components

We begin by constructing climatologies of the probability density function and CRE for each calendar month, denoted $P_{CLIM}(\omega, m)$ and $CRE_{CLIM}(\omega, m)$, respectively. These are calculated using the mean vertical velocity and CRE at each gridpoint for each calendar month. Here and throughout, area-weighting is used to account for changes in grid size with latitude. Next, we calculate CRE anomalies as a function of vertical velocity for individual instances of each month, $dCRE(\omega, m, y)$. To do this, we calculate anomalies relative to the monthly CRE climatologies at each gridpoint, $dCRE(lat, lon, m, y)$. We then subtract the non-cloud contribution to these anomalies, calculated using the CloudSat/CALIPSO radiative kernels combined with ERA5 atmospheric variables. Finally, we combine the kernel-adjusted anomalies with $\omega(lat, lon, m, y)$ to find $dCRE(\omega, m, y)$. To obtain $dP(\omega, m, y)$, we

calculate $P(\omega, m, y)$ from monthly-mean vertical velocities at each gridpoint and then calculate anomalies relative to the relevant monthly climatology, $P_{CLIM}(\omega, m)$. The tropical-mean surface temperature anomalies for each month, $d\bar{T}(m, y)$, are the anomalies at each timestep relative to the monthly climatology, $\bar{T}_{CLIM}(m)$.

To estimate the trends in $dP(\omega, m, y)$, $dCRE(\omega, m, y)$ and $dP(\omega, m, y)dCRE(\omega, m, y)$ for each calendar month, we linearly regress anomalies against years for each vertical velocity regime individually using the ordinary least squares method. Similarly, $d\bar{T}(m, y)/dy$ is calculated by regressing the tropical-mean surface temperature anomalies against years for each month. Note that by performing the regressions for each calendar month individually we remove the influence of the seasonal cycle. Performing regressions over the full deseasonalised timeseries instead does not qualitatively affect the results.

To estimate the variables $dP(\omega, m, y)/d\bar{T}(m, y)$, $dCRE(\omega, m, y)/d\bar{T}(m, y)$ and $[dCRE(\omega, m, y)dP(\omega, m, y)]/d\bar{T}(m, y)$ from year-to-year variability $dP(\omega, m, y)$, $dCRE(\omega, m, y)$ and $dP(\omega, m, y)dCRE(\omega, m, y)$ are regressed directly against $d\bar{T}(m, y)$ for each month. Additionally, for all variables, the linear trend for each calendar month is removed prior to regression. For $dCRE(\omega, m, y)$ the trend is removed at each gridpoint, and for $dP(\omega, m, y)$ the trend is removed within each vertical velocity regime.

When presenting our results, we average over all calendar months and quote the feedback components and their constituent quantities in annual-mean form. We rewrite the constituent quantities as follows: $\langle CRE_{CLIM}(\omega, m) \rangle = CRE(\omega)$, $\langle P_{CLIM}(\omega, m) \rangle = P(\omega)$, $\langle dCRE(\omega, m, y)/d\bar{T}(m, y) \rangle = dCRE(\omega)/d\bar{T}$, $\langle dP(\omega, m, y)/d\bar{T}(m, y) \rangle = dP(\omega)/d\bar{T}$ and $\langle dCRE(\omega, m, y)/d\bar{T}(m, y) \rangle = (dP(\omega)dCRE(\omega))/d\bar{T}$.

Errors are calculated for each vertical velocity regime. The errors on the monthly climatologies, $P_{CLIM}(\omega, m)$ and $CRE_{CLIM}(\omega, m)$, are taken to be the standard errors (σ s) on the mean of $dP(\omega, m, y)$ and $dCRE(\omega, m, y)$ for that month, i.e., a measure of year-to-year variability. For the feedbacks calculated from trends, the errors on $dP(\omega, m, y)/d\bar{T}(m, y)$, $dCRE(\omega, m, y)/d\bar{T}(m, y)$ and $[dP(\omega, m, y)dCRE(\omega, m, y)]/d\bar{T}(m, y)$ are propagated from the standard errors on

the slopes of the regressions of $dP(\omega, m, y)$, $d\text{CRE}(\omega, m, y)$, $dP(\omega, m, y)d\text{CRE}(\omega, m, y)$ and $d\bar{T}(m, y)$ against year. For the feedbacks calculated from variability, the errors on these terms are the standard errors on the slopes of the regressions of $dP(\omega, m, y)$, $d\text{CRE}(\omega, m, y)$, and $dP(\omega, m, y)d\text{CRE}(\omega, m, y)$ against $d\bar{T}(m, y)$. For DEEP-C we additionally include an area-independent estimate of the standard error associated with instrument uncertainty which, based on calculations by Liu et al. (2020) and our own error propagation, we find to be $0.66 \text{ W m}^{-2}\text{K}^{-1}$. A more detailed discussion of this instrument error can be found in Appendix A. Errors on the dynamic, non-dynamic and nonlinear components, and on the annual mean forms of all terms, are calculated via error propagation.

For $d\text{CRE}(\omega, m, y)$ and $dP(\omega, m, y)d\text{CRE}(\omega, m, y)$, we require at least 5 values per vertical velocity regime to perform a regression. When this criterion is not fulfilled, the feedback is determined by linear interpolation of feedbacks from neighboring vertical velocity regimes. For $dP(\omega, m, y)$, months in which a vertical velocity regime is empty are included in the regression.

Caveats

The usefulness of the decomposition summarised by Equation (2.3) lies in the insight it provides into the physical processes that control tropical cloud feedbacks. However, this framework does not represent all the ways in which circulation changes can influence cloud feedbacks. Clearly, the monthly-mean vertical velocity at 500 hPa is an imperfect proxy for the full time-varying 3D circulation and cloud feedbacks can be driven by circulation changes not associated with vertical motion at 500 hPa. But there are several more subtle caveats to applying the framework. First, the tropical-mean relationship between CRE and ω is not necessarily the same as the local relationship. Therefore, a change in the locations contributing to a particular vertical velocity regime can lead to a change in the mean CRE for that regime. In the decomposition, this effect will appear as a non-dynamic feedback despite being driven by circulation shifts. A change in the locations contributing to a regime could result from, for example, a shift in the Intertropical Convergence Zone (ITCZ).

Second, circulation changes may impact clouds in other vertical velocity regimes via teleconnections mediated by variables other than ω . In this decomposition this effect will also appear as a non-dynamic feedback.

Although we refer to the cloud changes discussed here as feedbacks, we cannot assume that CO₂-induced temperature changes are the single cause of the cloud changes. Other factors, including rapid adjustments to CO₂ forcing and the effects of other forcing agents – particularly aerosols – also contribute. Furthermore, the observed trends cannot be assumed to be forced: internal variability may also contribute. Finally, we note that the use of monthly-mean data may obscure the influence of sub-monthly variability (such as the Madden-Julian Oscillation) so results could be different for daily data, for example.

2.3.2 Mapping the spatial distribution of the decomposition components

To better characterise the trend-derived dynamic and non-dynamic feedback components we map their spatial distributions. We begin by calculating the total cloud feedback at each gridpoint using the kernel-adjusted CRE anomalies and the tropical-mean surface temperature:

$$\text{Total feedback} = \left\langle \frac{dCRE(lat, lon, m, y)}{dT(m, y)} \right\rangle. \quad (2.5)$$

Here, the derivative is calculated following Equation (2.4): monthly CRE trends are calculated via linear regression at each gridpoint and divided by monthly trends in tropical-mean surface temperature before averaging over months. The error at each gridpoint is propagated from the standard errors on the CRE and temperature trends.

We then approximate the circulation-driven component of the feedback at each gridpoint. To do this, we create an artificial CRE dataset, denoted $\widehat{CRE}(lat, lon, m, y)$, in which the CRE is determined from $\omega(lat, lon, m, y)$ combined with the relevant $CRE_{CLIM}(\omega, m)$ curve. Then, at each gridpoint, we find $d\widehat{CRE}(lat, lon, m, y)$ by taking anomalies relative to the monthly climatology. $d\widehat{CRE}(lat, lon, m, y)$ can be

interpreted as the part of the CRE anomalies attributed solely to changes in vertical velocity. The dynamic component of the cloud feedback is then

$$\text{Dynamic component} = \left\langle \frac{d\widehat{CRE}(lat, lon, m, y)}{dT(m, y)} \right\rangle. \quad (2.6)$$

Finally, we can write:

$$\text{Non-dynamic component} = \left\langle \frac{dCRE(lat, lon, m, y)}{dT(m, y)} - \frac{d\widehat{CRE}(lat, lon, m, y)}{dT(m, y)} \right\rangle, \quad (2.7)$$

assuming the nonlinear term is negligible. As for Equation (2.5), the derivatives in Equations (2.6) and (2.7) are calculated following Equation (2.4).

Tropical-mean net, longwave and shortwave feedback components calculated using Equations (2.5)-(2.7) lie within twice the regression error of components calculated using Equations (2.3)-(2.4) (not shown). However, this method is only intended to approximate the local feedback components. To focus on the large scales and to retain consistency with the tropics-wide decomposition above, we have chosen to use the tropics-wide $CRE_{CLIM}(\omega, m)$ monthly climatologies to calculate the dynamic component at each gridpoint. Therefore, the existence of a local non-dynamic component could mean that the local relationship between CRE and ω is not captured by the tropical-mean relationship. Additionally, by calculating dynamic feedbacks for each gridpoint, rather than for each vertical velocity regime we introduce a degree of spatial smoothing.

2.4 Tropical cloud feedbacks estimated from observed multidecadal trends

To understand the drivers behind tropical cloud feedbacks estimated from observed multi-decadal trends, we examine $P(\omega)$, $CRE(\omega)$, $dP(\omega)/dT$ and $dCRE(\omega)/dT$. We then consider how these terms combine to produce the dynamic and nondynamic feedback components which, in combination with the nonlinear feedback component, sum to give the total feedback.

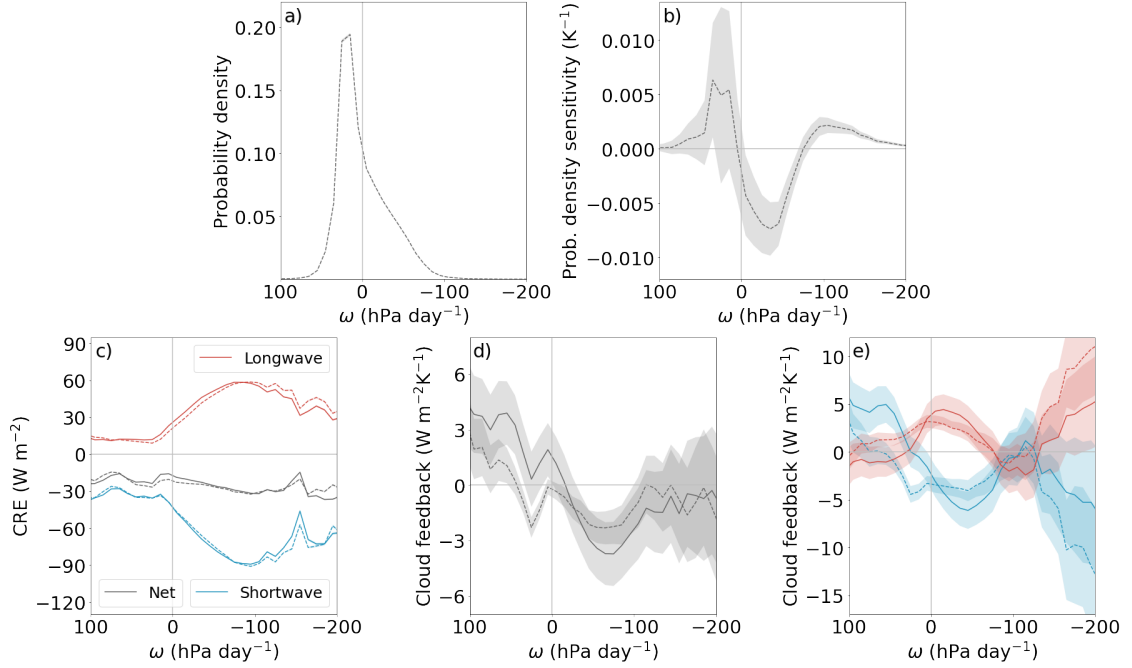


Figure 2.1: DEEP-C (solid lines) and ERA5 (dashed lines) estimates of (a) the time-mean probability density, $P(\omega)$, (b) the probability density sensitivity, $dP(\omega)/dT$, (c) the time-mean CRE(ω) distribution, and the (d) net and (e) longwave and shortwave cloud feedbacks, $dCRE(\omega)/dT$. Feedbacks are calculated from trends between 1985 and 2020 and climatologies are from the same period. Shading shows twice the standard errors. Here, and for similar subsequent figures, the x axis has been reversed, so ascending regions are on the right.

2.4.1 Circulation climatology and trends

The time-mean probability distribution of vertical velocity regime occupancy, $P(\omega)$, peaks sharply in regions of weak descent and is skewed, with faster vertical motion more common in ascending regions (Fig. 2.1a). Figure 2.1b shows $dP(\omega)/dT$, the change in probability density with increasing tropical-mean surface temperature. With warming, there is a reduction in weak ascent frequency balanced by a combination of increased strong ascent frequency and a non-significant increase in descent frequency. This suggests a narrowing and strengthening of ascending regions across the tropics. The change in area covered by ascent is -2.13 ± 0.70 % K⁻¹ (or -0.35 ± 0.11 % decade⁻¹). Here, and throughout the text, the errors quoted are twice the standard error unless otherwise specified. This exceeds the reduction found in other reanalysis datasets but agrees with observed trends based on outgoing longwave radiation, precipitation minus evaporation and column

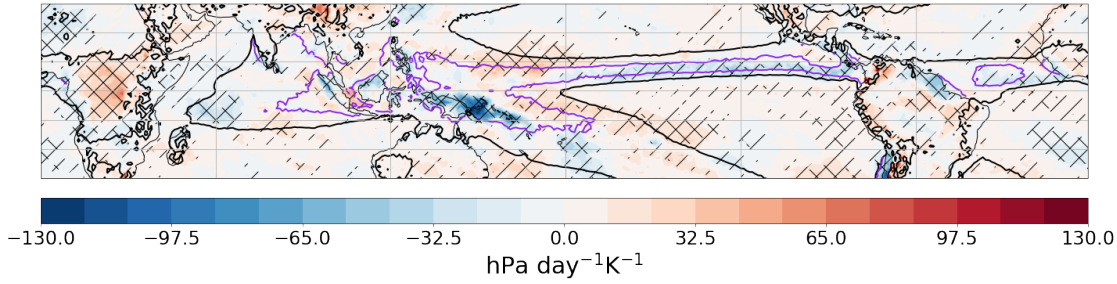


Figure 2.2: Changes in vertical velocity per degree tropical warming calculated from trends between 1985 and 2020. Regions where the magnitude of the sensitivity to warming is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. The black contour divides regions of climatological ascent and descent. Note that in ascending regions blue shading corresponds to strengthening ascent and red shading corresponds to weakening ascent while in descending regions red shading corresponds to strengthening descent and blue shading corresponds to weakening descent. The purple contour shows oceanic regions in which $\omega < -70$ hPa day $^{-1}$ more than 15 % of the time.

relative humidity (Su et al., 2020). The increase in area covered by strong ascent ($\omega < -80$ hPa day $^{-1}$) is 1.70 ± 0.39 % K $^{-1}$ (or 0.27 ± 0.06 % decade $^{-1}$). Reanalyses disagree on both the direction and magnitude of the trend in descending regions [see Figure 3 of Su et al. (2020)].

At a regional scale circulation changes are more complex, with a clear contrast in behaviours over land and ocean. Figure 2.2 shows the local sensitivity of vertical velocity to tropical-mean warming. Over the Central and East Pacific and the Atlantic, we see narrowing and strengthening of the ITCZ in agreement with previous studies (Wodzicki & Rapp, 2016; Byrne et al., 2018). Despite more complex trends over the West Pacific and the Maritime Continent, we see some evidence of strengthening of the Walker cell. Ma and Zhou (2016) found strengthening of the zonal mass streamfunction over the Pacific between 5°N and 5°S across seven reanalyses. Considering Figure 2.2, our results largely agree with this, comprising strengthened ascent over the West Pacific and strengthened descent over the East Pacific. This strengthened descent is combined with strengthened easterlies at 850 hPa, and some evidence of strengthened westerlies at 200 hPa (Figs. 2.3 and 2.4, respectively). However, we note that the increase in ascent strength is concentrated

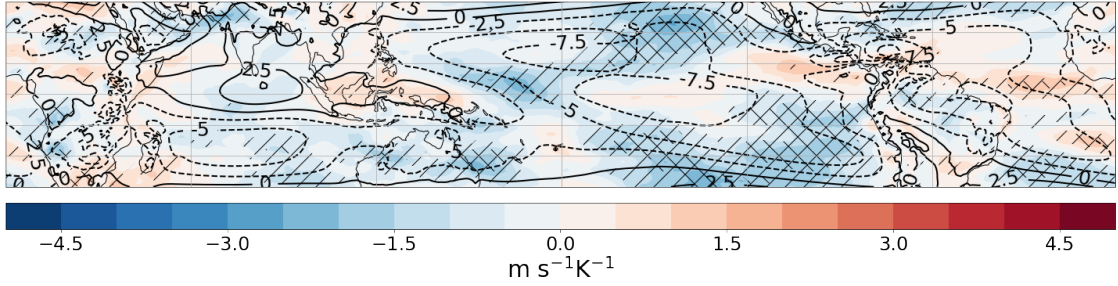


Figure 2.3: Changes in eastward wind at 850 hPa per degree tropical warming calculated from trends between 1985 and 2020. Regions where the magnitude of the sensitivity to warming is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. Black contours show the climatology.

in the South Pacific Convergence Zone (SPCZ), and there is a decline in the ascent strength of the West Pacific ITCZ.

The trend towards narrowing and strengthening ascent is less evident over land, despite the land-only $dP(\omega)/dT$ distribution showing similar behaviour to the tropics-wide case (not shown). This suggests that the boundaries of the regions of climatological ascent do not necessarily narrow over land, rather we increasingly find smaller regions of stronger ascent with a more complex spatio-temporal distribution than over ocean.

Alongside this, we find shifts in the location of ascent over land. There is a substantial reduction in ascent over central equatorial Africa, present in all seasons. Changes in ascent location are less clear over South America, but over both continents we see a weakening of the westerlies at 200 hPa during JJA and SON (Fig. 2.4). The weakening is centred south of the climatological maximum suggesting a trend towards reduced northward progression of the ITCZ during boreal summer over both continents.

2.4.2 $\text{CRE}(\omega)$ climatology and trends

The climatological relationship between vertical velocity and the longwave, shortwave and net CREs is shown in Figure 2.1c. Interestingly, although the longwave and shortwave CREs exhibit substantial variation with vertical velocity, they combine to produce a relatively constant net CRE across vertical velocity regimes. In regions

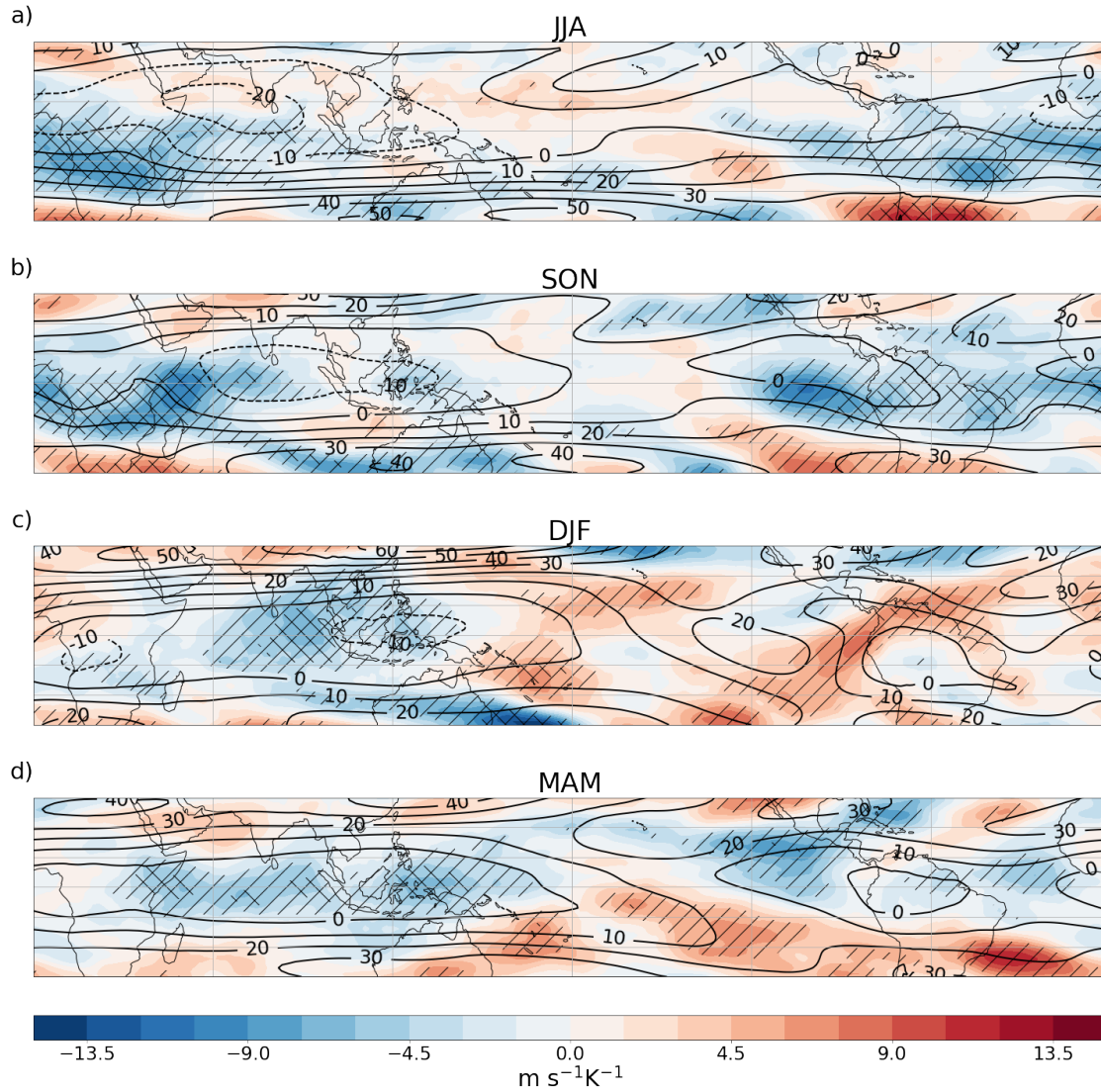


Figure 2.4: Changes in eastward wind at 200 hPa per degree tropical warming calculated from trends between 1985 and 2020 averaged over (a) June-August, (b) September-November, (c) December-February and (d) March-May. Regions where the magnitude of the sensitivity to warming is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. Black contours show the climatology.

of strong descent ($\omega > 25$ hPa day⁻¹) the longwave and shortwave CREs do not vary with ω . In these regions clouds are generally confined to low elevations and this result suggests that their properties may be decoupled from vertical velocity at 500 hPa and instead determined by boundary-layer processes. In regions of ascent and weak descent we find increasing longwave and shortwave CRE magnitudes with increasing ω . Given that ω is the monthly-mean ascent, its value is set not only by ascent strength, but also the frequency of ascent versus descent. Thus this positive relationship may be associated with both increasing frequency and increasing strength of convection. In regions of very strong ascent the longwave and shortwave CREs no longer strengthen with increasing ω . One possible explanation for this nonlinear relationship between CRE and vertical velocity is that less persistent updrafts (leading to a lower monthly-mean ascent) may lead to stronger CRE than more consistent upward motion because high clouds can linger during downdrafts and, because the atmosphere is drier during these periods, there is greater contrast between clear- and cloudy-sky regions (Datseris et al., 2022). Another possibility is that, given stronger ascent is more spatially localised and more likely to occur over land than weaker ascent (not shown), the nonlinearity could reflect regional variability in the relationship between CRE and vertical velocity. For example, cloud formation over land may be inhibited by limited moisture availability. However, speculation as to the drivers of the vertical velocity-CRE relationship must be caveated with the important note that the controls on cumulonimbus CRE are highly complex 1.3.2.

Cloud feedbacks within individual vertical velocity regimes are shown in Figure 2.1d,e. We find that, to first order, the slopes of the CRE(ω) relationships have steepened over the period 1985–2020, i.e. the tropics-wide coupling between clouds and circulation has strengthened. Considering the relationship between cloud feedback and vertical velocity more closely, we see significant strengthening of the longwave and shortwave CREs with increasing tropical-mean surface temperature in weakly descending and in ascending regions. There are two interesting nuances here: First, the variation of feedback strength with ω differs for the longwave and

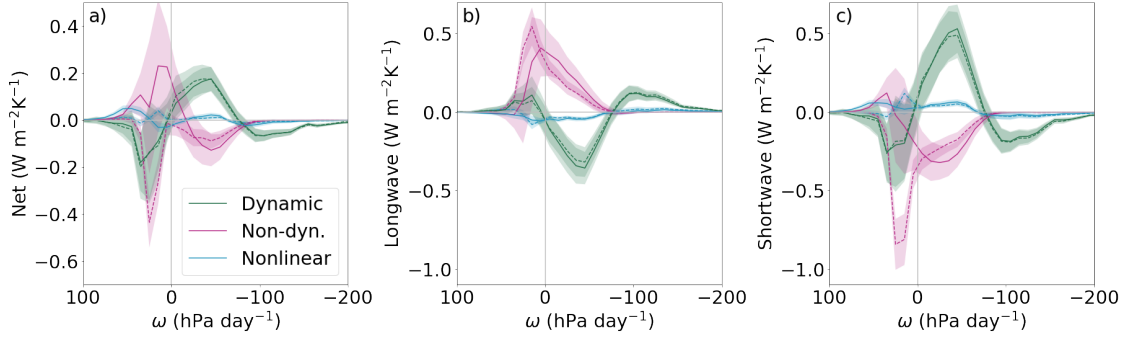


Figure 2.5: DEEP-C (solid lines) and ERA5 (dashed lines) estimates of the contribution of each vertical velocity regime to the dynamic $[CRE(\omega) \times dP(\omega)/dT]$, non-dynamic $[P(\omega) \times dCRE(\omega)/dT]$ and nonlinear $[(dP(\omega)dCRE(\omega))/dT]$ components of the tropical-mean (a) net, (b) longwave and (c) shortwave cloud feedbacks. Feedbacks are calculated from trends between 1985 and 2020 and are split into components following Equation (2.3). Shading shows twice the standard errors.

shortwave CREs in these regions (Fig. 2.1e). The longwave feedback is larger for $25 \text{ hPa day}^{-1} > \omega > -20 \text{ hPa day}^{-1}$ and the shortwave feedback is larger for $-20 \text{ hPa day}^{-1} > \omega > -80 \text{ hPa day}^{-1}$. Second, ERA5 and DEEP-C disagree on shortwave feedbacks in regions of weak descent, with ERA5 showing strong negative feedbacks. In regions of very strong ascent we again find positive longwave and shortwave feedbacks but they are not statistically significant. In regions of strong descent longwave feedbacks are weak, and ERA5 and DEEP-C once again disagree on shortwave feedbacks, with DEEP-C showing a strong positive feedback and ERA5 showing no significant feedback. The drivers of these feedbacks will be discussed in more detail in Section 2.4.3.

2.4.3 Dynamic and non-dynamic components of the tropical-mean cloud feedback

Figure 2.5 shows the contribution of each vertical velocity regime to the dynamic, non-dynamic and nonlinear components of the tropical-mean cloud feedback. In weakly ascending regions ($0 < \omega < -80 \text{ hPa day}^{-1}$), the dynamic and nondynamic components are of similar magnitude but opposite signs. In descending regions the non-dynamic component controls the longwave feedback, while the shortwave feedback includes both dynamic and non-dynamic contributions. Interestingly,

feedbacks are almost entirely circulation-driven in regions of strong ascent ($\omega < -80$ hPa day⁻¹). The nonlinear component is small in all circulation regimes, but makes a statistically significant contribution in regions of weak ascent and descent.

The dynamic component reflects changes in CRE resulting from changes in the large-scale circulation: changing frequency of circulation regime occupancy drives CRE changes irrespective of changes in cloud properties. We find that, although the net dynamic feedback varies with vertical velocity (Fig. 2.5a), cancellation between positive feedbacks in regions of weak ascent and negative feedbacks elsewhere leads to a neutral tropical-mean influence: -0.13 ± 0.33 and -0.11 ± 0.37 W m⁻²K⁻¹ for DEEP-C and ERA5, respectively. Both the longwave and shortwave tropical-mean dynamic feedbacks are larger than the net dynamic feedback (e.g., -0.61 ± 0.36 and $+0.48 \pm 0.66$ W m⁻²K⁻¹, respectively, for DEEP-C, although only the longwave tropical-mean dynamic feedback is significantly nonzero). Figure 2.5b,c shows the longwave and shortwave dynamic feedbacks as a function of vertical velocity. Because the climatological longwave and shortwave CRE(ω) relationships mirror each other (Fig. 2.1c), so do the dynamic feedbacks. However, the shortwave dynamic feedback dominates in all vertical velocity regimes because the magnitude of the climatological shortwave CRE is larger. Figure 2.6d-f show the spatial distribution of the DEEP-C dynamic component calculated following Section 2.3.2. The distribution can be understood through comparison to the spatial distribution of changes in vertical velocity (Fig. 2.2) and the climatological relationship between vertical velocity and CRE (Fig. 2.1c). Where ascent strengthens, we find strengthening CREs and where ascent weakens, we find weakening CREs.

The non-dynamic component of the cloud feedback reflects CRE changes driven by processes other than changes in $P(\omega)$. Because $P(\omega)$ peaks in regions of weak descent and ascent, these regions contribute most substantially to the non-dynamic component of the cloud feedback. For DEEP-C, we find a neutral tropical-mean net non-dynamic feedback of $+0.28 \pm 1.35$ W m⁻²K⁻¹ resulting from compensating longwave and shortwave feedbacks of $+2.15 \pm 1.35$ W m⁻²K⁻¹ and -1.87 ± 1.36 W m⁻²K⁻¹, respectively.

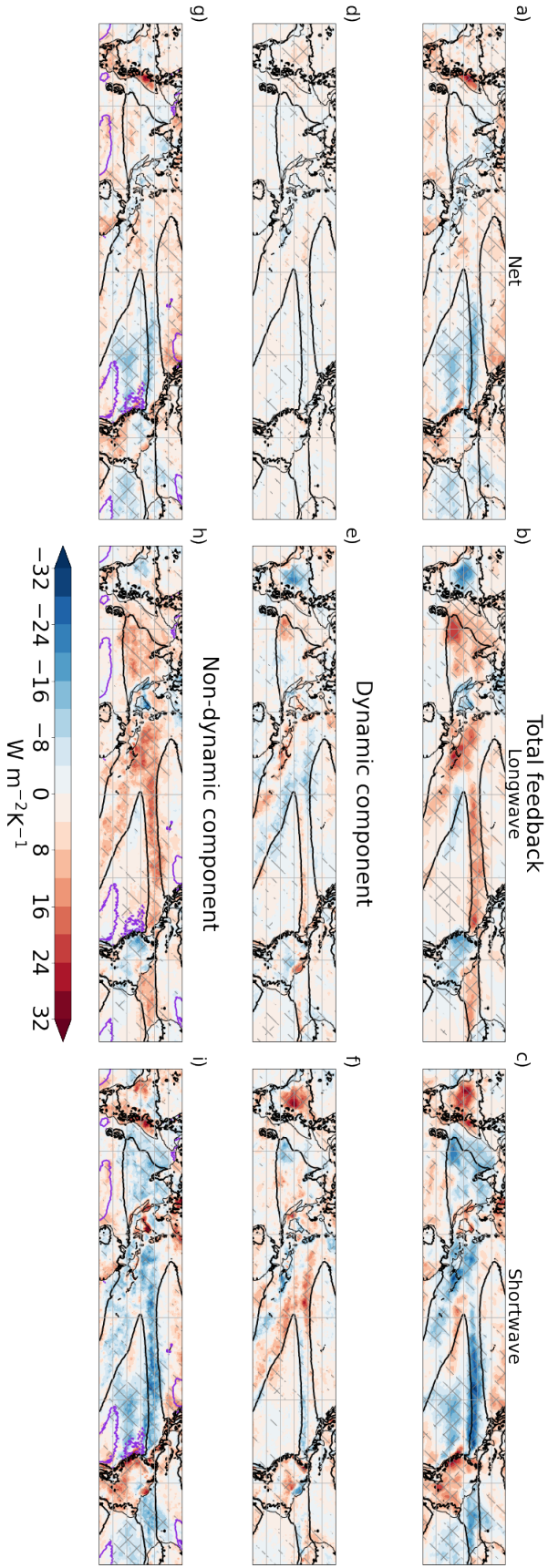


Figure 2.6: DEEP-C estimates of the total (a) net, (b) longwave and (c) shortwave cloud feedbacks calculated at each latitude and longitude. Panels (d), (e) and (f) show the dynamic component and panels (g), (h) and (i) show the non-dynamic component of the net, longwave and shortwave cloud feedbacks respectively, calculated following the method outlined in Section 2.3.2. Feedbacks are calculated from trends between 1985 and 2020. Regions where the magnitude of the feedback is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. The black contour divides regions of climatological ascent and descent. In panels (g-i), the purple contour shows oceanic regions in which $\omega > 25$ hPa day^{-1} more than 60% of the time.

Although the longwave and shortwave non-dynamic feedbacks both reflect strengthening CRE with increasing surface temperature, the spatial distribution of this strengthening is different. Consequently net non-dynamic feedbacks are positive in descending regions and negative in weakly ascending regions (Fig. 2.5). We turn to Figure 2.6g-i to explore the spatial distribution of these trends further.

We find that non-dynamic longwave and shortwave CRE strengthening is confined to oceanic regions while over land they generally weaken, especially in regions of ascent. Identifying the sources of non-dynamic CRE changes is challenging given we do not have compatible datasets to estimate trends in cloud properties over the same time period. However, we hypothesise that in ascending regions over ocean observed increases in surface temperature and specific humidity (Byrne & O’Gorman, 2018) have led to increasing CRE via increasing cloud fraction and/or thickness. In contrast, observations show that the land relative humidity has declined over recent decades (Byrne & O’Gorman, 2018; Simmons et al., 2021) which may have caused CRE reductions over continents (Kamae et al., 2016).

In regions of oceanic descent the spatial pattern is more complex. Figure 2.6i shows that the non-dynamic strengthening of shortwave CRE originates from regions of weak descent in the southern subtropical regions of the Pacific and Atlantic. Consequently we suggest it is induced by warming West Pacific SSTs (Zhou et al., 2016). The warming SSTs lead to increased local convection which (due to weak temperature gradients in the tropical free troposphere) is able to increase the tropics-wide static stability and so strengthen the inversion in descending regions. This stability change combined with approximately constant local surface temperatures leads to increased low cloud [see Section 4.2 of Sherwood et al. (2020) for further discussion of this mechanism]. If stability is indeed the controlling variable, this is an example of non-local circulation influences on CRE contributing to the non-dynamic feedback.

In contrast, the spatial structure of the longwave non-dynamic component in regions of weak descent is less clear (Fig. 2.6h), possibly indicating that the clouds contributing to this feedback are less spatially localised. There is some suggestion

that strengthening longwave CRE occurs at the edges of ascending regions and there is also strengthening in the East Pacific, co-located with the shortwave strengthening. Williams and Pierrehumbert (2017) show that high clouds, which largely control longwave feedbacks, can occur in both stable and marginally stable regimes, although most optically thick clouds occur in deep convective regimes. Thus we hypothesise that the longwave feedbacks in descending regions are associated with high clouds which could be cirrus formed in-situ, anvils which have been advected away from regions of climatological ascent or, given our ω data are monthly means, high clouds resulting from occasional local convection.

The change in sign of the shortwave cloud feedbacks when transitioning from regions of weak to strong descent ($\omega > 25$ hPa day⁻¹) suggests that different mechanisms are at play once the local inversion strengthens (Fig. 2.1e). These regions include the stratocumulus decks west of Africa and South America (Fig. 2.6g-i, purple contours).

Comparing DEEP-C and ERA5 we find that the previously identified disagreement on shortwave feedbacks in the ~ 20 hPa vertical velocity regime leads to very different non-dynamic feedbacks. Furthermore, scrutiny of the CRE timeseries in descending regions for DEEP-C (Fig. 2.7) reveals no obvious spurious short-term variability, for example associated with the transition from ERBS WFOV to CERES during 1999–2000, which may influence the trends. Indeed the ERA5 shortwave cloud feedback is more negative than the DEEP-C feedback over both the ERBS WFOV and CERES periods. We therefore hypothesise that the discrepancy between datasets may be associated with the challenge of capturing low-cloud feedbacks in the reanalysis given CRE is a modeled, rather than assimilated, variable. Additionally, we find that the spatial distribution of the discrepancies between the ERA5 and DEEP-C feedbacks (Fig. 2.8) mirrors the spatial distribution of discrepancies in the climatological CRE (Fig. 2.9), meaning if ERA5 feedbacks are indeed biased, this may result from biases in the mean state. The causes of these biases could be further investigated by comparing ERA5 cloud properties to observations.

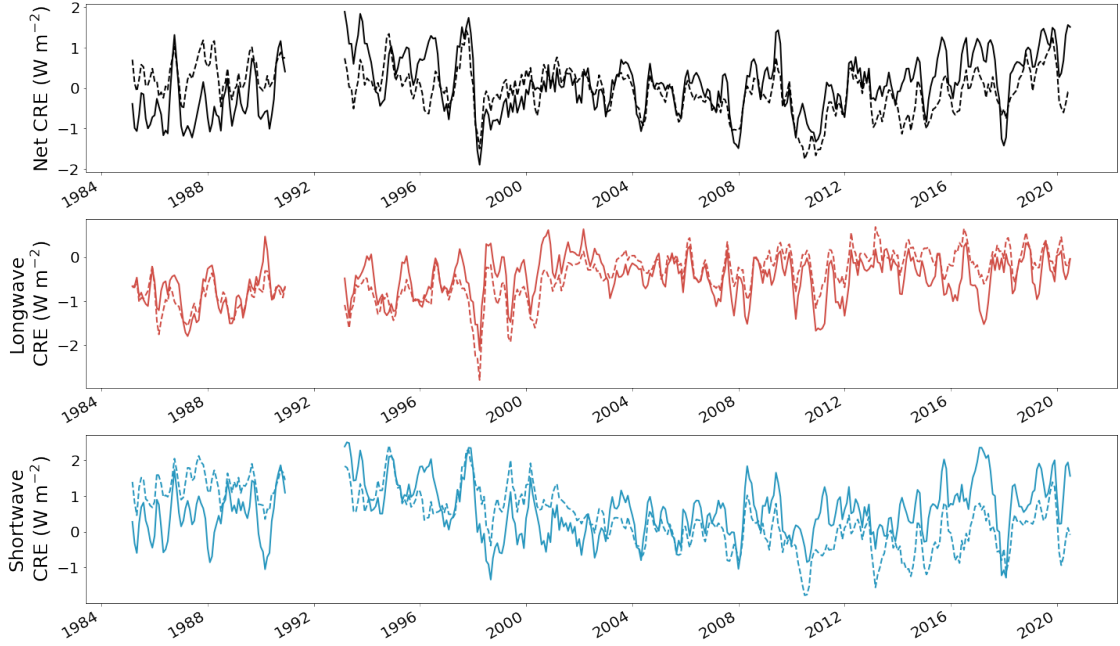


Figure 2.7: DEEP-C (solid lines) and ERA5 (dashed lines) estimates of the (a) net, (b) longwave and (c) shortwave kernel-adjusted deseasonalised CRE anomalies between 1985 and 2020 averaged over tropical descending regions (i.e. where $\omega > 0$ hPa day $^{-1}$) only. Years 1991–1992 are excluded due to the effect of volcanic aerosol from the Pinatubo eruption on TOA fluxes. To allow comparison with Liu et al. (2020) Figure 1, anomalies are taken relative to the 2001–2005 climatology and a three-month running mean is applied.

The nonlinear component is a function of changes in both $P(\omega)$ and $\text{CRE}(\omega)$ [see Equation (2.3)]. Although the nonlinear component is small for most circulation regimes, it is generally negative for longwave feedbacks and positive for shortwave feedbacks. This consistency leads to tropical-mean feedback values similar in magnitude to the dynamic component: -0.37 ± 0.07 W m $^{-2}$ K $^{-1}$, $+0.43 \pm 0.09$ W m $^{-2}$ K $^{-1}$ and $+0.06 \pm 0.05$ W m $^{-2}$ K $^{-1}$ for the DEEP-C longwave, shortwave and net feedbacks, respectively.

2.4.4 Total cloud feedbacks

Figures 2.10a-c show the total contribution of each vertical velocity regime to the tropical-mean net, longwave and shortwave cloud feedbacks respectively (i.e., the sum of the dynamic, non-dynamic and nonlinear components). We find that dynamic feedbacks control the sign of longwave and shortwave feedbacks in ascending regions,

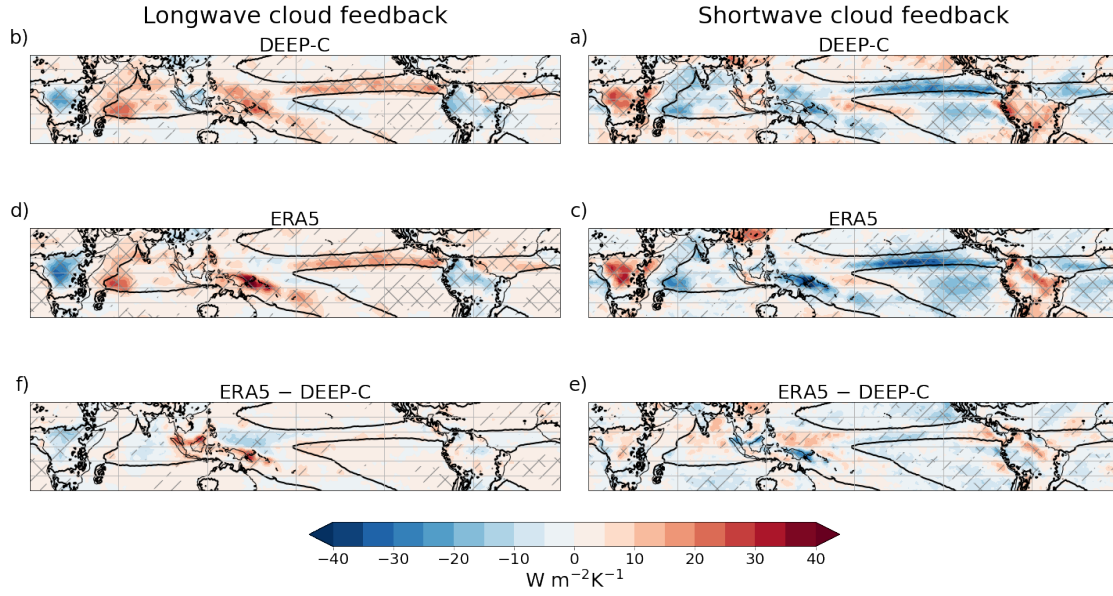


Figure 2.8: The longwave and shortwave cloud feedbacks calculated from trends between 1985 and 2020 estimated using (a,c) DEEP-C and (b,d) ERA5. Panels (e) and (f) show the differences between the datasets for the longwave and shortwave feedbacks, respectively. Regions where the magnitude of the feedback is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. The black contour divides regions of climatological ascent and descent.

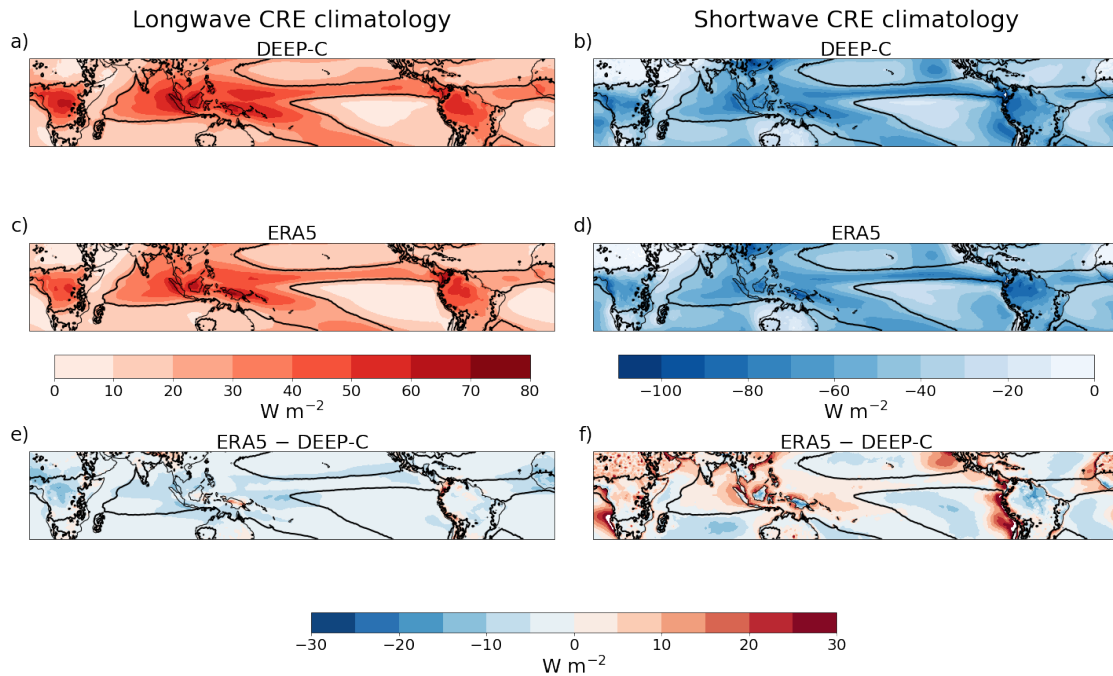


Figure 2.9: The longwave and shortwave CRE climatology over 1985 to 2020 estimated using (a,c) DEEP-C and (b,d) ERA5. Panels (e) and (f) show the differences between the datasets for the longwave and shortwave climatologies, respectively. The black contour divides regions of climatological ascent and descent.

while non-dynamic feedbacks are more impactful in neutral and descending regions. We further find, within individual vertical velocity regimes, that longwave and shortwave feedbacks largely cancel. However, shortwave feedbacks are stronger in all regimes except for regions of very weak descent, where positive longwave feedbacks dominate.

To calculate tropical-mean feedbacks, we sum over all vertical velocity regimes. Further cancellation between opposing shortwave feedbacks in different vertical velocity regimes leads to a neutral tropical mean cloud feedback of $+0.21 \pm 1.39$ $\text{W m}^{-2}\text{K}^{-1}$. Considering the tropical-mean longwave and shortwave feedbacks individually, we find that both reflect an overall strengthening of CRE over the period 1985–2020, with values of $+1.17 \pm 1.40$ $\text{W m}^{-2}\text{K}^{-1}$ and -0.96 ± 1.52 $\text{W m}^{-2}\text{K}^{-1}$, respectively, although this is not significant to 2σ . As expected, ERA5 estimates of the tropical-mean feedback differ substantially from DEEP-C estimates, with ERA5 showing a negative tropical-mean net cloud feedback of -1.30 ± 0.42 $\text{W m}^{-2}\text{K}^{-1}$ and longwave and shortwave tropical-mean feedbacks of $+1.87 \pm 0.38$ $\text{W m}^{-2}\text{K}^{-1}$ and -3.17 ± 0.72 $\text{W m}^{-2}\text{K}^{-1}$, respectively. We note that, due to the inclusion of instrument error, the DEEP-C tropical-mean feedback estimates have larger errors than the ERA5 estimates and previous observational estimates. However, we believe these estimates remain valuable given they are based on trends, rather than variability, and use a previously unexplored multi-decadal dataset (See Table 2.1, discussed in the conclusion, for a more detailed comparison to other observational datasets).

Appendix B compares these results to estimates calculated using trends in tropical-mean CRE anomalies. We find that, although the feedback estimates are not identical, they agree closely and the net and shortwave feedbacks agree within regression error. Differences may arise for a range of reasons, but we highlight that we do not incorporate the standard errors on the tropical-mean or vertical velocity regime-mean CREs or on the surface temperature mean into the regressions.

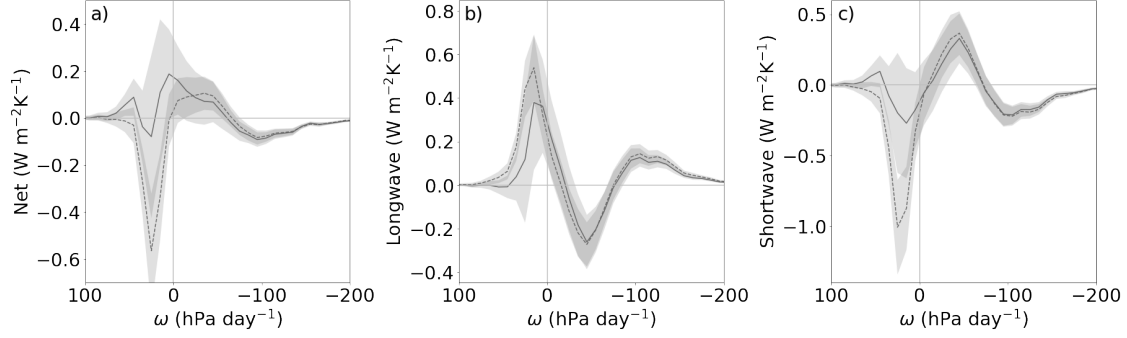


Figure 2.10: DEEP-C (solid lines) and ERA5 (dashed lines) estimates of the contribution of each vertical velocity regime to the tropical-mean (a) net, (b) longwave and (c) shortwave cloud feedbacks. Feedbacks are calculated from trends between 1985 and 2020. Shading shows twice the standard errors.

2.5 Implications for interpreting cloud feedbacks

2.5.1 Small tropical-mean dynamic component

Despite recent decades displaying significant trends in the tropical circulation (Fig. 2.1b), and large circulation-driven cloud feedbacks across a range of vertical velocity regimes (Fig. 2.5a), we find that, when averaged over the tropics, the dynamic components of both the longwave and shortwave cloud feedbacks are small compared to the non-dynamic components (Section 2.4.3). Furthermore, the tropical-mean net dynamic feedback is not significantly non-zero for DEEP-C or ERA5. To interpret these results, we consider mass-budget constraints on the dynamic feedback. Following Wyant et al. (2006) and Byrne and Schneider (2018), we explore the implications for the dynamic feedbacks of a linear relationship between CRE and vertical velocity. Assuming $\text{CRE}(\omega, m) = a(m) + b(m)\omega$, where a and b are arbitrary constants, and substituting this linear relationship into the expression for the dynamic component we find:

$$\sum_{\omega} \left\langle \text{CRE}(\omega, m) \frac{dP(\omega, m, y)}{d\bar{T}(m, y)} \right\rangle = \sum_{\omega} \left\langle a(m) \frac{dP(\omega, m, y)}{d\bar{T}(m, y)} + b(m)\omega \frac{dP(\omega, m, y)}{d\bar{T}(m, y)} \right\rangle. \quad (2.8)$$

By construction, the integral of $dP(\omega, m, y)/d\bar{T}(m, y)$ over all vertical velocity regimes is zero for each month. The global integral of $\omega dP(\omega, m, y)/d\bar{T}(m, y)$ is also expected to be zero for each month, as maintaining constant atmospheric mass

requires equal trends in upward and downward mass fluxes. Thus the global-mean dynamic component, in the limit of linear $\text{CRE}(\omega, m)$ relationships, is zero. The tropics is not a closed mass system, so the mass-flux requirement does not necessarily hold in this study. However, evaluating the integral of $\omega dP(\omega, m, y)/d\bar{T}(m, y)$ results in an area-weighted vertical velocity trend of $-0.20 \pm 0.24 \text{ hPa day}^{-1}\text{K}^{-1}$, i.e. no significant trend.

Now we know that this framework can be approximately applied to interpret our results, we turn to the observed climatological relationship between CRE and ω (Fig. 2.1c). As discussed in Section 2.4.2, we find that the longwave and shortwave $\text{CRE}(\omega)$ relationships exhibit substantial nonlinearity. In descending regions the curves plateau and in ascending regions the curve is approximately quadratic, with weakening longwave and shortwave CREs as ω decreases beyond $\sim -100 \text{ hPa day}^{-1}$. Interestingly, these observational estimates of $\text{CRE}(\omega)$ contradict the quasi-linear relationships found for the multi-model mean of CMIP5 models (Byrne & Schneider, 2018). Rather, the relationships align more closely with results from cloud resolving models (Mackie & Byrne, 2023) although, in the multi-model mean, these models do not show a decline in CRE magnitude beyond $\sim -100 \text{ hPa day}^{-1}$. Similar behaviour in regions of strong ascent can be found in earlier analyses of satellite data (Bony et al., 2004; Wyant et al., 2006). Recent work also finds substantial nonlinearity in $\text{CRE}(\omega)$ estimated from CERES-EBAF data, with implications for GCM estimates of dynamic feedbacks (Hill et al., 2023). However, we find that the nonlinearity produces only modest longwave and shortwave tropical-mean dynamic feedbacks. This is because the magnitude of the dynamic component depends on the relative location in ω -space of nonlinearities in the $\text{CRE}(\omega)$ functions and the circulation changes (Hill et al., 2023; Mackie & Byrne, 2023).

The nonlinearity of the relationship between net CRE and ω is determined by the relative shapes of the longwave and shortwave $\text{CRE}(\omega)$ relationships. As the nonlinearities in these relationships are mirrored, the net $\text{CRE}(\omega)$ curve is quasi-linear (Fig. 2.1c), leading to a neutral net dynamic feedback. Because the neutrality of this feedback is a consequence of the climatological relationship between net CRE

and ω , we suggest that this finding is approximately independent of the nature of the circulation change. However an important caveat to this conclusion is that vertical velocities are challenging to observe and as such are not assimilated in the reanalysis, meaning net $\text{CRE}(\omega)$ could be more non-linear in reality. A secondary caveat is that imperfections in the linearity of our $\text{CRE}(\omega)$ curve imply that a larger dynamic component in the future is plausible, however this would require future circulation changes to differ substantially (in ω space) from recent trends.

The constraints imposed by the atmospheric mass budget on circulation-driven changes in clouds and CRE have implications for how we analyse and interpret cloud feedbacks. As shown in Figure 2.5, the negligible tropical-mean dynamic component results from the cancellation of large dynamic feedbacks in different vertical velocity regimes. This means that current estimates of feedbacks associated with individual cloud types (e.g., Sherwood et al., 2020) likely include substantial dynamic components. However, when area averaged, these dynamic components are expected to approximately cancel, so it may be useful to isolate the *non-dynamic components* when estimating feedbacks for individual cloud types. It is these non-dynamic components that are expected to dominate cloud feedbacks on the large scales relevant for climate sensitivity estimates, for example, but which are often conflated with dynamic components in traditional feedback decompositions. Focusing on the non-dynamic components of feedbacks associated with individual cloud regimes may provide new insights into the relative magnitudes of both the feedbacks themselves and the uncertainties in their estimates.

2.5.2 Estimating feedbacks using trends versus variability

Due to the limited timespan of satellite datasets, observational estimates of cloud feedbacks have previously focused on short-term co-variability between temperature and CRE (e.g., Dessler & Loeb, 2013). However, the extent to which cloud feedbacks estimated using short-term variability are representative of longer-term, anthropogenically-forced cloud feedbacks is an open question. To gain insight

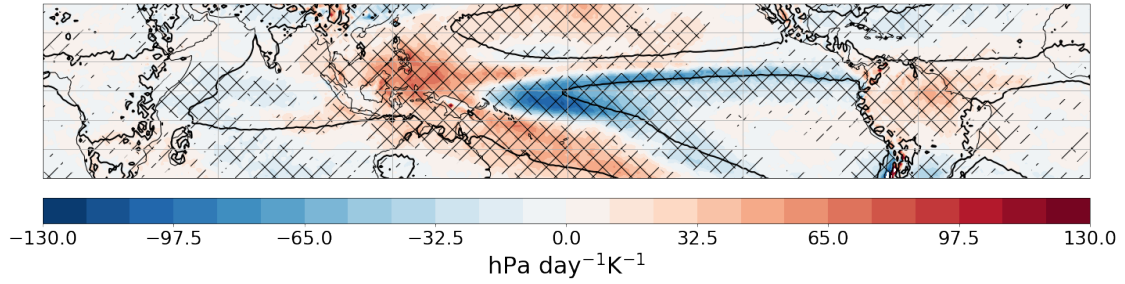


Figure 2.11: Changes in vertical velocity per degree tropical warming calculated from detrended inter-annual variability between 1985 and 2020. Regions where the magnitude of the sensitivity to warming is larger than the standard error are hatched and regions where it is larger than twice the standard error are cross-hatched. The black contour divides regions of climatological ascent and descent.

into this question, we repeat our analysis using detrended short-term variability rather than multi-decadal trends.

The substantial contribution of the dynamic component to trend-derived cloud feedbacks within individual vertical velocity regimes (Fig. 2.5) suggests that, for variability-derived feedbacks to resemble these results, the sensitivities of circulation to tropical-mean temperature variability and trends must be similar. Comparison of Figures 2.2 and 2.11, which show changes in vertical velocity per degree tropical-mean warming derived from trends and from detrended inter-annual variability, respectively, indicates that this is not the case. Inter-annual circulation sensitivity in the tropics is dominated by ENSO, but the pattern of long-term circulation sensitivity is distinct. In vertical velocity space, the circulation sensitivities have similar shapes (Fig. 2.12a versus 2.1b) but the magnitude of the variability-derived circulation sensitivity is substantially smaller across regimes. Furthermore, the variability-derived case does not reproduce the reduction in frequency of very weak ascent ($-30 < \omega < 0$ hPa day⁻¹) or the increase in frequency of very strong ascent ($\omega < -80$ hPa day⁻¹) seen in the trend-derived case. Note that, as expected given the conclusions of Section 2.5.1, the variability-derived tropics-wide dynamic component is of a similar magnitude to the trend-derived estimate and is not significantly non-zero (e.g., $+0.16 \pm 0.30$ W m⁻²K⁻¹ for DEEP-C).

Figure 2.12b,c shows the variability-derived cloud feedbacks that are not associated with changes in the vertical velocity distribution. Comparison to the

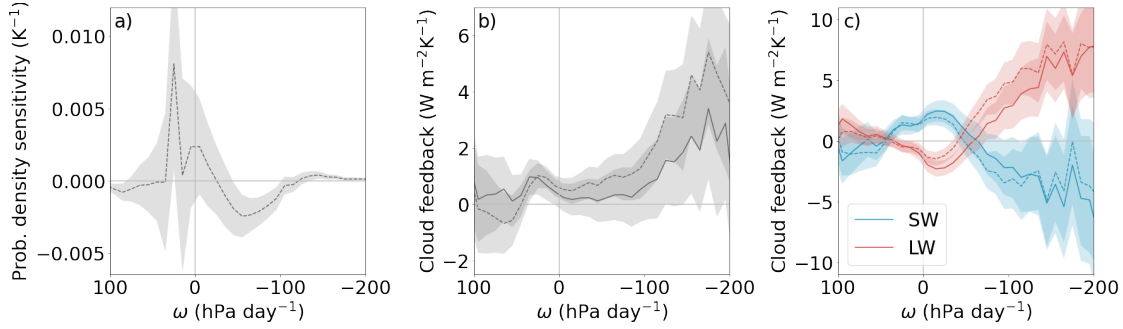


Figure 2.12: DEEP-C (solid lines) and ERA5 (dashed lines) estimates of (a) the probability density sensitivity, $dP(\omega)/dT$, and the (b) net and (c) longwave and shortwave cloud feedbacks, $dCRE(\omega)/dT$. Feedbacks are calculated from detrended inter-annual variability between 1985 and 2020. Shading shows twice the standard errors.

trend-derived feedbacks (Fig. 2.1d,e) shows that these also differ substantially, meaning it is not just the circulation sensitivities which differ on the two timescales. In fact, the trend-derived and variability-derived non-dynamic feedbacks differ in sign in many vertical velocity regimes for both the longwave and shortwave feedbacks. We hypothesise that an important contribution to the dissimilarity could be the thermodynamic impact of different surface warming patterns associated with trends versus inter-annual variability.

In conclusion, we find that both the dynamic and the non-dynamic mechanisms through which clouds respond to surface temperature changes are different for trends versus variability. This suggests a nuanced approach is needed when estimating cloud feedbacks from variability. An example of this is the use of cloud controlling factors (CCFs) (Klein et al., 2018; Ceppi & Nowack, 2021; Myers et al., 2021; Datseris et al., 2022). In this framework, the response of CRE to a change in mean surface temperature is mediated by the responses of a set of other variables, or CCFs. The relationship between changes in CCFs and changes in CRE are assumed to be independent of the temporal scale considered, because clouds typically respond to their surroundings on sub-daily timescales. However, the relationship between CCFs and mean surface temperature must be calculated over the time period of interest.

2.5.3 Estimation of the combined tropical anvil area and albedo feedback

The response of tropical anvil area and albedo to warming are leading sources of uncertainty in estimates of the total cloud feedback and the climate sensitivity. As discussed in Sherwood et al. (2020), GCMs and cloud resolving models likely provide poor estimates of these feedbacks due to challenges in parametrising sub-grid-scale processes. Consequently, observations constitute an important data source for investigating these feedbacks. Sherwood et al. (2020) assess likely values of the combined anvil area and albedo feedback (which they call the ‘tropical anvil cloud area feedback’) using a study by Williams and Pierrehumbert (2017) of observed year-to-year co-variability of CRE and surface temperature in the tropics. Here, we use understanding developed in earlier sections of this work to expand on the results of Williams and Pierrehumbert (2017) and provide new estimates of this important feedback. To do this, we make use of the DEEP-C dataset, i.e., DEEP-C all-sky fluxes combined with ERA5 clear-sky fluxes and vertical velocities.

First, we estimate the tropical anvil area feedback using observed trends rather than variability. We use the same method as in previous sections, except the analysis is performed over tropical oceans only and the global-mean (rather than tropical-mean) temperature time-series is used for consistency with Sherwood et al. (2020). Additionally, we only integrate over vertical velocity regimes with $\omega < 0$ hPa day⁻¹ to isolate the contribution of ascending regions.

The contribution from these regimes to the net tropical-ocean-mean cloud feedback is -0.65 ± 0.41 W m⁻²K⁻¹. This includes an instrument error of 0.19 W m⁻²K⁻¹ (1σ). There are two reasons why the instrument error is lower for these estimates than for the tropical-mean cloud feedback estimates discussed in Section 2.4.4. First, the instrument error depends inversely on the temperature trend and the global mean temperature trend exceeds the tropical mean temperature trend. Second, we scale the tropical-ocean-mean instrument error by the ratio of the area of ascent over tropical oceans to the total tropical ocean area to find the contribution to the tropical-ocean-mean instrument error from regions of oceanic

ascent. Note that the regression errors are also reduced relative to the tropical-mean case. This is because, to study ascending regions only, we consider fewer vertical velocity regimes meaning fewer individual regression errors are combined to form the overall regression error.

To convert into an estimate of the global anvil area and albedo feedback, we first remove the cloud altitude feedback, estimated to be $0.40 \text{ W m}^{-2}\text{K}^{-1}$ locally following Sherwood et al. (2020). This requires scaling the feedback by the ratio of the area of ascent over tropical oceans to the total tropical ocean area to find the contribution to the tropical-ocean-mean feedback ($0.15 \text{ W m}^{-2}\text{K}^{-1}$). We assume there is no error on the altitude feedback estimate. Second, we convert from a tropical-ocean-wide anvil area and albedo feedback to a global-mean feedback by scaling the feedback estimate and the associated error by the fraction of the earth covered by tropical ocean.

We obtain a negative global anvil area and albedo feedback of $-0.30 \pm 0.16 \text{ W m}^{-2}\text{K}^{-1}$, suggesting changes in these cloud properties have had a robust stabilising influence on TOA radiative fluxes over recent decades. In contrast, variability-derived estimates do not exclude a weak feedback. Repeating the calculation for detrended inter-annual variability gives a feedback of $-0.14 \pm 0.11 \text{ W m}^{-2}\text{K}^{-1}$. Note also that the trend-derived feedback estimate lies outside of the 2σ error range of the variability-derived estimate. Previous variability-derived estimates of the global anvil-area and albedo feedback by Sherwood et al. (2020) and Chao et al. (2024) are $-0.20 \pm 0.08^1 (1\sigma) \text{ W m}^{-2}\text{K}^{-1}$ and $+0.01 \pm 0.05 \text{ W m}^{-2}\text{K}^{-1}$ (90% confidence level), respectively. There are likely multiple contributors to the different variability-derived feedback estimates. For example, differences may arise due to the time period considered, the observational dataset used, and whether the data are detrended. Furthermore, Chao et al. (2024) used a substantially different method, focusing their analysis on high clouds and using CERES-FBCT and MODIS-COSP data combined with cloud radiative kernels to quantify the sensitivity of TOA radiation to cloud top pressure and cloud visible optical depth.

¹Sherwood et al. (2020) subsequently assign a standard deviation of $0.20 \text{ W m}^{-2}\text{K}^{-1}$ to the feedback as mentioned in Chapter 1 and discussed in their Section 3.3.3.

Second, we estimate the tropical anvil area feedback using only the non-dynamic component of the trend-derived feedback, given our results suggest that, tropics-wide, dynamic feedbacks largely cancel. In this case, we obtain a feedback of $-0.28 \pm 0.14 \text{ W m}^{-2}\text{K}^{-1}$. Cancellation of the longwave and shortwave dynamic feedbacks in ascending regions means that the magnitude of the net tropical anvil area feedback is only slightly impacted by the change in methodology, however the error on the result is reduced by 8%.

In our methodology, we define the combined anvil area and albedo feedback as the feedback in regions where $\omega < 0 \text{ hPa day}^{-1}$ minus the cloud altitude feedback. However this is a significant simplification of reality. Changes in CREs in ascending regions are not exclusively associated with anvils (i.e., there will be contributions from lower clouds and from non-anvil cirrus). Furthermore, anvils may be advected into regions of monthly-mean descent over the course of their lifetime.

Because the CRE of tropical anvils varies over their lifetime (Hartmann et al., 2018), our feedback estimate could be more influenced by CRE changes in convective cores than during later stages of the anvil lifetime. Indeed, Sokol et al. (2024) find a neutral anvil area and albedo feedback resulting from cancellation between a negative feedback in the cores and a positive feedback in the remainder of the anvil. Raghuraman et al. (2024) estimated short-term area and albedo feedbacks for high clouds over the entire tropics (comprising tropical anvils and in-situ cirrus) using CERES-FBCT. They find an area feedback of $-0.03 \pm 0.03 \text{ W m}^{-2}\text{K}^{-1}$ and an albedo feedback of $+0.03 \pm 0.05 \text{ W m}^{-2}\text{K}^{-1}$, again suggesting that focusing on regions of climatological ascent may exclude a positive feedback component from regions of climatological descent.

A further caveat to these results is that the estimate we use for the cloud altitude feedback is obtained from the response of GCMs to an abrupt quadrupling of CO_2 . Aside from potential problems with the models themselves, this feedback is estimated from a radiative forcing that is different to that acting over the time period considered here.

2.6 Summary and discussion

Tropical cloud feedbacks remain a key source of uncertainty in estimates of equilibrium climate sensitivity (Sherwood et al., 2020). This study leverages the DEEP-C all-sky radiative flux dataset and combines it with ERA5 clear-sky fluxes to explore the processes driving the tropical cloud feedbacks associated with multi-decadal trends in CRE and tropical-mean surface temperature. Isolation of the circulation-driven component of the feedback following Bony et al. (2004) allows insight into the role of interactions between clouds and the large-scale atmospheric circulation in CRE changes.

We find that circulation changes induce substantial tropical cloud feedbacks. For a given vertical velocity regime, the magnitudes of the dynamic and non-dynamic feedback components are comparable, and in regions of strong ascent the feedbacks are almost entirely dynamically driven (Fig. 2.5). The origin of the dynamic component is primarily a narrowing and strengthening of regions of tropical ascent. However, while circulation-driven feedbacks play an important role in determining regional cloud feedbacks, their contribution to the tropical-mean net cloud feedback is small and not significantly different from zero. The dynamic feedback is constrained by the atmospheric mass budget which, combined with the approximately linear relationship between net CRE and vertical velocity, limits the contribution of circulation changes to cloud feedbacks on large scales. Because this limitation is independent of the nature of the circulation change, it is likely that the dynamic component will remain small as the anthropogenically-forced climate change signal emerges. We suggest that focusing on the non-dynamic components of individual cloud feedbacks may provide new perspectives on the relative magnitudes of these feedbacks, their errors, and their influence on climate sensitivity.

Non-dynamically-driven changes dominate the tropical-mean cloud feedback. Exploring the spatial distribution of these changes we find that, over land, CREs weaken. If, as we hypothesise, this is driven by decreasing relative humidity over land, this may continue with increasing CO₂ forcing (Byrne & O’Gorman, 2016). In regions of climatological ascent over ocean, CREs strengthen. Here we hypothesise

that this is due to increasing humidity and surface temperature which, again, is likely to continue in future (Held & Soden, 2006). In regions of climatological descent over ocean, we find strengthening shortwave CRE, likely a result of increasing West Pacific SSTs leading to increased local ascent, tropics-wide static stability and low cloud amount (Zhou et al., 2016). GCMs suggest CO₂ forcing will reduce the east-west SST gradient and decrease low cloud, however Wills et al. (2022) show these models are largely unable to capture the observed trend. Chao et al. (2022) highlight that the pattern of Pacific SSTs is of fundamental importance to the global-mean cloud feedback.

We also show that both dynamic and non-dynamic cloud feedbacks estimated using short-term co-variability between CRE and tropical-mean surface temperature differ substantially from those estimated using trends (Figs. 2.1, 2.12), suggesting variability-derived feedback estimates should be interpreted with caution. The dynamic component of the feedback differs because the circulation change mechanisms are different on the two timescales: Unlike multi-decadal trends, circulation variability is dominated by ENSO. As past estimates of the uncertain and influential anvil area and albedo feedbacks have relied on variability, we follow Williams and Pierrehumbert (2017) and Sherwood et al. (2020) to produce new trend-derived estimates of the total and non-dynamic components of this feedback ($-0.30 \pm 0.16 \text{ W m}^{-2}\text{K}^{-1}$ and $-0.28 \pm 0.14 \text{ W m}^{-2}\text{K}^{-1}$, respectively). Note that in the methodology used here and by Williams and Pierrehumbert (2017), the anvil area and albedo feedback is defined using a simplified approach: it is taken as the total feedback in ascending regions minus the cloud altitude feedback.

Integrating over all vertical velocity regimes yields estimates of tropical-mean cloud feedbacks. For the period 1985–2020, we obtain a neutral net cloud feedback of $+0.21 \pm 1.39 \text{ W m}^{-2}\text{K}^{-1}$. This neutral feedback appears to result from cancellation between strengthening longwave and shortwave feedbacks ($+1.17 \pm 1.40$ and $-0.96 \pm 1.52 \text{ W m}^{-2}\text{K}^{-1}$, respectively) but large errors, primarily associated with gaps in the DEEP-C record, render these results inconclusive.

Dataset	All-sky Clear-sky	DEEP-C ERA5	CERES-EBAF ERA5	CERES-EBAF CERES-EBAF	ERA5 ERA5
Tropical- mean cloud feedback ($\text{W m}^{-2}\text{K}^{-1}$)	Net	+2.35 (0.37)	+2.35 (0.37)	−0.23 (0.31)	+0.73 (0.39)
	LW	−0.68 (0.39)	−0.69 (0.39)	−2.45 (0.39)	+0.56 (0.35)
	SW	+3.03 (0.64)	+3.05 (0.63)	+2.22 (0.59)	+0.17 (0.62)

Table 2.1: Net, longwave (LW) and shortwave (SW) tropical-mean cloud feedbacks estimated from trends between March 2000 and July 2020 following Equation 2.2. CERES-EBAF Ed. 4.1 (NASA/LARC/SD/ASDC, 2019) is used. The CERES-EBAF clear-sky data is type ‘t’, i.e., it is for the total region, not just clear portions. Errors are the combined regression and instrument standard error (1σ) to allow comparison of datasets. Recall that the net, LW and SW tropical-mean cloud feedbacks are $+0.21$ (0.70), $+1.17$ (0.70) and $−0.96$ (0.76) $\text{W m}^{-2} \text{K}^{-1}$ when calculated using DEEP-C all-sky fluxes and ERA5 clear-sky fluxes and $−1.30$ (0.21), $+1.87$ (0.19) and $−3.17$ (0.36) $\text{W m}^{-2} \text{K}^{-1}$ when calculated using ERA5 all-sky and clear-sky fluxes over January 1985 - July 2020 following Equation 2.2.

The feedback estimates presented in this study have several limitations. Importantly, the extent to which the estimates are representative of CO_2 -forced changes is unclear given the confounding influences of aerosol forcing and natural variability. This is exemplified by the differences in trend-derived feedback estimates calculated over the CERES (2000–2020) versus DEEP-C (1985–2020) periods (Table 2.1). Furthermore, we do not separate the surface temperature-mediated cloud feedbacks from rapid cloud adjustments. Raghuraman et al. (2023) show that the contribution from cloud adjustments to recent CRE trends is substantial. Although their method relies on model estimates for this adjustment, thus potentially introducing errors, it presents an interesting avenue for further exploration of the DEEP-C dataset.

We also note that we use relatively simple tools to explore trends in the data. Consideration of the impact of regression method, start and end dates, and the degree of autocorrelation in the timeseries would add to the reliability of the results. More broadly, we suggest that the sensitivity of trend-derived feedback estimates to methodological choices and to observational dataset selection should be systematically explored, particularly given the short period over which we have observations. In addition, the role of reanalysis uncertainty warrants explicit attention: key quantities used here – including vertical velocity and clear-sky radiative fluxes – are not directly observed globally and are influenced in

reanalyses by model physics and radiative transfer assumptions. A practical way to quantify this uncertainty is to assess the spread in derived feedback estimates across multiple modern reanalysis products, treating this spread as a measure of structural uncertainty associated with dataset choice. Consistent with this, we note that use of CERES-EBAF versus ERA5 clear-sky fluxes significantly affects longwave feedback estimates (Table 2.1), underscoring the importance of dataset choice.

This study presents a number of avenues for future work. First, we identify several interesting questions: What controls the climatological relationship between the longwave and shortwave CREs and ω ? And why is the climatological net CRE relatively insensitive to vertical velocity? Second, while the simple decomposition of Bony et al. (2004) provides new physical insight into observed cloud feedbacks, it cannot fully characterise the complex connections between CRE and atmospheric circulation. Can the decomposition be extended to capture the effects of spatial shifts in circulation on cloud feedbacks? Or to explore how circulation changes couple to remote cloud feedbacks? Finally, the relationships between clouds and circulation presented here provide an observational benchmark against which GCMs and the emerging global storm-resolving models can be compared.



AOPP, 11 Aug 2023

3

Radiative influences of clouds, water vapour and CO₂ on tropical $P-E$

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3.1 Introduction

The climatic impact of rising atmospheric CO₂ arises because it alters the Earth’s top-of-atmosphere (TOA) radiative balance. Although a range of rapid adjustments and feedbacks modulate the CO₂ forcing, the responses of water vapour and clouds are particularly influential, affecting the magnitude and spatial pattern of the radiative perturbation with important consequences for regional climate (Hall & Manabe, 1999; Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Clark et al., 2018).

The radiation locking technique disentangles this picture by estimating how radiative changes in CO₂, water vapour, and clouds individually influence the climate system (Wetherald & Manabe, 1988; Hall & Manabe, 1999; Schneider et al., 1999; Voigt et al., 2021). The method has been widely applied to investigate how clouds influence circulation responses to forcing, including their role in the poleward expansion of the Hadley circulation, shifts in the Intertropical Convergence Zone (ITCZ), and changes in extratropical jets (e.g., Ceppi & Hartmann, 2016; Voigt et al., 2019). Radiation locking has also been used to separate the contributions of different radiative processes to polar amplification (Langen et al., 2012) and to shifts of the eddy-driven jet (Ceppi & Shepherd, 2017).

In the tropics, radiation locking studies have so far been restricted to aquaplanet configurations. Voigt and Shaw (2015) separated changes in precipitation minus evaporation, $P - E$, driven by a uniform +4 K sea surface temperature (SST) increase into contributions from the SST warming itself, and from the associated radiative changes in clouds and water vapour. Building on this, Byrne and Zanna (2020) examined how radiative changes in CO₂, clouds and water vapour affect the axisymmetric monsoon circulation using a slab-ocean aquaplanet without ocean heat transport. Both studies found that cloud-radiative changes play an important role in shaping $P - E$ changes via their influence on the circulation.

Here, we build on these aquaplanet studies by investigating how the tropical $P - E$ response to CO₂ forcing is shaped by radiative changes in CO₂, clouds, and water vapour in a model with more realistic boundary conditions, including continents. We conduct experiments with either fixed SSTs or a slab ocean forced by realistic

prescribed q -fluxes. This allows separation of cloud- and water vapour-driven changes into components occurring via the ‘atmospheric/land pathway’ (i.e., independently of SST changes) and those occurring via the ‘SST-mediated pathway’ (Voigt et al., 2019, 2021). Our primary objective is to determine whether cloud-radiative changes remain a substantial influence on $P-E$ under these more realistic conditions. Alongside this, we examine how water vapour and CO₂ radiative changes affect $P-E$.

Introducing spatio-temporal variability in surface boundary conditions represents a large increase in complexity relative to the idealised aquaplanet setup. Therefore, to develop an overview of the tropical $P-E$ response to CO₂ forcing we analyse changes as a function of the climatological $P-E$ distribution. This framing provides a simplified perspective on the hydrological cycle – analogous to the vertical-velocity framework used in Chapter 2 – and enables direct comparison with the thermodynamic scaling proposed by Held and Soden (2006),

$$\delta(P - E) \approx \alpha(P - E)\delta T_s, \quad (3.1)$$

which we adopt as a baseline for interpreting climate responses. Here, T_s is the local surface temperature and $\alpha = \frac{L_v}{RT_s^2} \sim 0.07 \text{ K}^{-1}$ near the surface.

The Held and Soden (2006) scaling predicts that increasing surface temperatures cause climatologically wet regions to get wetter and climatologically dry regions to get drier. This follows from the assumption that $P-E$ changes are governed solely by changes in saturation vapour pressure, while circulation and relative humidity remain constant. Because saturation vapour pressure is determined by temperature via the Clausius–Clapeyron relation, changes in $P-E$ can be directly linked to changes in T_s . This scaling reproduces the multi-model mean zonal-mean oceanic $P-E$ difference between SSP585 (2081–2100) and historical (1995–2014) simulations in CMIP6 reasonably well (Lambert et al., 2025) and has provided a useful starting point for understanding $P-E$ changes over tropical land (Byrne & O’Gorman, 2015).

In this chapter we provide an overview of the ICON global climate model, the simulations analysed here, and their use—together with the radiation-locking

methodology—to estimate the climate impacts of cloud-, water vapour-, and CO₂-driven changes. We then present the atmospheric moisture budget framework, which is used alongside the Held and Soden (2006) scaling to diagnose the mechanisms by which each radiative perturbation affects $P - E$. Before turning to the main results, we evaluate key biases in ICON and compare its response to CO₂ forcing with other models. After presenting our results and conclusions, we include a brief outlook section and note some nuances of the radiation locking methodology identified while conducting the analysis.

3.2 Model

3.2.1 Description

The simulations are performed using the ICON global climate model (GCM) in two configurations. The first configuration, denoted ‘SLAB’, comprises the atmospheric component of ICON v2.6.2.2 (Giorgetta et al., 2018), the JSBACH land model (Jungclaus et al., 2022), and a slab ocean of depth 50 m. In the second configuration, ‘P-SST’, the slab ocean is replaced with prescribed SSTs and sea ice. In both cases, present-day continents and a seasonal cycle of insolation were used.

All simulations used in this thesis were originally performed by Huber (2022). Their study focused on the cloud-radiative impact on the circulation response to CO₂ forcing in the extratropics. Note that in Huber (2022), the P-SST simulations are called ‘SLAB-SST’.

The horizontal grid of the model is icosahedral, with a resolution of ~ 160 km (grid R2B04, see Zängl et al., 2015). In the vertical, ICON employs a hybrid height-based terrain-following coordinate, with 47 vertical levels that follow the orography near the surface and transition to constant geometric height levels aloft, with a model top at about 80 km (Giorgetta et al., 2018). The model was run with a timestep of 20 minutes, and data were output as monthly means. For ease of use, the output data were conservatively remapped to a $2^\circ \times 2^\circ$ regular longitude–latitude grid. In the vertical, the native height-based coordinate system was used, except when producing

plots that include the vertical dimension, in which case data were interpolated to pressure levels. Our analyses focus on the tropics, defined as 30°N–30°S.

Slab ocean model

In the SLAB configuration, the ocean is represented as a motionless mixed-layer of fixed depth, with prognostic sea surface temperatures (SSTs) that evolve in response to the net surface energy flux. The mixed-layer temperature tendency is determined from a surface energy budget of the form

$$\underbrace{\rho_W c_W H \frac{\partial T_s}{\partial t}}_{Q^{storage}} = NEI_S + Q^{flux}, \quad (3.2)$$

where ρ_W and c_W are the density and specific heat capacity of seawater, H is the mixed-layer depth, T_s is SST, $Q^{storage}$ is the energy stored in the mixed layer, NEI_S is the net energy input at the ocean surface (positive downwards). Q^{flux} represents the climatological convergence of ocean heat transport. This is necessary because the slab ocean contains no explicit ocean dynamics. In this set up, SSTs can respond thermodynamically to perturbations in radiative forcing, while ocean heat transport itself remains fixed. Q^{flux} is seasonally and spatially varying and was diagnosed from a simulation with a fully coupled ocean that was otherwise the same as the climatological set up (see Section 3.2.2).

An important distinction between the SLAB and P-SST configurations relates to energy conservation. In the SLAB configuration, changes in the net surface energy flux are balanced by changes in mixed-layer heat content through the prognostic SST equation. In contrast, in the P-SST configuration SSTs and sea ice are prescribed, so the ocean surface cannot adjust to surface energy imbalances. Perturbations to the net surface energy flux therefore imply an artificial residual heat sink or source that maintains the imposed SSTs, meaning that the coupled system is not energetically closed. This limitation is inherent to prescribed-SST experiments and should be considered when interpreting circulation changes.

JSBACH

The JSBACH land surface model computes surface sensible and latent heat fluxes and surface stress, and represents the land hydrological cycle through a multi-layer soil scheme in which soil temperature and soil moisture evolve prognostically (Jungclaus et al., 2022). This allows precipitation, evapotranspiration, infiltration, and run-off to modify soil moisture availability and therefore regulate land evaporation and boundary-layer humidity. Land surface parameters such as albedo, roughness length, and vegetation characteristics are prescribed.

ICON-A

ICON-A is a global atmospheric model that solves the equations of atmospheric motion using a non-hydrostatic dynamical core on an icosahedral grid (Giorgetta et al., 2018). In our configuration, ICON-A employs the Max Planck Institute physics packages which originates from the ECHAM6 GCM and has been adapted to the ICON dynamical framework. The model prognoses the horizontal wind components, temperature, and the mixing ratios of water vapour, cloud liquid water, and cloud ice.

The following unresolved physical processes are represented through parameterisations: radiative transfer, moist convection, cloud microphysics, surface fluxes and vertical turbulent diffusion in the boundary layer, and subgrid momentum sources such as orographic and non-orographic gravity wave drag. These parameterisations provide tendencies which are applied to the prognostic variables of the dynamical core. We will now briefly discuss the parameterisations of particular relevance to our study, namely those influencing the representation of clouds and the interactions between clouds and the large-scale circulation.

Moist convection is represented using a bulk mass-flux scheme based on Tiedtke (1989) with adaptations by Nordeng (1994). The scheme represents the net effect of an ensemble of sub-grid convective plumes as a single entraining and detraining bulk plume with associated downdrafts, and distinguishes between shallow, mid-level, and deep convection (Tiedtke, 1989; Nordeng, 1994). Shallow and mid-level convection are closed using sub-cloud moisture convergence, while deep convection is closed

using a CAPE-based quasi-equilibrium approach in which CAPE is relaxed on a fixed timescale (Nordeng, 1994; Arakawa, 2004). Deep convection is additionally subject to triggering criteria, including positive low-level moisture convergence and positive buoyancy of the convective updraft relative to the environment (Nordeng, 1994). The scheme computes tendencies for temperature and moisture (including latent heating) and provides tendencies for cloud condensate. Convective precipitation formation is parameterised based on convective cloud liquid water content and a height-dependent autoconversion coefficient, while ice-phase conversion processes are represented primarily through the large-scale microphysics scheme (Giorgetta et al., 2018).

Large-scale (stratiform) clouds in ICON-A are represented using prognostic cloud condensate together with cloud fraction diagnosed from relative humidity following the Sundqvist scheme (Sundqvist et al., 1989; Giorgetta et al., 2018). Stratiform cloud microphysics is parameterised using the bulk single-moment scheme of Lohmann and Roeckner (1996), which represents the conversion of condensate to precipitation and thereby influences both the atmospheric water budget and cloud radiative properties (Lohmann & Roeckner, 1996; Giorgetta et al., 2018). Warm-rain and mixed-phase processes are included through parameterised autoconversion, accretion, and freezing pathways. Droplet number concentration influences autoconversion rates but is prescribed using fixed vertical profiles with a land–ocean contrast; consequently, aerosol–cloud microphysical interactions are not explicitly represented (Giorgetta et al., 2018).

Convection interacts with the large-scale cloud and microphysics scheme in two main ways. First, convective transport modifies the humidity profile, altering relative humidity and therefore the diagnosed cloud fraction. Second, detrainment from convective plumes provides condensate to the prognostic large-scale cloud liquid water and cloud ice fields (Giorgetta et al., 2018). This coupling is particularly important for upper-tropospheric cloudiness, including anvil clouds, which strongly affect longwave radiation.

Radiative transfer is computed using the PSrad scheme, which is based on the Rapid Radiative Transfer Model correlated-k approach and divides both the

longwave and shortwave spectra into 16 bands (Mlawer et al., 1997; Giorgetta et al., 2018). Multiple scattering is included in the shortwave calculation, while longwave scattering is neglected (Giorgetta et al., 2018). Cloud radiative effects are computed using a stochastic subcolumn method (McICA), in which the grid box is represented by an ensemble of randomly sampled cloudy and clear subcolumns consistent with the grid-box cloud fraction and condensate. Radiative fluxes are computed for each subcolumn and averaged, which reduces biases that arise from the nonlinear dependence of radiation on sub-grid cloud structure (Giorgetta et al., 2018). PSrad takes as direct input the modelled cloud fraction, cloud liquid water, and cloud ice fields, allowing cloud radiative effects to be modified explicitly by prescribing these variables in the locked simulations described below.

In ICON-A, parameterisations are applied using a mixed parallel–serial coupling strategy designed to maintain numerical stability and tracer conservation (Giorgetta et al., 2018). Radiation, vertical diffusion (including surface exchange), and gravity-wave processes are treated in a parallel-split framework, while the processes acting most directly on water species are applied sequentially to ensure tracer conservation. In particular, vertical diffusion, convection, and cloud microphysics are serialised, so that convective transport and detrainment modify humidity and condensate before microphysical conversion processes act on the prognostic cloud water and cloud ice fields (Giorgetta et al., 2018). The resulting cloud fraction and condensate determine radiative fluxes and heating rates through the PSrad radiation scheme, and the associated radiative heating modifies atmospheric stability and the circulation, thereby closing the feedback loop.

3.2.2 Simulations

Two sets of simulations were performed using the SLAB and P-SST configurations described above.

Beginning with the SLAB configuration, two free-running simulations were performed: (i) a control run [in line with Voigt et al. (2019) and denoted ‘CTRL’];

and (ii) a perturbed run in which the CO₂ concentration was quadrupled relative to the control (denoted ‘*PERT*’).

In the CTRL simulation, well-mixed greenhouse gases are held constant at values averaged over the 1979–2008 AMIP period: CO₂ = 359 ppmv, CH₄ = 1693 ppbv, N₂O = 311 ppbv, CFC-11 = 237 pptv, and CFC-12 = 462 pptv (where ppmv, ppbv, and pptv denote parts per million, billion, and trillion by volume, respectively). Monthly ozone fields are prescribed from the 1979–2008 climatology, while aerosols are fixed to the year 2000 distribution from the Max Planck Institute Aerosol Climatology (Kinne et al., 2013), excluding stratospheric aerosols of volcanic origin. Total solar irradiance is set to 1361 W m⁻².

Eight further SLAB simulations were performed in which cloud radiative effects, water vapour radiative effects, and CO₂ radiative effects were fixed to either their control or perturbed values from the free-running simulations (*CTRL* and *PERT*, respectively). These simulations were run for 40 years, with the first decade discarded as spin-up. At every model timestep, cloud radiative effects were fixed by prescribing cloud fraction, cloud water, and cloud ice; water-vapour radiative effects were fixed by prescribing specific humidity; and CO₂ radiative effects were fixed by prescribing the CO₂ concentration, all within the PSrad radiation scheme. Importantly, only the radiative calculation is modified in this way; the model’s prognostic cloud and water vapour fields continue to evolve freely and remain coupled to convection and dynamics. The prescribed variables are time varying and comprise a ten-year period of the free-running simulations, which is repeated for the duration of the locked runs.

The full list of locked simulations is: *F1C1W1*, *F1C1W2*, *F1C2W1*, *F1C2W2*, *F2C1W1*, *F2C1W2*, *F2C2W1*, and *F2C2W2*. In this notation, simulations with radiative effects fixed to control or perturbed values are labelled ‘1’ or ‘2’, respectively, and radiative effects associated with clouds, water vapour, and CO₂ are labelled ‘C’, ‘W’, and ‘F’. For example, *F2C2W1* has imposed CO₂ and cloud radiative effects from *PERT* and water vapour radiative effects from *CTRL*.

A similar set of P-SST simulations was conducted, in which free-running CTRL and PERT configurations match the SLAB case, except that SSTs and sea ice were

prescribed using monthly means from the SLAB CTRL and PERT simulations. Eight locked simulations were also performed, again identical to the SLAB runs except for the treatment of SSTs and sea ice. In this case, SSTs and sea ice were locked to their CTRL or PERT values such that they co-vary with CO₂. Consequently, ‘F’ labels the state of atmospheric CO₂, SSTs, and sea ice, rather than CO₂ alone, in this set of experiments. The P-SST free-running simulations were run for 33 years, with the first 4 years discarded as spin-up, while the locked simulations were run for 30 years, with the first year discarded.

This experimental design allows the circulation response to CO₂ forcing to be decomposed into contributions associated with changes in cloud radiative effects, water vapour radiative effects, and CO₂ radiative effects.

Note that the output vertical velocity data were found to be corrupted, so estimates of this variable were instead computed by vertically integrating horizontal wind convergence (see Appendix C for details).

3.3 Methods

3.3.1 Radiation locking

Radiation locking is used to estimate the individual impacts of radiative changes in clouds, water vapour and CO₂ on the climate system. The method, first introduced by Wetherald and Manabe (1988) and recently reviewed by Voigt et al. (2021), involves reconstructing the difference between the free-running CTRL and PERT simulations using the simulations in which cloud, water vapour and CO₂ radiative effects are locked to their CTRL or PERT values (see Section 3.2.2). For example, comparing variable X in the locked experiments $F1C1W1$ (in which all radiative effects are set to their CTRL values) and $F1C2W1$ (in which cloud radiative effects are set to their PERT values) estimates the cloud radiative effect-driven component of the change in X .

The approach assumes that the changes in variable X driven by radiative changes in clouds, water vapour and CO₂ individually will reconstruct the full change in X between CTRL and PERT. However, this linearity is not given: for

instance, the cloud effect on X could depend on concurrent water vapour changes (Mauritsen et al., 2013). A further complication is that weather systems differ between simulations, meaning that, over short timescales, the imposed radiation fields are not spatially correlated with the rest of the climate system. The method relies on this relationship being preserved over longer timescales (as shown in Fig. 2 of Voigt et al., 2021). Following earlier studies (e.g., Ceppi & Hartmann, 2016), we mitigate for these limitations where possible. Additionally, we assess the reliability of our results using the ‘trustworthiness criteria’ introduced below.

To apply the radiation-locking method, we begin by requiring that the free-running simulations *CTRL* and *PERT* are well approximated by their respective locked counterparts, F1C1W1 and F2C2W2. Letting δX^{free} denote the difference in variable X between CTRL and PERT, and δX^{lock} the difference between F1C1W1 and F2C2W2, we can then write

$$\delta X^{free} \approx \delta X^{lock} = \delta X_C + \delta X_W + \delta X_F, \quad (3.3)$$

where δX_C , δX_W , and δX_F quantify the impacts on X of radiative changes in clouds, water vapour and CO₂, respectively:

$$\begin{aligned} \delta X_C = \frac{1}{4} \times & [(X_{F1C2W1} - X_{F1C1W1}) + (X_{F2C2W1} - X_{F2C1W1}) \\ & + (X_{F1C2W2} - X_{F1C1W2}) + (X_{F2C2W2} - X_{F2C1W2})], \end{aligned} \quad (3.4)$$

$$\begin{aligned} \delta X_W = \frac{1}{4} \times & [(X_{F1C1W2} - X_{F1C1W1}) + (X_{F2C1W2} - X_{F2C1W1}) \\ & + (X_{F1C2W2} - X_{F1C2W1}) + (X_{F2C2W2} - X_{F2C2W1})], \end{aligned} \quad (3.5)$$

and

$$\delta X_F = \frac{1}{2} \times [(X_{F2C1W1} - X_{F1C1W1}) + (X_{F2C2W2} - X_{F1C2W2})]. \quad (3.6)$$

In Equations (3.4)–(3.6), $\delta X_{C,W,F}$ are mathematically constructed such that they sum to δX^{lock} . Furthermore, each bracketed pair of terms provides an estimate

of $\delta X_{C,W,F}$. Averaging across multiple pairs has two advantages: it reduces the impact of differing internal variability across the simulations and, to some extent, it accounts for interactions between different radiative changes.

Applying the decomposition to the SLAB and P-SST simulation setups individually allows separation of cloud- and water vapour-driven changes into those that occur via changes in SST and those which occur via changes in atmospheric and land surface temperatures (the atmospheric/land pathway, previously termed the ‘atmospheric pathway’; Voigt & Shaw, 2015). This is because, in the SLAB simulations, atmosphere, land and ocean temperatures all respond to changes in radiation and, in turn, influence the climate system. However, in the P-SST simulations, the SSTs are fixed to their CTRL or PERT values meaning radiative changes only influence atmospheric and land temperatures. Thus, changes occurring via the atmospheric/land pathway are those obtained when applying the radiation-locking technique to the P-SST simulations, and changes occurring via the SST-mediated pathway are calculated by subtracting the P-SST results from the SLAB results.

Trustworthiness criteria

We develop a set of trustworthiness criteria to help assess the reliability of the radiation-locking technique in separating the change in variable X into cloud-, water vapour- and CO₂-driven components. Then, we impose a cut-off value to each of these criteria, beyond which the method cannot be considered trustworthy. The criteria address the extent to which several assumptions hold, the first of which is that the difference (or residual) between δX^{free} and δX^{lock} is small. The second is that the change in X associated with an individual radiative effect is independent of other radiative effects. Finally, to separate changes into those occurring via the atmospheric/land pathway and those occurring via the SST-mediated pathway, we assume that δX^{free} is the same for the SLAB and the P-SST experiments.

Free minus lock requirement: The difference between δX^{free} and δX^{lock} is required to be less than half the total change in that variable, i.e. $|\delta X^{free} - \delta X^{lock}| <$

$\frac{1}{2}|\delta X^{free}|$. An exception is made if the total change is less than half of the change driven by individual radiative effects (i.e., when there is substantial cancellation of individual radiative effects). In this case, we require that the difference between δX^{free} and δX^{lock} is less than half of the largest change driven by an individual radiative effect (e.g., if $|\delta X^{free}| < \frac{1}{2}|\delta X_C|$, require $|\delta X^{free} - \delta X^{lock}| < \frac{1}{2}|\delta X_C|$).

State-dependence requirement: We require that all pairs of experiments contributing to an estimate of δX_C , δX_W or δX_F [denoted $(\cdot)$ in Equations (3.4)-(3.6)] agree on the sign of the change. This condition is required unless the change in the variable is within the smallest 1/3 of changes for all contributing pairs of experiments as, in this case, a difference in sign does not signify significant state dependence.

SLAB minus P-SST requirement: We require that the SLAB and the P-SST simulations agree on the sign of the total change in a variable, δX^{free} .

Trustworthiness criteria are applied to the metric we are interested in rather than to the underlying spatio-temporal fields. For example, when assessing the reliability of the decomposition for the change in tropical-mean precipitation, δX is defined as the change in tropical-mean precipitation. Which trustworthiness criteria we apply depends on which simulations we are using. When using the SLAB simulations, we apply the free minus lock and state-dependence requirements. When using the P-SST simulations to study the atmospheric/land pathway, we additionally apply the SLAB minus P-SST requirement. When using the SLAB and the P-SST experiments to study the SST-mediated pathway, we apply the free minus lock and state-dependence requirements to both sets of simulations and additionally apply the SLAB minus P-SST requirement.

3.3.2 The moisture budget

To understand how radiative perturbations affect the tropical hydrological cycle, we use the atmospheric moisture budget to explore whether changes in $P-E$ are dynamically or thermodynamically driven (e.g., Seager et al., 2010).

The vertically-integrated moisture budget can be written as

$$P - E = -\frac{1}{g} \int_{p_T}^{p_B} \left(\frac{\partial q}{\partial t} + \mathbf{u} \cdot \nabla q + \omega \frac{\partial q}{\partial p} \right) dp, \quad (3.7)$$

where $g = 9.81 \text{ m s}^{-2}$ is the gravitational acceleration, p is pressure with p_B being the pressure at the bottom level of the atmospheric model and p_T being the pressure at the top level, q is the specific humidity, $\mathbf{u} = (u, v)$ is the horizontal wind and ω is the vertical pressure velocity (hereafter ‘vertical velocity’).

Steady-state changes in the moisture budget are given by:

$$\delta(P - E) = -\frac{1}{g} \int_{p_T}^{p_B} \left([\mathbf{u} \cdot \nabla + \omega \frac{\partial}{\partial p}] \delta q + [\nabla q \cdot \delta \mathbf{u} + \frac{\partial q}{\partial p} \delta \omega] \right) dp + \text{nonlinear terms.} \quad (3.8)$$

We define thermodynamically driven changes in moisture and transport as those arising from changes in specific humidity gradients while dynamically driven changes are associated with changes in the horizontal or vertical components of the atmospheric circulation.

In practice, we compute the budget on model levels. This introduces terms associated with changes in atmospheric density. Consequently, we combine nonlinear terms and density related terms under ‘other terms’. However, it should be noted that density-related terms are always small.

Several further effects are represented through a residual term in the budget. First, all quantities in Equation (3.8) are defined to be monthly means. In general, there will be contributions to the budget associated with transient eddies, i.e., sub-monthly correlations between velocities and gradients in humidity. These high-frequency terms can be important in the tropics (e.g., Byrne & Schneider, 2016a) but, due to the lack of data at sub-monthly resolution, we do not calculate them directly. Furthermore, it can be challenging to precisely close the moisture budget due to discretisation errors and other limitations of the data output by the model (Inoue et al., 2024). Using data on model vertical levels reduces errors associated with vertical integration (Seager & Henderson, 2013). Additionally, we

use the advective forms of the budget as computation of flux divergences leads to larger errors (Inoue et al., 2024). The decomposition residuals are shown wherever relevant (e.g., Fig. 3.8).

3.4 Results

3.4.1 Model evaluation

Before beginning our analysis, we assess the SLAB CTRL climatology against observations to identify biases and evaluate their magnitude relative to other GCMs. We also compare the simulated response to CO_2 quadrupling (i.e., the difference between the SLAB CTRL and SLAB PERT climatologies) to CMIP ensembles. As our ICON configuration includes an idealised representation of the ocean (a slab model) we expect that the realism of the model will be somewhat limited compared to fully coupled GCMs.

We begin by comparing the annual-mean shortwave and longwave cloud radiative effect climatologies to CERES EBAF Ed4.1 (Loeb et al., 2018) averaged over 2001–2020 (Figs. 3.1, 3.2; Loeb et al., 2018). At TOA, biases in ICON are primarily driven by shortwave cloud radiative effects which are overly negative over midlatitude ocean regions and overly positive over tropical oceans (Figs. 3.1b). These biases are of comparable magnitude to the multi-model mean bias in the CMIP3 and 5 ensembles (Lauer & Hamilton, 2013). In their analysis of a closely related version of ICON-A (version ID: ICON-AES-1.3.00), Crueger et al. (2018) found a similar bias, which they tie to under-representation of low clouds. While other GCMs exhibit this bias (e.g., Fig. 2 of Voigt et al., 2024, demonstrates this for CMIP6 models), the issue seems particularly pronounced for ICON.

Biases in TOA longwave cloud radiative effect are smaller than in the shortwave, with the largest negative anomalies located over the Maritime Continent, eastern parts of the Atlantic, and Central Africa. The largest positive anomalies can be found over the Indian Ocean, the Tibetan Plateau and the Andes. These patterns reflect larger biases within the atmosphere that are partly offset by opposing surface biases (Fig. 3.2d,f).

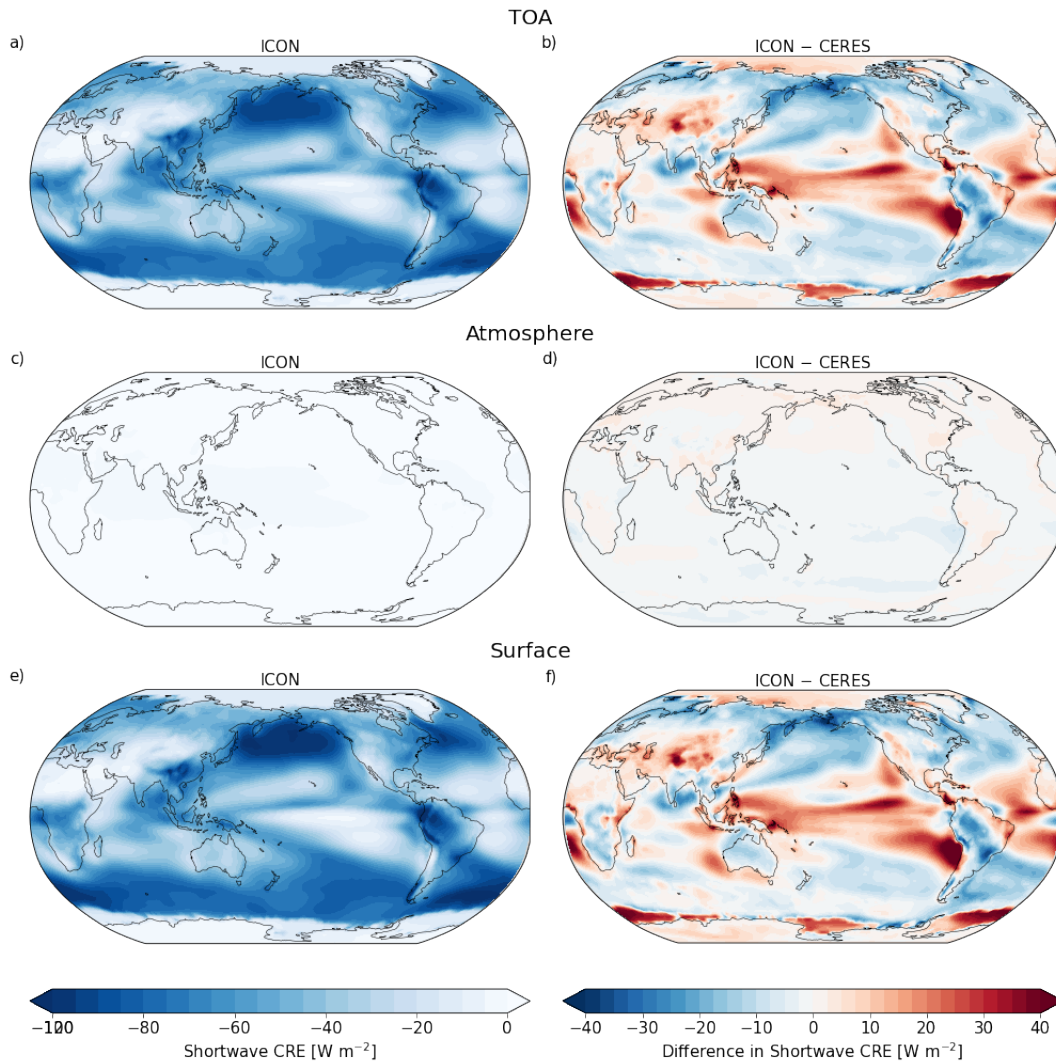


Figure 3.1: Annual-mean shortwave cloud radiative effect simulated by ICON (SLAB CTRL) and differences relative to the 2001 – 2020 CERES EBAF Ed4.1 climatology (Loeb et al., 2018) (a,b) at TOA, (c,d) within the atmosphere (vertically integrated), and (e,f) at the surface.

Within the atmosphere, longwave cloud radiative effects are too positive across most of the tropics, and too negative over the Maritime Continent and most tropical land. In the extratropics, longwave cloud radiative effects are generally too negative, but are too positive over the Tibetan Plateau, the Andes, Antarctica and Greenland. The biases appear closely tied to vertical velocity biases 3.5d, reflecting the close relationship between the climatological circulation and cloud radiative effects (Bony et al., 2004). At the surface, longwave cloud radiative effects are generally too negative across most of the tropics and subtropics, and too positive in the

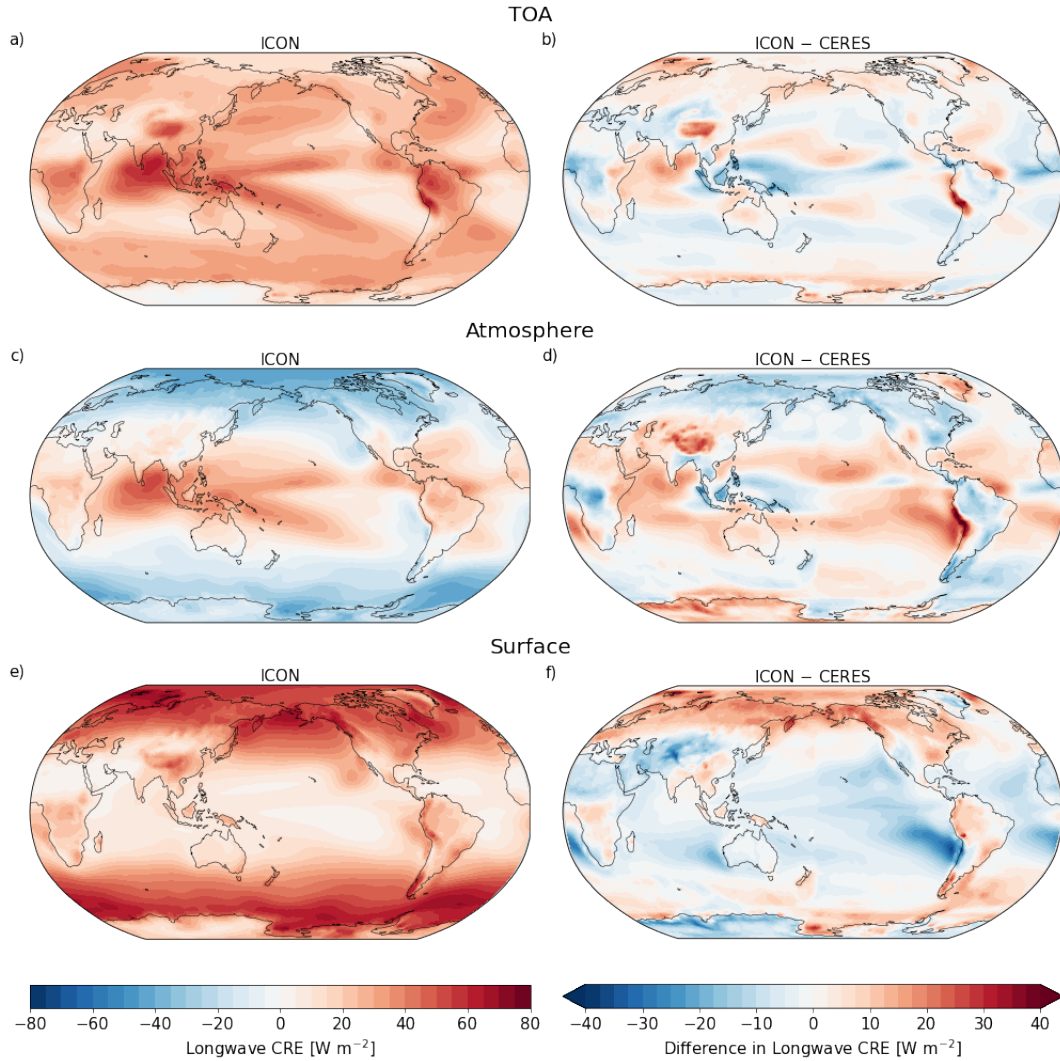


Figure 3.2: Annual-mean longwave cloud radiative effect simulated by ICON (SLAB CTRL) and differences relative to the 2001 – 2020 CERES EBAF Ed4.1 climatology (Loeb et al., 2018) (a,b) at TOA, (c,d) within the atmosphere (vertically integrated), and (e,f) at the surface.

midlatitudes and polar regions, with any exceptions primarily occurring over land.

Following CO_2 quadrupling, ICON simulates a positive cloud radiative effect response at TOA across the tropics, subtropics, and midlatitudes (Fig. 3.3a). These changes lie within the CMIP5 model spread reported by Voigt et al. (2021, Fig. 1.8a). However, unlike many CMIP5 models, ICON shows little change in net cloud radiative effect near 60°S. This muted response may reflect the absence of changes in ocean heat transport in our simulations (e.g., Li et al., 2022; Kang et al., 2023).

Consistent with the CMIP5 ensemble (Fig. 1.8b,c), ICON’s atmospheric cloud

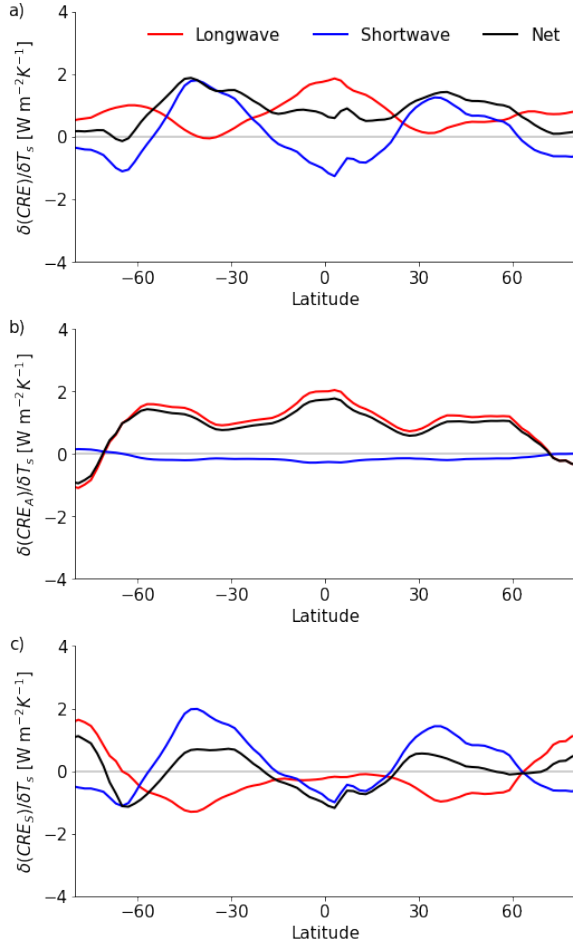
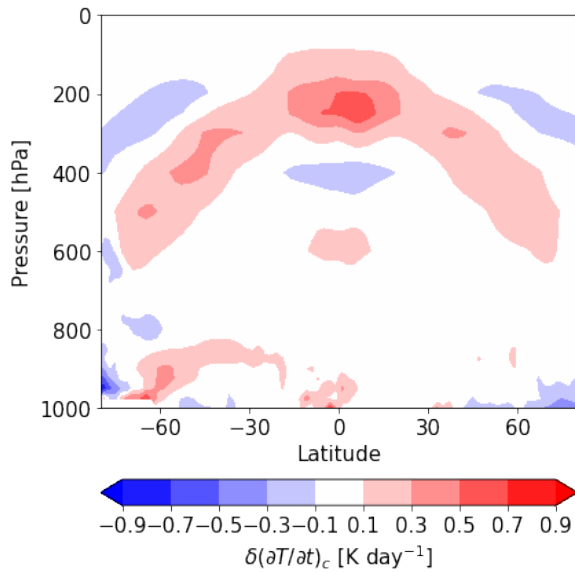


Figure 3.3: Annual-mean changes in longwave, shortwave, and net cloud radiative effects simulated by ICON following CO_2 quadrupling (a) at TOA, (b) within the atmosphere (vertically integrated), and (c) at the surface. Changes are calculated using the partial radiative perturbation technique applied to the SLAB simulations (see Section 4.2.1) and are normalised by the global-mean surface warming (+5.4 K).

Figure 3.4: Annual-mean changes in atmospheric cloud-radiative heating simulated by ICON following CO_2 quadrupling calculated using the partial radiative perturbation technique applied to the SLAB simulations (see Section 4.2.1).



radiative effect changes are dominated by longwave contributions (Fig. 3.3b), while both longwave and shortwave changes contribute at the surface (Fig. 3.3c). Similarly, vertically resolved changes in cloud-radiative heating (Fig. 3.4) are fairly consistent with a subset of CMIP6 models (Fig. 1.9).¹ Notably, ICON’s increase in atmospheric cloud radiative effect lies near the upper bound of the CMIP5 spread, particularly in the subtropics. Whether this remains true in comparison to CMIP6 models is less clear, although ICON does show relatively weak lower-tropospheric changes, likely linked to the lack of low clouds. At the surface, ICON’s net cloud radiative effect change is again broadly consistent with CMIP5 but it exhibits a pronounced meridional gradient between the midlatitudes and tropics that is somewhat unusual. ICON also produces stronger longwave and shortwave feedbacks between 30–50°N/S and weaker feedbacks near $\sim 60^\circ\text{S}$ compared to the CMIP5 multi-model mean.

In Figure 3.5, we compare the ICON column-mean vertical velocity, surface temperature, and $P-E$ climatologies to ERA5 averaged over 1979 – 2020 (Hersbach et al., 2020). Evaluation of vertical velocity is complicated by the corruption of the original output, which required reconstruction from horizontal wind convergence. This procedure introduced additional imperfections, particularly as it was performed on a longitude–latitude grid rather than the native ICON grid, leading to substantial errors in polar regions (see Appendix C for more information). Despite these issues, we can identify broad-scale biases relative to ERA5 in the tropics. ICON produces a broader ITCZ over the Pacific and the Atlantic with weaker ascent, as well as stronger ascent over the Indian Ocean and parts of the tropical Pacific. Biases in $P-E$ are similar, with positive and negative biases coinciding with anomalously strong and weak ascent, respectively (Fig. 3.5d). The magnitude of these biases slightly exceeds the CMIP5/6 multi-model mean bias, and their spatial distribution relative to ERA5 suggests a double-ITCZ bias, a common feature among CMIP models (Adam et al., 2023, Fig. 1b).

¹The cloud-radiative heating changes reported by McGraw et al. (2025) are based on simulations with a uniform +4 K SST increase and so are not directly comparable to ours, but they provide a useful point of contrast.

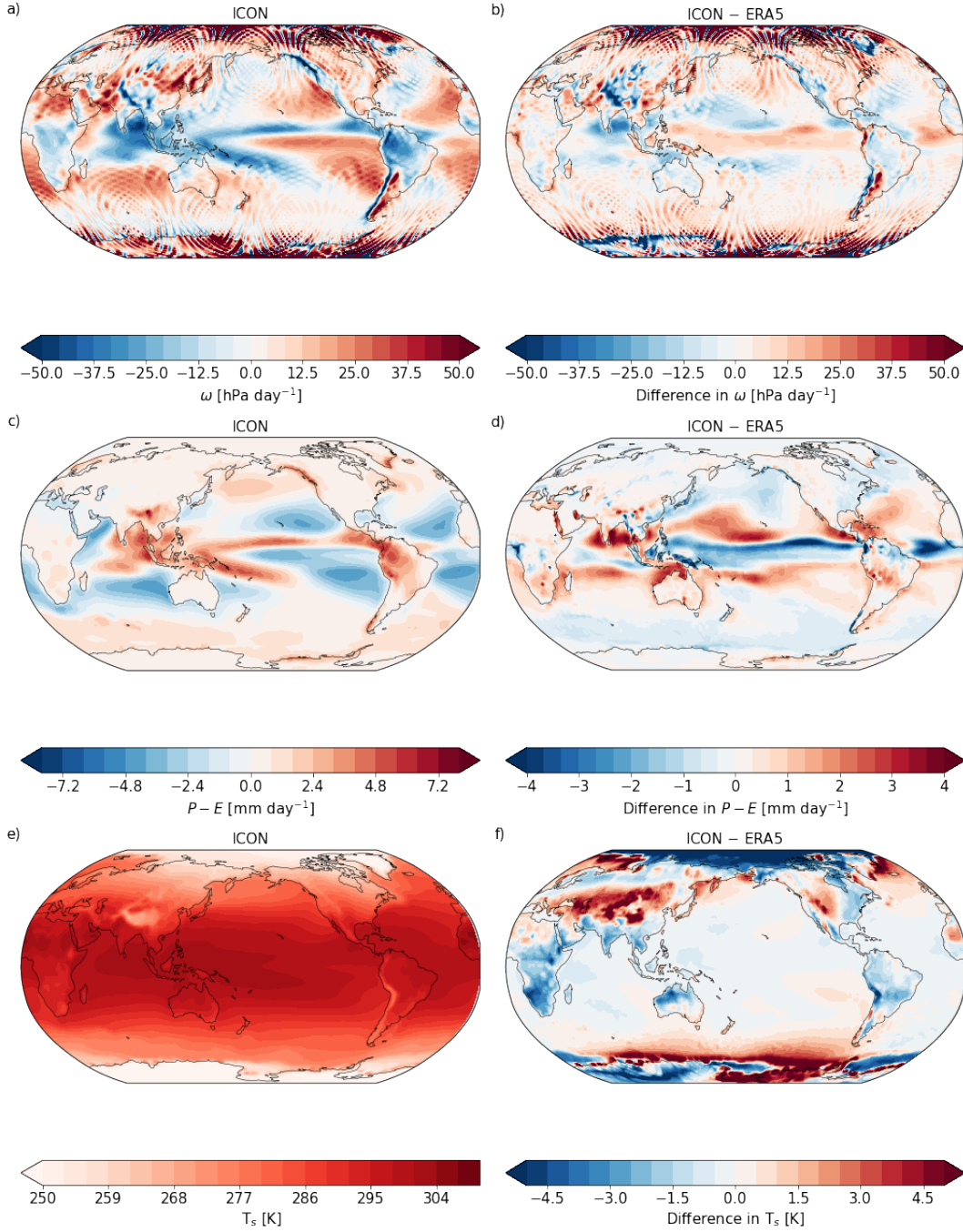


Figure 3.5: Annual-mean (a) column-mean vertical velocity, (c) $P-E$, and (e) surface temperature (T_s) simulated by ICON (SLAB CTRL), and (b,d,f) their differences relative to the 1979 – 2020 ERA5 climatology (Hersbach et al., 2020).

Biases in oceanic surface temperatures are relatively small, but ICON consistently simulates cooler tropical land temperatures than ERA5 (Fig. 3.5f). This may be tied to biases in shortwave cloud radiative effect (Fig. 3.1f).

The annual-mean change in $P-E$ simulated by ICON is shown in Fig. 3.6a.

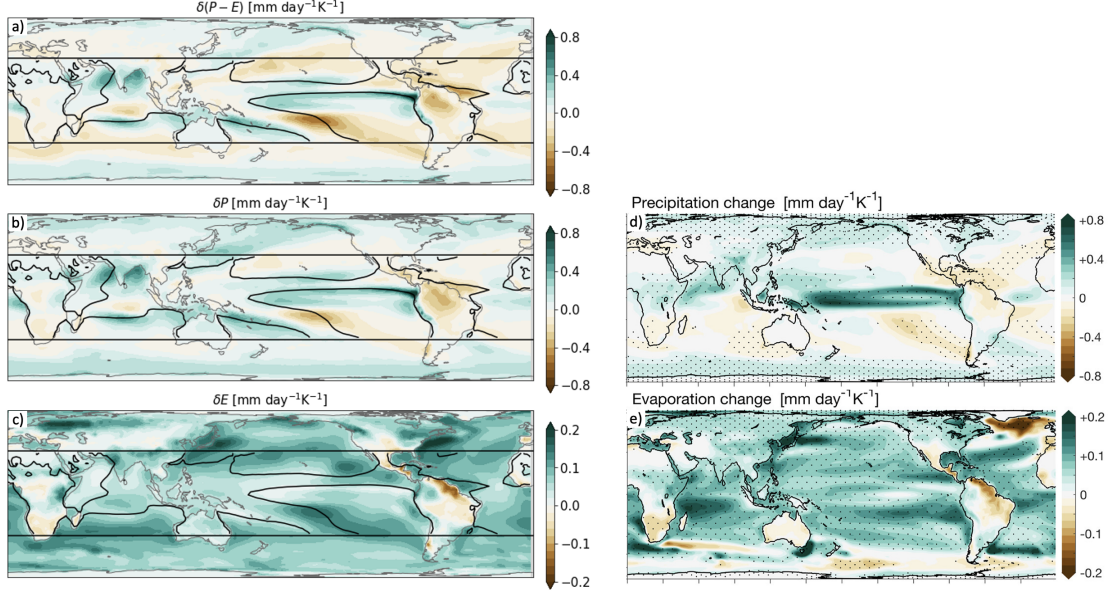


Figure 3.6: Annual-mean changes in (a) $P-E$, (b) P , and (c) E simulated by ICON following CO₂ quadrupling. For comparison, CMIP5/6 ensemble-mean changes between high-emission (RCP8.5/SSP585, 2080–2099) and historical (1980–1999) simulations are shown for (d) P and (e) E . All changes are normalised by the tropical-mean near-surface air temperature change. In (a–c), black contours denote where $P-E = 0 \text{ mm day}^{-1}$ in the SLAB CTRL climatology, and horizontal black lines denote the tropics (30°N–30°S). Panels (d–e) are from Adam et al. (2023), with stippling indicating regions where at least 80% of models agree on the sign of change.

Decomposition into changes in P and E (Fig. 3.6b,c) enables comparison with the multi-model mean difference between high-emissions and historical simulations in CMIP5/6 (Fig. 3.6d,e).² Overall, the sensitivity of precipitation and evaporation to warming in ICON is similar to the CMIP5/6 mean, but there are some exceptions. Precipitation increases over the equatorial Pacific are weaker in ICON, and rainfall increases at the southern edge of the South Pacific Convergence Zone, a feature absent from the multi-model mean though inter-model spread is large here (see stippling in Fig. 3.6d). Differences also arise in the location of peaks in evaporation change over the oceans.

²The CMIP5/6 forcing includes aerosols in addition to CO₂ and other greenhouse gases, so these results are not directly comparable to ours, but they provide a useful point of contrast.

3.4.2 Changes in $P - E$

We begin by examining the $P - E$ response to CO_2 quadrupling in the SLAB simulations and the contributions to this response from radiative changes in clouds, water vapour and the isolated CO_2 . We analyse $P - E$ changes as a function of the climatological $P - E$, allowing an overview of the tropics-wide hydrological response which can later be compared to expectations based on the Held and Soden (2006) thermodynamic scaling.

We separate the tropics into hydrological regimes, denoted $(P - E)_{CLIM}$, with each regime comprising regions in which the climatological $P - E$ lies within a 1 mm day^{-1} interval in the SLAB CTRL simulation. For a given regime, the change in $P - E$ (or any other variable) is computed as an area-weighted mean over contributing regions. This calculation is done monthly before taking the annual mean to account for seasonal shifts in the climatological $P - E$ distribution.

Figure 3.7a shows the total change in $P - E$ as a function of $(P - E)_{CLIM}$ along with the contributions driven by radiative changes in clouds, water vapour, and CO_2 diagnosed using radiation locking. Cloud changes drive wet regions [where $(P - E)_{CLIM} > 0 \text{ mm day}^{-1}$] to become drier and dry regions [where $(P - E)_{CLIM} < 0 \text{ mm day}^{-1}$] to become wetter. In contrast, water vapour changes drive a wet-gets-wetter, dry-gets-drier response. CO_2 -driven changes are smaller: both wet and dry regions become drier and regions where $(P - E)_{CLIM}$ is small become wetter. Strong cancellation between the cloud- and water vapour-driven changes leaves the total change broadly resembling the CO_2 -driven change, but with a larger amplitude.

The area fraction contributing to individual $(P - E)_{CLIM}$ regimes is shown in Figure 3.7b. Dry regions [$(P - E)_{CLIM} < 0 \text{ mm day}^{-1}$] occupy a relatively large area, consistent with the broad spatial extent of tropical subsidence, whereas the compensating ascent – and its associated heavy rainfall – is more spatially confined (e.g., Bony et al., 2004).

In Figure 3.7a, we also show the residual $\delta(P - E)^{free} - \delta(P - E)^{lock}$, which is negligible except for a small peak where $0 < (P - E)_{CLIM} < 2 \text{ mm day}^{-1}$. Because $P - E$ changes are small here, the residual peak causes them to fail the ‘free minus

lock’ requirement (defined in Section 3.3.1). In addition, water vapour-driven $P-E$ changes in very wet regions fail the ‘state-dependence’ requirement, as the sign of the change differs among the experiment pairs in Equation (3.5) (see Fig. 3.12a).

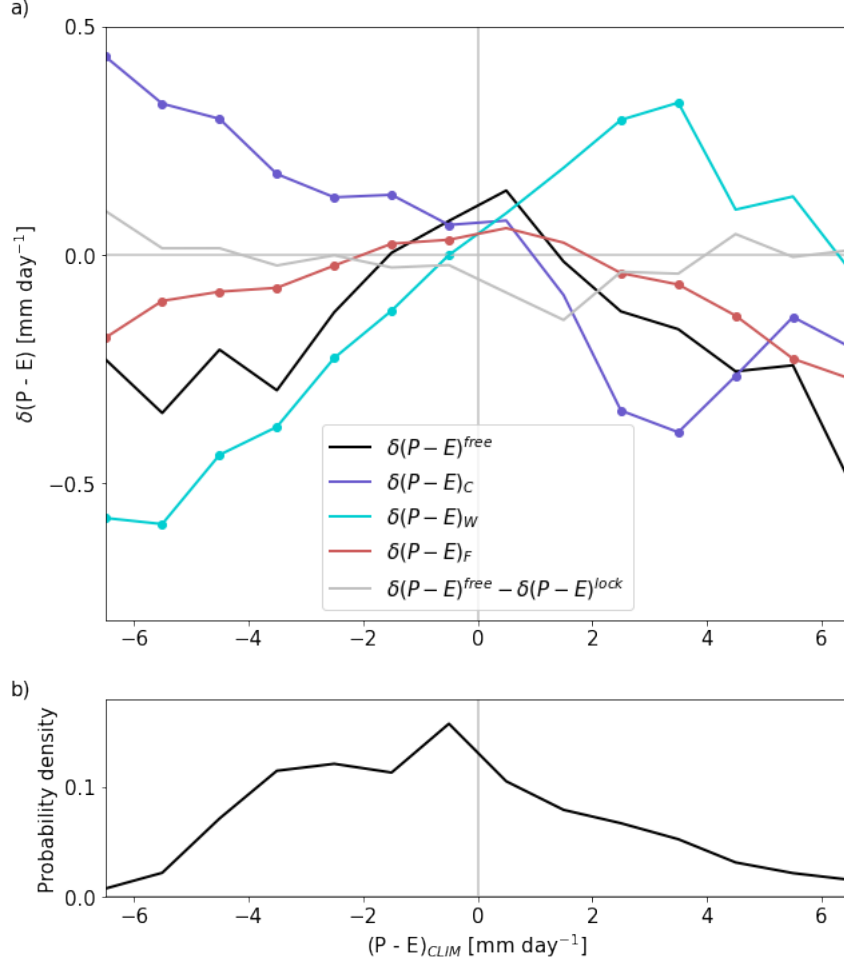


Figure 3.7: Annual-mean (a) $P-E$ response to CO_2 quadrupling (black), decomposed into contributions driven by radiative changes in CO_2 (red), clouds (purple), and water vapour (light blue) using the radiation-locking technique, along with the radiation-locking residual (grey), shown as a function of climatological $P-E$ in the SLAB CTRL simulation; and (b) probability density of climatological $P-E$ regimes. In (a), dots indicate responses that meet the trustworthiness criteria defined in Section 3.3.1.

3.4.3 Role of dynamic and thermodynamic moisture transport changes

To understand the mechanisms behind the $P-E$ response, we use the moisture budget [Eq. (3.8)] to decompose changes into dynamic, thermodynamic, and nonlinear

components. This is done separately for cloud-, water vapour-, and CO₂-driven changes, as well as for the total $P-E$ change (Fig. 3.8). We then compare these results with the Held and Soden (2006) thermodynamic scaling [Eq. (3.1)].

All three radiative changes cause increased tropical-mean surface temperatures (Fig. 3.8, top right of each panel). Based on this, the Held and Soden (2006) scaling predicts that they will all enhance the climatological $P-E$ distribution, with the magnitude of this enhancement proportional to the surface temperature change they induce.

However, the scaling fails to accurately capture the $P-E$ changes because each radiative perturbation triggers substantial dynamic changes. Furthermore, while the scaling generally reproduces the structure of the thermodynamic components of the $P-E$ changes, and correctly ranks their relative magnitudes, it often underestimates their amplitudes.

Dynamically driven changes in $P-E$ broadly counterbalance the thermodynamic response. For clouds, the dynamic component is approximately linear with respect to $(P-E)_{CLIM}$ and larger in magnitude than the thermodynamic component (Fig. 3.8a). The CO₂- and water vapour-driven dynamic components are similar to one another (cf. Fig. 3.8b and Fig. 3.8c): both reduce moisture transport linearly with $(P-E)_{CLIM}$ in wet regions, but the relationship flattens in dry regions.

Alongside the thermodynamic and dynamic components, there are contributions to $P-E$ changes from nonlinear terms and – recalling that we conduct the decomposition on model levels rather than pressure levels – linear terms associated with changes in air density. Contributions from these terms (labelled ‘Other terms’ in Fig. 3.8) reinforce the dynamically driven response across all radiative perturbations. They arise from nonlinear moisture-circulation interactions, captured by the decomposition terms $-\frac{1}{g} \int \frac{\partial \delta q}{\partial p} \delta \omega dp$ and $-\frac{1}{g} \int \nabla \delta q \cdot \delta \mathbf{u} dp$. The total changes in these decomposition terms are shown as solid lines in Figure 3.11.

As discussed in Section 3.3.2, the moisture budget includes a residual term (Fig. 3.8). This residual is small for cloud-driven $P-E$ changes, but for water vapour and CO₂ it is often comparable in size to the dynamical component. Because we use

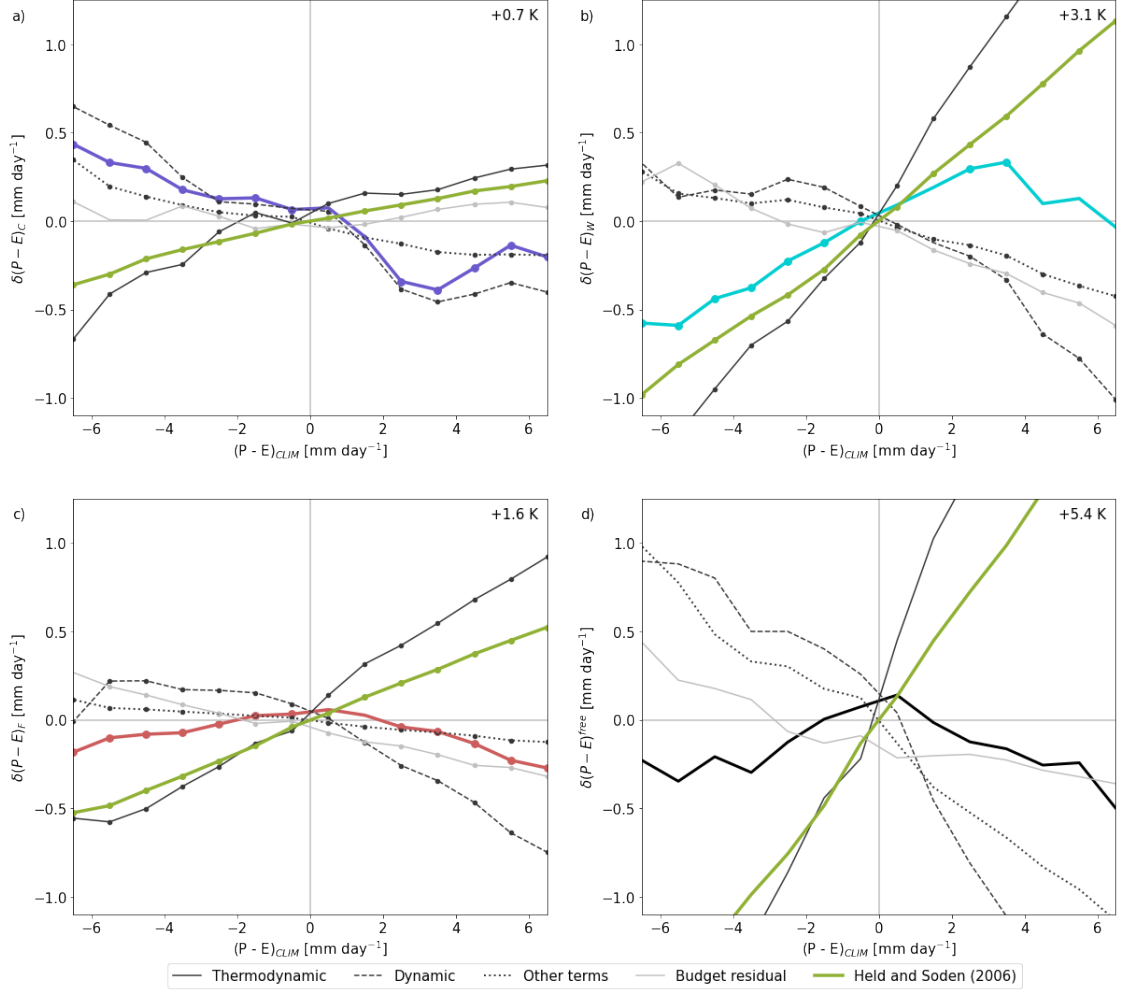


Figure 3.8: Annual-mean $P-E$ response to radiative changes in (a) clouds, (b) water vapour, and (c) CO_2 ; and (d) the total $P-E$ change (thick purple, light blue, red and black lines, respectively) decomposed using the moisture budget into thermodynamic and dynamic components and the contribution from other terms in the budget (solid, dashed and dotted thin black lines, respectively), and the budget residual (grey line). The radiative perturbations are driven by CO_2 quadrupling and, in panels (a-c), the responses are calculated using radiation locking, with dots indicating changes that meet the trustworthiness criteria (Section 3.3.1). In each panel, a simple estimate of $P-E$ changes [see Eq. (3.1)] and the change in tropical-mean surface temperature are also shown.

monthly-mean data, the residual includes the contributions to $P-E$ changes from changes in transient eddies, which are likely substantial (Byrne & O’Gorman, 2015).

Our results differ from previous modelling and observational studies showing that the scaling reproduces zonal-mean oceanic $P-E$ changes reasonably well (Lambert et al., 2025). Since our analysis includes land regions, where the scaling is known

to break down (Byrne & O’Gorman, 2015), this might seem a likely explanation. However, our results are largely driven by oceanic $P-E$ changes (not shown). We suggest that the discrepancy instead reflects differences in the spatial averaging approach. Consistent with this, Figure 2 of Byrne and O’Gorman (2015) shows that the scaling performs poorly in capturing local over-ocean differences in $P-E$ between the RCP8.5 and historical CMIP5 simulations.

3.4.4 Role of atmospheric/land and SST-mediated pathways

To gain further insight into the mechanisms through which radiative changes in clouds and water vapour influence $P-E$, we decompose the cloud- and water vapour-driven changes into contributions from the atmospheric/land pathway and the SST-mediated pathway. This also enables comparison with Voigt and Shaw (2015), who analysed cloud- and water vapour-driven $P-E$ changes occurring via the atmospheric pathway in two aquaplanet models.³

For clouds, the dynamic wet-gets-drier, dry-gets-wetter response occurs primarily via the atmospheric/land pathway (Fig. 3.9a). This agrees with Voigt and Shaw (2015), who also found that clouds act mainly through circulation changes, although with model-dependent outcomes: in MPI-ESM strengthening of climatological ascent and descent amplified the $P-E$ distribution, whereas in IPSL-CM5A weakened ascent and descent dampened it (their Fig. 2). Via the SST-mediated pathway, cloud-driven changes in moisture transport produce opposing thermodynamic and nonlinear contributions (‘other terms’ in Fig. 3.9) so that the dynamic response again dominates, particularly in wet regions where circulation reduces $P-E$ where $2 < (P-E)_{CLIM} < 4 \text{ mm day}^{-1}$.

Water vapour radiative effects, in contrast, act mainly through the SST-mediated pathway (Fig. 3.10). The atmospheric/land pathway plays a minor role, enhancing the thermodynamically driven wet-gets-wetter, dry-gets-drier response. This likely explains why the Held and Soden (2006) scaling [Eq. (3.1)], which

³In addition to differences in boundary condition complexity, our study differs from Voigt and Shaw (2015) in that their imposed cloud and water vapour changes do not include rapid adjustments to CO₂ forcing.

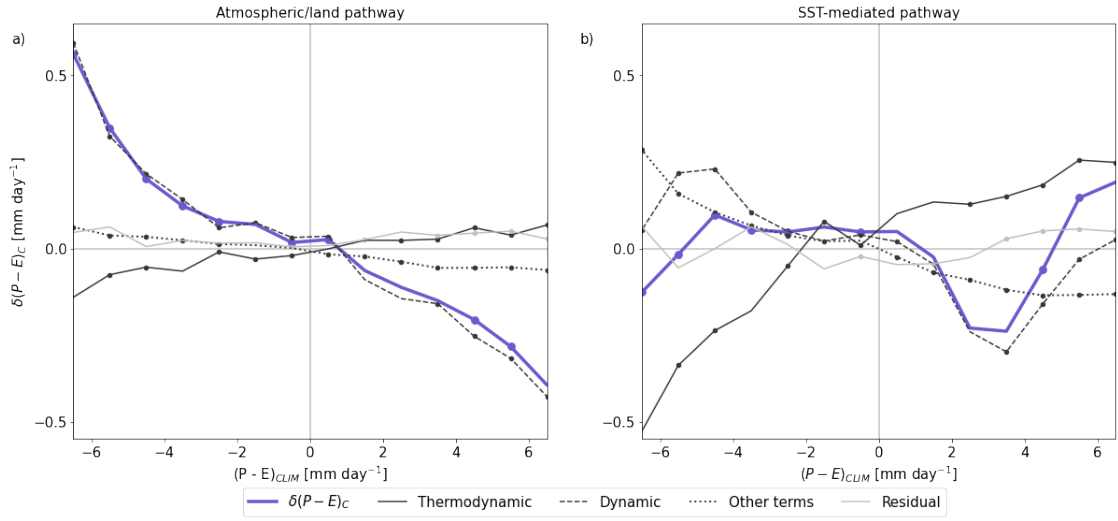


Figure 3.9: Annual-mean changes in $P-E$ driven by cloud-radiative changes via (a) the atmospheric/land pathway and (b) the SST-mediated pathway (solid purple lines), decomposed using the moisture budget into thermodynamic and dynamic components and the contribution from other terms in the budget (solid, dashed and dotted thin black lines, respectively), and the budget residual (grey line). The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate changes that meet the trustworthiness criteria (Section 3.3.1).

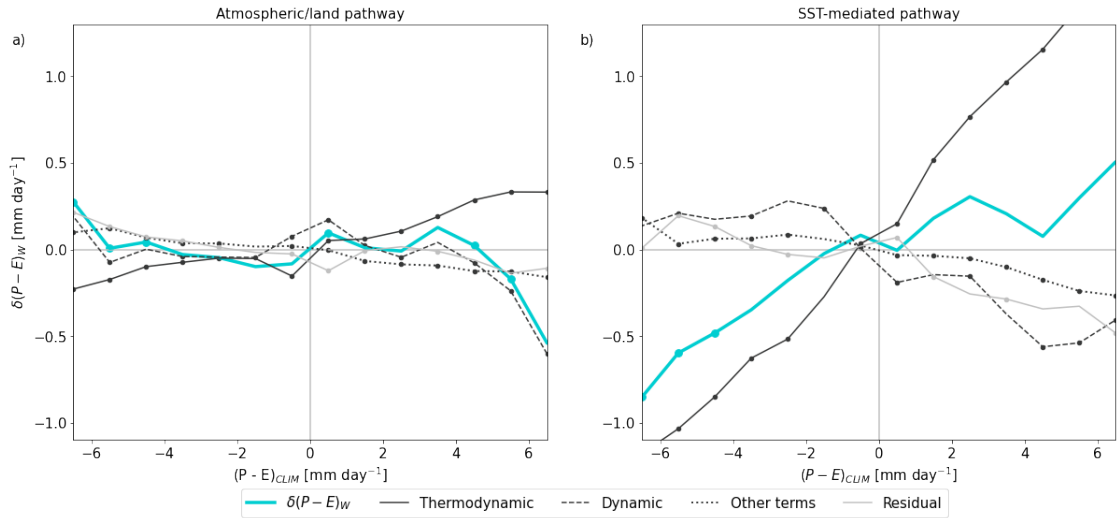


Figure 3.10: Annual-mean changes in $P-E$ driven by water vapour radiative changes via (a) the atmospheric/land pathway and (b) the SST-mediated pathway (solid purple lines), decomposed using the moisture budget into thermodynamic and dynamic components and the contribution from other terms in the budget (solid, dashed and dotted thin black lines, respectively), and the budget residual (grey line). The water vapour radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate changes that meet the trustworthiness criteria (Section 3.3.1).

assumes SST-driven thermodynamic changes, underestimates the thermodynamic contribution. The small atmospheric/land influence is consistent with Voigt and Shaw (2015), although their results suggest a somewhat larger role for dynamic changes (their Fig. S2).

Separating cloud- and water vapour-driven changes in $P-E$ into atmospheric/land and SST-mediated pathways requires the use of the P-SST simulations. This reduces the reliability of the radiation-locking methodology relative to $P-E$ changes calculated using the SLAB, as determined by the trustworthiness criteria. This is not unexpected as we apply more trustworthiness requirements to the data when using the two suites of simulations in concert (Section 3.3.1).

For cloud-driven changes occurring via the atmospheric/land pathway, our results remain robust; however, the SST-mediated pathway is more uncertain, particularly where $0 < (P-E)_{CLIM} < 4 \text{ mm day}^{-1}$. We find that $P-E$ changes in this region do not meet the trustworthiness criteria because they do not meet the 'free minus lock' requirement i.e., the changes in $P-E$ are too small compared to $|\delta(P-E)^{free} - \delta(P-E)^{lock}|$. However, as shown in Figure 5.1a, changes in P and E individually do meet the trustworthiness criteria, suggesting that the small size of changes in $P-E$ relative to the residual may not mean they are unphysical.

The decomposition is less reliable for water-vapour-driven changes. This is because water vapour-driven changes occurring via the atmospheric/land pathway are small in many $(P-E)_{CLIM}$ regimes, leading to a consistent failure of the state-dependence requirement. While this requirement was designed to accommodate small changes in a variable, it does not account for *consistently* small changes, which is a flaw in its construction.

3.5 Conclusion

In this chapter, we used the radiation-locking technique to investigate how radiative changes in clouds, water vapour, and CO_2 shape the tropical $P-E$ response to CO_2 forcing. Using ICON GCM simulations from Huber (2022), our analysis extends earlier aquaplanet studies (Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Byrne &

Zanna, 2020) by incorporating a realistic land–sea distribution. To our knowledge, this is the first study to apply radiation locking to tropical hydroclimate in a setting with more complex surface boundary conditions, achieved by combining realistic continents with a slab ocean model.

We analyse tropical $P-E$ changes as a function of the climatological $P-E$, which provides a simplified perspective on the hydrological cycle, while allowing direct comparison with the thermodynamic scaling proposed by Held and Soden (2006): $\delta(P-E) \approx \alpha(P-E)\delta T_s$. To further probe the underlying mechanisms, we decompose $P-E$ changes into dynamic and thermodynamic components using the moisture budget and separate cloud- and water vapour-driven changes into contributions arising through the atmospheric/land pathway (i.e., independent of SST changes) and the SST-mediated pathway (mediated by changing SSTs; Voigt et al., 2019, 2021).

We find that cloud-radiative changes play a critical role in the total $P-E$ response, producing a pronounced dry-gets-wetter, wet-gets-drier pattern. These changes occur via the atmospheric/land pathway and are largely dynamically driven, consistent with the findings of Voigt and Shaw (2015). Clouds also influence moisture transport via the SST-mediated pathway, decreasing $P-E$ in regions where the climatological $P-E$ lies between $2 - 4 \text{ mm day}^{-1}$.

The cloud-driven $P-E$ changes oppose a wet-gets-wetter, dry-gets-drier response driven by water vapour radiative changes. As a result, although CO_2 -driven $P-E$ changes are relatively small, they shape the overall response: wet and dry regions both experience drying, with slight moistening where climatological $P-E$ is near zero.

The thermodynamic scaling of Held and Soden (2006) fails to reproduce the simulated $P-E$ changes, highlighting the fundamental role of circulation in shaping the response. This is not surprising, since GCMs consistently project a weakening of tropical overturning circulations (e.g., Chadwick et al., 2013), but it is nevertheless striking that all three radiative perturbations drive circulation changes. We hypothesise that this may result from thermodynamic changes introducing energy gradients within the atmosphere which are then smoothed out by the

dynamics. It is also important to note that the scaling relates $P-E$ to T_s rather than to radiative forcing, and therefore does not attempt to account for rapid adjustments to the CO_2 forcing.

Alongside our analysis, we develop a set of ‘trustworthiness criteria’ which we use to establish whether the radiation-locking methodology reliably separates the change in a given variable into cloud- water vapour- and CO_2 -driven components. The criteria suggest that the method is largely reliable for changes in $P-E$ averaged over $(P-E)_{CLIM}$ regimes. Cloud-driven changes occurring via the atmospheric pathway are also reliable, but the changes driven by the SST-mediated pathway do not meet our trustworthiness criteria, suggesting they should be interpreted with care. This is discussed further in Chapter 5.

We additionally described the ICON model in detail and conducted an analysis of model biases. We found that ICON captures the broad spatial structure of observed cloud radiative effects and tropical circulation, and that its CO_2 -forced cloud-radiative response lies largely within the spread of CMIP ensembles. However, the control climatology exhibits systematic biases, including overly weak tropical low-cloud cooling and regional errors in longwave cloud radiative effects, alongside a broader and weaker ITCZ and associated biases in ascent and $P-E$. While a full attribution is beyond the scope of this chapter, these errors are plausibly linked to the parameterised representation of boundary-layer clouds and warm-rain microphysics in the low-cloud regime, and to the coupling between deep convection, stratiform condensate, and radiation in the high-cloud regime. Consistent with this, circulation biases closely co-vary with cloud-radiative heating biases, emphasising the tight coupling between clouds, radiation, and dynamics in ICON.

3.6 Outlook

Overall, these findings support earlier aquaplanet results that clouds are central to shaping the tropical $P-E$ response to CO_2 forcing. Our results also comprise a first step toward elucidating the underlying mechanisms under more realistic conditions; setting the agenda for the remainder of the thesis: Chapter 4 investigates the

processes through which clouds act via the atmospheric/land pathway, and Chapter 5 examines SST-mediated mechanisms operating through the SST-mediated pathway.

At the same time, our analysis highlights important open questions about how cloud, water vapour and CO₂ radiative changes combine to influence tropical $P-E$. First, the anti-correlation between cloud- and water vapour-driven $P-E$ changes is intriguing and suggests the possibility of a broader physical constraint. Second, this thesis does not address the mechanisms through which water vapour and CO₂ radiative changes influence $P-E$. However, our results highlight that understanding these mechanisms is an open question. The thermodynamic scaling of Held and Soden (2006) does not reproduce the thermodynamic component of these changes particularly well. This suggests a role for relative humidity variations, possibly linked to land-atmosphere interactions, that merits further investigation. Furthermore, both water vapour and CO₂ radiative changes induce substantial circulation responses. Understanding these dynamical contributions is essential for understanding the overall impact of these radiative changes on the hydrological cycle.

Previous studies provide useful context for future exploration of the mechanisms controlling the water vapour and CO₂ driven responses. Bony et al. (2013) showed that the fast response to CO₂ quadrupling plays a key role in the CMIP5 multi-model mean $P-E$ change, dynamically producing a dry-gets-wetter, wet-gets-drier pattern. This dynamic response strengthens with surface warming but is offset by a thermodynamically driven wet-gets-wetter tendency. Although they did not isolate the influences of individual radiative changes, they suggested that the fast response originates from direct CO₂ effects: enhanced longwave absorption increases static stability and weakens vertical motion [Eq. (1.4)]. In contrast, Merlis (2015) showed that the weakening is driven by spatial variability in the CO₂ radiative perturbation caused by cloud masking. Because ascending regions are cloudier than descending regions, direct CO₂ forcing is weaker there, reducing the energy contrast between the two branches of the Hadley circulation, the need for poleward energy transport, and thus the strength of the overturning circulation.

Our results are consistent with this interpretation: limited CO_2 -driven $P-E$ changes likely reflect weakened vertical velocities caused by direct CO_2 effects counterbalancing the increased moisture transport associated with surface warming. By analogy, we hypothesise that the dynamic component of water vapour-driven $P-E$ changes operates through a similar mechanism to that proposed by Merlis (2015) for CO_2 , but acting via the SST-mediated pathway. Specifically, cloud masking may damp the SST response to enhanced water vapour radiative effects in wet regions, reducing the energy contrast between wet and dry areas and thereby reducing the need for energy transport.

Testing these hypotheses offers a promising avenue for future work. This will likely require a new set of radiation-locking simulations with daily or even hourly output, since the moisture budget residual is relatively large for CO_2 - and water vapour-driven changes in our simulations – likely reflecting contributions from transient eddies that cannot be captured by monthly-mean data.

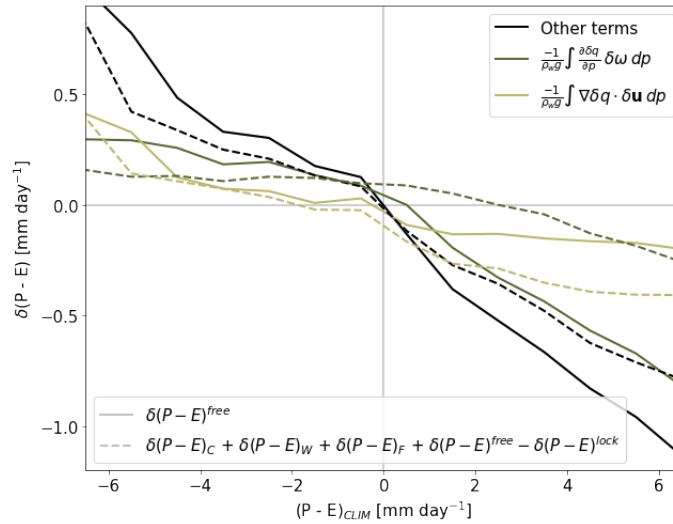


Figure 3.11: The total change in $P-E$ driven by ‘other terms’ in the moisture budget [Eq. (3.8)] (solid black line) and the contributions to this from the nonlinear interactions between moisture gradients and the vertical (solid green line) and horizontal (solid yellow line) winds. Dashed lines show the same quantities when calculated as the sum of cloud-, water vapour-, and CO_2 -driven changes (calculated using radiation locking) plus the residual between locked and free-running simulations.

3.7 On the radiation-locking methodology

Before turning to the cloud-driven component of changes in the hydrological cycle in Chapters 4 and 5, we briefly reflect on some methodological nuances of the radiation-locking approach identified during this analysis. In particular, the method is mathematically constructed such that the estimated contributions driven by each radiative change sum to the locked change, δX^{lock} [Eq. (3.3)]. To maintain this equality, $\delta X_{C,W,F}$ must be treated consistently. Consequently, for quantities that depend on both the climatology and the radiatively driven change in a variable, the climatological component is taken from the free-running SLAB CTRL simulation. Strictly speaking, this is somewhat unphysical, since each pair of locked simulations in Equations (3.4)–(3.6) has its own ‘control’ simulation in which the radiative effect of interest is locked to its CTRL values.

For example, Figure 3.12a compares $\delta(P-E)_{C,W,F}$ plotted as a function of the SLAB CTRL $P-E$ (i.e., in the same way as in Figs. 3.7, 3.8) to $\delta(P-E)$ calculated for each pair of simulations in Equations (3.4)–(3.6) and plotted as a function of $P-E$ from the control simulation of that pair (shown as thin lines). While this choice has limited impact in regions where $(P-E)_{CLIM} < 0$, the agreement between methods is lower for cloud- and water vapour-driven changes as $(P-E)_{CLIM}$ becomes more positive.

For cloud-driven changes, the relationship between $P-E$ changes and $(P-E)_{CLIM}$ is broadly consistent across pairs, but binning by the SLAB CTRL $P-E$ distorts the relationship where $(P-E)_{CLIM}$ is strongly positive. We hypothesise that this is linked to differences among simulations in the spatial distribution of convection. For water vapour, an additional effect seems to be at play as there is spread in the $P-E$ changes calculated using individual pairs of simulations. This suggests that dependence of the $P-E$ changes on the base state. To help account for these effects, we use the appropriate pair control simulation when applying the state-dependence requirement (Section 3.3.1).

Figure 3.12b makes the same comparison for the P-SST simulations. Here, discrepancies between methods are smaller for cloud- and water vapour-driven

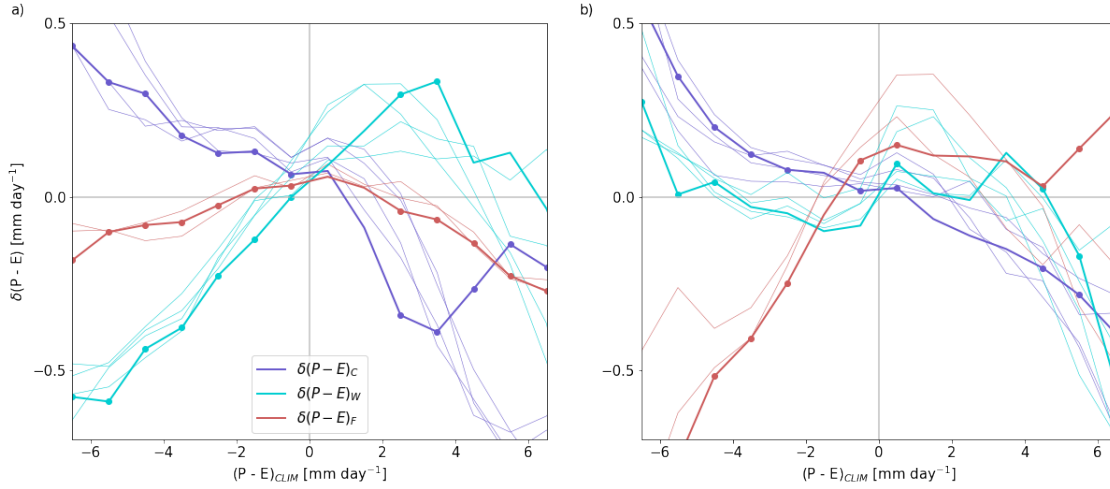


Figure 3.12: Annual mean (a) change in $P-E$ driven by radiative changes in CO_2 (red), clouds (purple), and water vapour (light blue); and (b) the cloud- and water vapour-driven components of the change occurring via the atmospheric/land pathway (purple and light blue, respectively) and the CO_2 - and SST-driven components of the change combined (red). The radiative perturbations are driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate changes which meet the trustworthiness criteria (Section 3.3.1). The changes from each pair of simulations described in Equations (3.4)-(3.6) are also shown (thin lines).

changes but are larger for changes driven by the combination of changing SSTs and CO_2 radiative effects. Given the close relationship between SST pattern and ascent location, it makes sense that the discrepancies are smaller for cloud- and water vapour-driven changes when only including the atmospheric/land pathway.

A second nuance concerns the treatment of nonlinear terms in the moisture budget [Eq. (3.8)]. The total change in these terms can be decomposed into contributions from radiative changes in clouds, water vapour, and CO_2 , but it also includes contributions from cross-interactions between radiative changes. As shown in Figure 3.11, the sum of the cloud-, water vapour-, and CO_2 -driven nonlinear contributions, together with $(\delta[\text{nonlinear term}]^{free} - \delta[\text{nonlinear term}]^{lock})$, does not reproduce the full change, $\delta[\text{nonlinear term}]^{free}$. In Section 3.3.1, we defined ‘state dependence’ as the sensitivity of, for example, a cloud-driven change to the background water vapour radiative effect. The nonlinear behaviour discussed here points to a second type of state dependence: the sensitivity of the cloud-driven change to *changes* in water vapour radiative effects.



Queen's Lane, 7 Nov 2023

4

Cloud-radiative influences on $P - E$ via the atmospheric/land pathway

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4.1 Introduction

Uncertainty in how increasing CO₂ emissions will affect the tropical hydrological cycle remains substantial (e.g., Stevens & Bony, 2013). Thermodynamic changes are projected to amplify the climatological precipitation minus evaporation, $P - E$, pattern (e.g., Held & Soden, 2006; Byrne & O’Gorman, 2015; Lambert et al., 2025, Fig. 3.8d). Weakening of the large-scale overturning circulation is expected to counteract this effect (Manabe & Wetherald, 1975; Seager et al., 2010; Chadwick et al., 2013, Fig. 3.8d), but there is considerable inter-model spread in the magnitude of the associated changes in vertical velocity (e.g., Fig. 3 of Bony et al., 2013).

Cloud changes exert a strong influence on global top-of-atmosphere radiative fluxes, and persistent uncertainties in these changes have motivated detailed study of their role in climate sensitivity (e.g., Bony & Dufresne, 2005; Klein et al., 2018; Ceppi & Nowack, 2021; Vogel et al., 2022; Sokol et al., 2024). However, the radiative effects of clouds are also a major influence on regional atmospheric energy budgets and energy transport through the atmosphere (Roe et al., 2015), which are tightly coupled to precipitation, evaporation and the large-scale circulation (e.g., Seager et al., 2010; Muller & O’Gorman, 2011). Uncertainty in tropical circulation changes has been linked to a variety of processes including rapid adjustments to CO₂ forcing (Bony et al., 2013), changes in the meridional gradient of diabatic heating and in the static stability (Chemke & Polvani, 2021), and changes in gross moist stability (Duffy & O’Gorman, 2023). However, several studies suggest cloud-radiative changes may play a central role (Feldl & Bordoni, 2016; Oueslati et al., 2016; Xia & Huang, 2017; Duffy & O’Gorman, 2023).

However, the precise mechanisms through which clouds affect circulation and $P - E$ responses to forcing are not well understood. To address this gap, we apply the radiation-locking method, which allows the influence of cloud-radiative changes on other elements of the climate system to be isolated (Wetherald & Manabe, 1988; Ceppi & Hartmann, 2016; Voigt et al., 2019, 2021). We focus on the tropics (30°N–30°S) and use simulations performed by Huber (2022) with the ICON global climate model (GCM; Giorgetta et al., 2018) configured with

realistic continents, sea ice, and a seasonal cycle. Our analysis builds on earlier radiation-locking studies with idealised aquaplanet configurations, which revealed the strong influence of cloud-radiative changes on the tropical hydrological cycle (Voigt & Shaw, 2015; Byrne & Zanna, 2020). Following Voigt et al. (2019), we focus on cloud influences operating via through the ‘atmospheric/land pathway’ [i.e., independent of sea surface temperature (SST) changes] by using simulations with fixed SSTs (Section 3.3.1).

To build mechanistic understanding, we consider how changes in atmospheric energy flows contribute to establishing a new energetic equilibrium following the cloud-radiative perturbation. This allows us to identify the drivers of changes in moisture transport and hence $P-E$. Following Chapter 3, we partition the tropics into regimes based on the climatological $P-E$ distribution, which provides a simplified perspective on the hydrological cycle. We also use the same trustworthiness criteria to assess the reliability of the radiation-locking methodology for each diagnostic considered (Section 3.3.1).

The rest of the chapter is organised as follows. We first revisit the cloud-driven $P-E$ changes introduced in Chapter 3. We then characterise the cloud-radiative perturbation and the accompanying changes in cloud properties, before tracing how this perturbation drives changes in energy and moisture transports. We conclude by summarising the results and situating them within the broader literature.

4.2 Model and methods

The model simulations used here are the same as in Chapter 3, and are described in Section 3.2. The radiation-locking method is employed following Section 3.3.1.

4.2.1 Partial radiative perturbation

We use the partial radiative perturbation (PRP) analysis conducted by Huber (2022) to quantify the changes in atmospheric heating rates and surface radiative fluxes resulting from the cloud response to CO_2 quadrupling. PRP is used rather than radiation locking as the technique isolates the *instantaneous* cloud-driven

radiative perturbation, i.e., it does not include the clear-sky response to the cloud changes (Soden et al., 2008).

The PRP technique was introduced by Wetherald and Manabe (1988) and involves perturbing individual radiatively active quantities in a climate model’s radiative transfer scheme, while holding others fixed, to quantify their contributions to changes in radiative fluxes and atmospheric heating rates. For the PSrad radiation scheme in ICON-A (see Section 3.2 for more information), the relevant quantities for clouds are cloud fraction, cloud water and cloud ice – collectively denoted $\mathcal{C}$. Therefore the instantaneous atmospheric temperature tendency driven by cloud-radiative changes is

$$\delta\left(\frac{\partial T}{\partial t}\right)_C = \frac{1}{2}\left((\mathcal{R}[A_{\text{CTRL}}, \mathcal{C}_{\text{PERT}}] - \mathcal{R}[A_{\text{CTRL}}, \mathcal{C}_{\text{CTRL}}]) + (\mathcal{R}[A_{\text{PERT}}, \mathcal{C}_{\text{PERT}}] - \mathcal{R}[A_{\text{PERT}}, \mathcal{C}_{\text{CTRL}}])\right), \quad (4.1)$$

where $\mathcal{R}$ is the radiative heating rate calculated by the scheme, t is time, A denotes all other inputs (temperature, humidity, etc.), and CTRL and PERT denote the control and perturbed climates. The first difference on the right-hand side quantifies the impact of introducing PERT clouds into the CTRL climate, while the second quantifies the reverse case. Averaging the two reduces sensitivity to the choice of base climate, although we note that the results are qualitatively independent of the base climate (not shown).

4.2.2 Moist static energy budget

To understand how the cloud radiative perturbation affects the broader climate system, we use the atmospheric moisture budget (outlined in Section 3.3.2) in combination with the moist static energy budget. The moisture budget relates precipitation and evaporation to the transport of water vapour by the atmospheric circulation, while the moist static energy budget relates radiative and turbulent energy fluxes into the atmosphere to the transport of moist static energy. Taken together, these budgets provide a framework for diagnosing how radiative and

turbulent flux changes modify $P-E$ through their influence on large-scale energy and moisture transport.

The vertically integrated moist static energy budget can be written as (e.g., Kiranmayi & Maloney, 2011):

$$NEI_A = \frac{1}{g} \int_{p_T}^{p_B} \left(\frac{\partial h}{\partial t} + \mathbf{u} \cdot \nabla h + \omega \frac{\partial h}{\partial p} \right) dp, \quad (4.2)$$

where $g = 9.81 \text{ m s}^{-2}$ is the gravitational acceleration, p is pressure with p_B being the pressure at the bottom level of the atmospheric model and p_T being the pressure at the top level, q is the specific humidity, $\mathbf{u} = (u, v)$ is the horizontal wind, ω is the vertical pressure velocity (hereafter ‘vertical velocity’), h is the moist static energy [defined in Equation (1.2)] and NEI_A is the net energy input to the atmospheric column by radiative and turbulent fluxes. Alternatively, NEI_A can be expressed as

$$NEI_A = CRE_A + R_A^{CLR} + SH + L_v E, \quad (4.3)$$

where CRE_A denotes the atmospheric cloud radiative effect, R_A^{CLR} the clear-sky radiative flux into the atmospheric column, and SH and $L_v E$ the surface sensible and latent heat fluxes, respectively (L_v is the latent heat of vaporisation). All fluxes are defined as positive into the atmosphere.

Steady-state changes in the moist static energy budget are given by:

$$\delta CRE_A + \delta R_A^{CLR} + \delta SH + L_v \delta E = \frac{1}{g} \int_{p_T}^{p_B} \left([\mathbf{u} \cdot \nabla + \omega \frac{\partial}{\partial p}] \delta h + [\nabla h \cdot \delta \mathbf{u} + \frac{\partial h}{\partial p} \delta \omega] \right) dp + \text{nonlinear terms.} \quad (4.4)$$

We define thermodynamically driven changes in moist static energy transport as those arising from changes in moist static energy gradients while dynamically driven changes are associated with changes in the horizontal or vertical components of the atmospheric circulation.

As was the case for the moisture budget, there are challenges in precisely closing the moist static energy budget (Inoue et al., 2024). The associated budget

residual, in addition to contributions to moist static energy transport from sub-monthly eddies, are combined into a single residual term. This is discussed in more detail in section 3.3.2.

Finally, as noted in Section 3.2, the interpretation of energy budgets depends on the lower boundary condition. In the fixed-SST (P-SST) simulations used in this chapter, SST and sea ice are prescribed, so the ocean surface cannot adjust to anomalies in the net surface energy flux. Over ocean grid points, any change in the net surface energy flux therefore implies an implicit residual sink/source of energy that maintains the imposed SSTs, and the coupled atmosphere–ocean system is not energetically closed over the ocean. The diagnostics above nevertheless remain well defined, because they concern the atmospheric-column moist static energy budget, which relates radiative and turbulent fluxes into the atmosphere to changes in atmospheric energy transport (up to the residual discussed above).

4.3 Results

Cloud-radiative changes drive a ‘wet-gets-drier, dry-gets-wetter’ annual-mean $P-E$ response via the atmospheric/land pathway (Fig. 4.1a). This comprises reduced precipitation in climatologically wet regions [where $(P-E)_{CLIM} > 0 \text{ mm day}^{-1}$] and reduced evaporation in climatologically dry regions [where $(P-E)_{CLIM} < 0 \text{ mm day}^{-1}$]. Taking an area-weighted average over $(P-E)_{CLIM}$ regimes, we find a -4% change in $P-E$ per Kelvin tropical mean surface warming, increasing to -6% K^{-1} for $|(P-E)_{CLIM}| > 3.5 \text{ mm day}^{-1}$. Figure 4.1b shows the spatial distribution of these $P-E$ changes. The wet-gets-wetter, dry-gets-drier pattern is largely driven by oceanic regions. In contrast, many land regions exhibit a ‘wet-gets-wetter’ response. In Figure 4.1 and throughout, cloud-driven changes are denoted using $\delta[\cdot]$.

4.3.1 Cloud changes

To diagnose the drivers of the $P-E$ changes, we begin by characterising the cloud-driven radiative perturbation within the atmosphere and at the land surface using

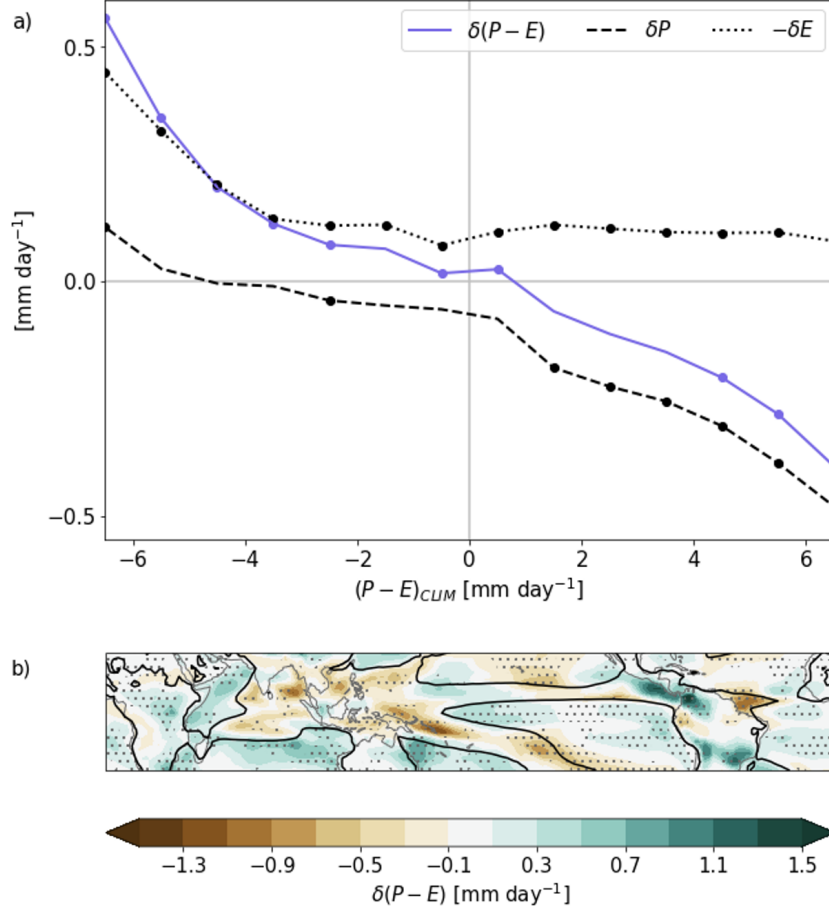


Figure 4.1: Annual-mean changes in (a) $P-E$ (purple solid line), P (black dashed line), and $-E$ (black dotted line) driven by cloud-radiative changes via the atmospheric/land pathway and shown as a function of the climatological $P-E$, and (b) a map of the $P-E$ changes. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. In panel (b), black contours denote where the climatological annual-mean $P-E = 0 \text{ mm day}^{-1}$. Dots and stippling indicate responses that meet the trustworthiness criteria (Section 3.3.1).

partial radiative perturbation (PRP) calculations (Section 4.2.1). We then relate our results to changes in the properties and spatial distribution of clouds.

The PRP calculations show that changes in cloud-radiative heating of the atmosphere are largest in climatologically wet, cloudy regions (Fig. 4.2a). The heating peaks between 200–300 hPa and below this the tendency alternates between cooling at 400 hPa and warming at 500–600 hPa (Fig. 4.2a). Changes in climatologically dry regions are comparatively weak, potentially reflecting under-representation of low clouds in our ICON configuration (Fig. 4.2a; Crueger et al.,

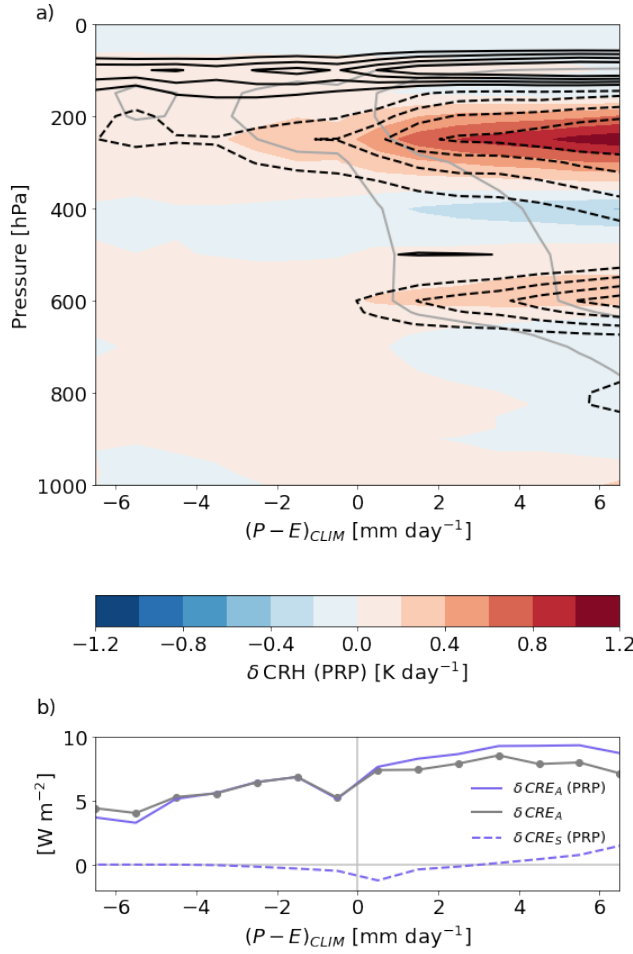
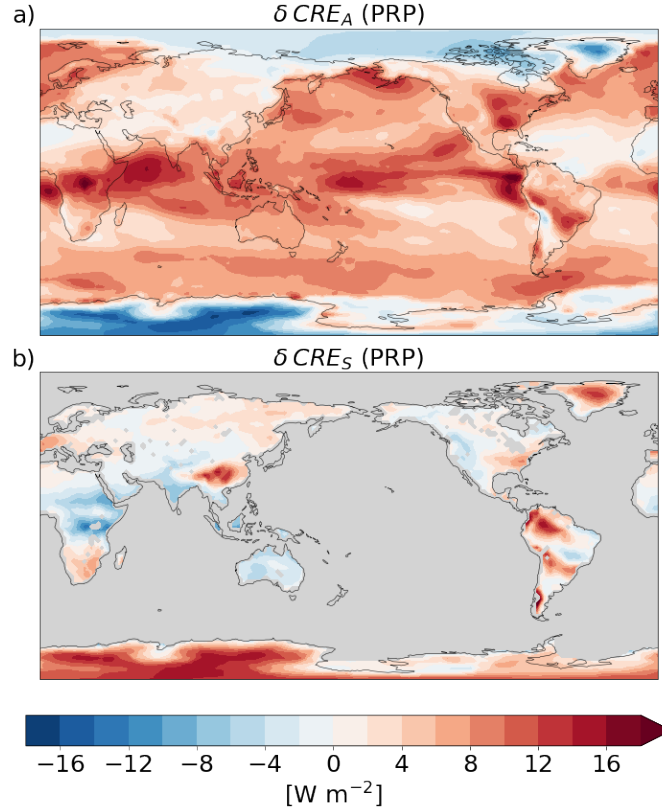


Figure 4.2: Annual-mean changes in (a) cloud-radiative heating calculated using PRP, and (b) atmospheric and surface cloud radiative effects calculated using PRP and atmospheric cloud radiative effects calculated using radiation locking (i.e., from the difference between all-sky and clear-sky column-mean atmospheric radiative fluxes). In panel (a), black contours show changes in cloud fraction (-8% to 8% at 2% intervals, excluding 0%), and gray contours show the climatological cloud fraction (10% and 20%). Changes are driven by CO_2 quadrupling. In panel (b), dots indicate changes that meet the trustworthiness criteria (Section 3.3.1).

2018). Beyond the tropics, changes in atmospheric cloud radiative effects, CRE_A , warm the midlatitudes while cooling the polar atmosphere (Fig. 4.3a).

Consistent with Voigt et al. (2024) and McGraw et al. (2025), the vertical structure of the tropical cloud-radiative heating perturbation closely follows the upward shift of high clouds, with the maximum heating located just below the perturbed cloud tops (Fig. 4.2a). This upward displacement of clouds is a robust response to warming documented in studies of both interannual variability and anthropogenic forcing and reflects the upward extension of the troposphere with surface warming (Singh & O’Gorman, 2012; Bretherton et al., 2014; Zelinka et al., 2016; Vaillant de Guélis et al., 2018). Because clouds rise roughly isothermally, longwave atmospheric heating is enhanced (Hartmann & Larson, 2002; Gasparini et al., 2024). Changes in cloud area and emissivity likely also shape the spatial pattern of heating (McGraw et al., 2025). In particular, the tropical upper-tropospheric

Figure 4.3: Annual-mean changes in (a) atmospheric cloud radiative effects and (b) surface cloud radiative effects calculated using PRP. Changes are driven by CO_2 quadrupling.



warming may be amplified by increases in the areal coverage of the highest clouds (black contours in Fig. 4.2a).

Because SSTs are prescribed in these simulations, changes in surface cloud radiative effects only lead to thermodynamic surface adjustment over land; over ocean they contribute to the implied residual required to maintain fixed SSTs. As a result, the thermodynamically impactful component of δCRE_S is much smaller than δCRE_A for a given $(P-E)_{CLIM}$ regime (Fig. 4.2b). Consequently, we largely focus on the climate response to δCRE_A . Nevertheless, local changes in land CRE_S can be substantial, particularly over northern South America, Central Africa and the Tibetan Plateau.

4.3.2 Moist static energy transport

To assess how the cloud-radiative perturbation modifies the flow of energy through the climate system, we examine changes in the moist static energy budget, shown in Equation (4.4).

In Equation (4.4), δCRE_A is defined as the difference between all-sky and clear-sky column-mean radiative fluxes. As a result, it includes a small non-cloud contribution, since the presence of clouds modifies clear-sky conditions within the atmospheric column. Comparison with the PRP method indicates that this effect is small in our simulations (Fig. 4.2b).

Additionally, although changes in CRE_S do not directly affect the atmospheric energy balance, they can influence land surface temperatures and the associated latent and sensible heat fluxes, which in turn affect the atmosphere.

Thermodynamic component of moist static energy transport

We begin by examining the thermodynamic component of changes in moist static energy transport. Atmospheric temperature changes are characterised by amplified upper tropospheric warming (Fig. 4.4a) which occurs at the same pressure levels as the original atmospheric cloud-radiative heating perturbation (Fig. 4.2a). However, the tropical atmosphere has equilibrated such that horizontal temperature gradients are weak (Sobel et al., 2001).

Changes in $g\delta z$ are comparatively small throughout most of the atmosphere. However, the increase in temperatures leads to larger values at low pressure levels, reflecting a modest upward extension of the troposphere (Fig. 4.4b). The contribution of changes in specific humidity to moist static energy changes is also small compared to the role of temperature changes (Fig. 4.4c). We note, however, that specific humidity changes are largest in the lower troposphere, meaning they slightly counterbalance the temperature-driven vertical gradient of the overall change in moist static energy.

To interpret the specific humidity changes (Fig. 4.4c), we rewrite $q \approx q_{sat} RH$ where q_{sat} is the saturation specific humidity and RH is the relative humidity. Because q_{sat} depends on temperature (via the Clausius–Clapeyron relationship), this permits changes in q to be separated into a thermodynamic component ($RH\delta q_{sat}$; Fig. 4.5a) and a component due to relative humidity changes, interpreted here as dynamically driven ($q_{sat} \delta RH$; Fig. 4.5b) and a nonlinear component ($\delta q_{sat} \delta RH$).

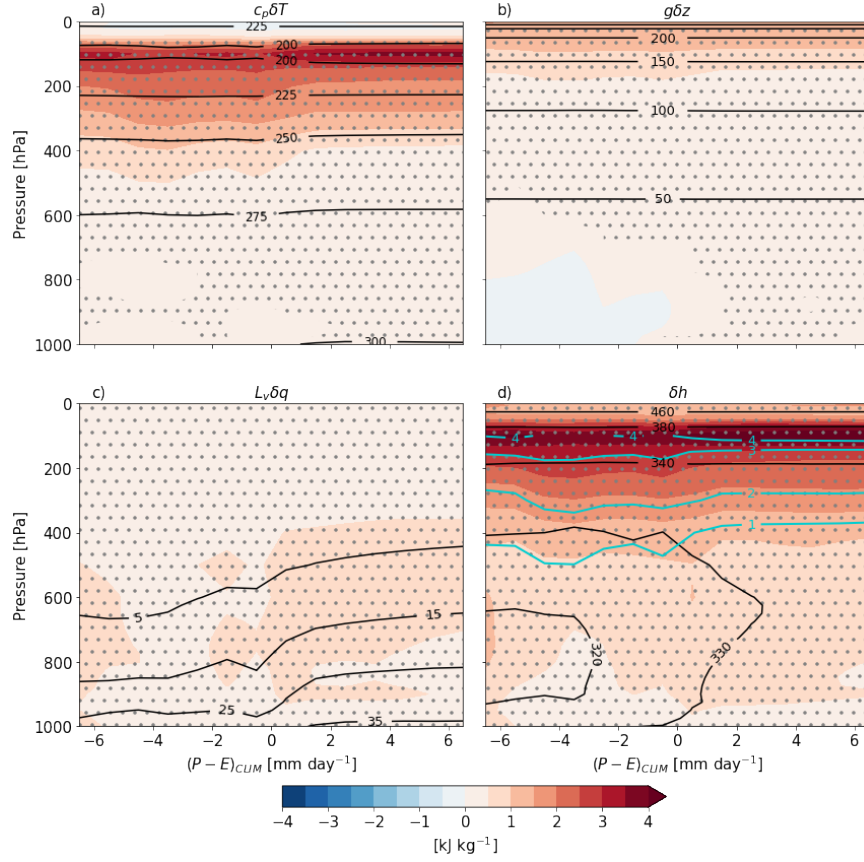


Figure 4.4: Annual-mean changes in (a) sensible heat ($c_p T$), (b) geopotential (gz), (c) latent heat ($L_v q$), and (d) moist static energy (shading) and saturation moist static energy (blue contours) driven by cloud-radiative changes via the atmospheric/land pathway, all in kJ kg^{-1} . The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Stippling indicates responses that meet the trustworthiness criteria (Section 3.3.1). In all panels, black contours show the climatological distribution of each variable.

Interpreting $RH \delta q_{sat}$ as dynamically-driven is motivated by the last-saturation paradigm for free-tropospheric humidity (e.g., Held & Soden, 2000; Pierrehumbert et al., 2007). In this framework, an air parcel’s specific humidity is set approximately by the saturation specific humidity at the point along its trajectory where it last experienced saturation and condensation. Thereafter, it is advected and mixed quasi-adiabatically to its current location with comparatively weak further moisture exchange. However, it should be noted that processes independent of atmospheric dynamics, such as changes in radiative heating or cloud microphysics may also influence the relative humidity.

Thermodynamically-driven changes in specific humidity are small because

warming is concentrated in the upper troposphere. Climatological temperatures are low here, so air retains limited moisture capacity even after the temperature increase. We will return to the dynamic component of the humidity changes later. Here, it is sufficient to note that it is of similar magnitude to the thermodynamically-driven component, but with a differing spatial structure. Thermodynamically driven specific humidity changes peak in climatologically wet regions, while dynamically driven changes are largest in very dry regions.

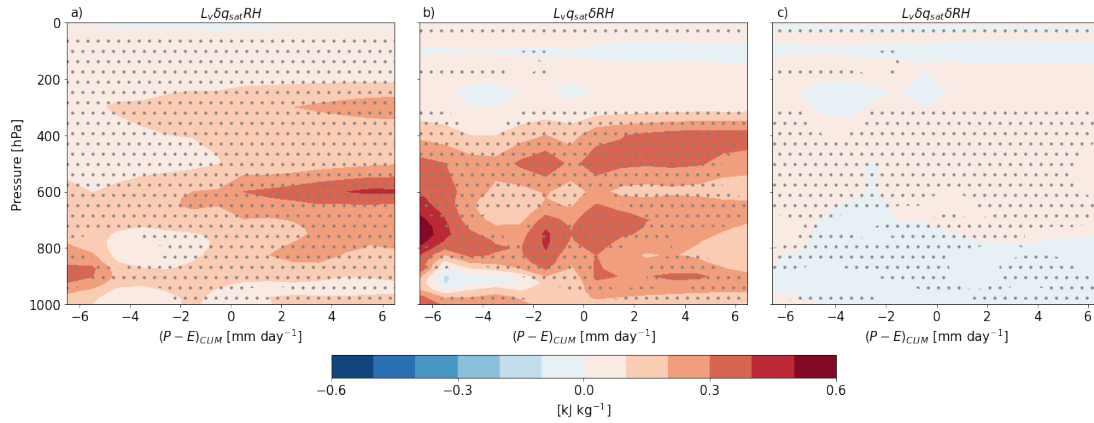


Figure 4.5: The (a) thermodynamic, (b) dynamic, and (c) nonlinear components of the annual-mean changes in latent heat driven by cloud-radiative changes via the atmospheric/land pathway. The cloud-radiative perturbation is driven by CO₂ quadrupling and the responses are calculated using radiation locking. Stippling indicates responses that meet the trustworthiness criteria (Section 3.3.1).

Strengthening or weakening of the moist static energy gradients across which the climatological circulation flows affects moist static energy transport. In our simulations, changes in horizontal moist static energy gradients are small, so thermodynamically-driven changes to horizontal advection of moist static energy are limited (Fig. 4.6a). However, changes in the vertical moist static energy gradient are substantial, leading to large thermodynamically-driven changes in vertical moist static energy advection. Comparing the change in the vertical moist static energy gradient (Fig. 4.7a) with the climatological vertical velocity distribution (Fig. 4.7b) – characterised by ascent where $(P - E)_{CLIM} > 0$ mm day⁻¹ and descent where $(P - E)_{CLIM} < 0$ mm day⁻¹ – shows that the $\omega \delta(\partial h / \partial p)$ term in Equation (4.4)

acts to increase the vertical-advection contribution to the MSE transport in wet regions and to decrease it in dry regions (Figs. 4.7c, 4.6a).

Cloud-driven changes in land temperatures and moisture availability may also play a role. However, small near-surface moist static energy gradients (Fig. 4.4d) suggest that any influence of surface temperature changes on the atmosphere likely occurs in convective regions, where moist static energy anomalies are transported aloft. Convective parcels approximately conserve their saturation moist static energy beyond the lifting condensation level, meaning we would expect changes in saturation moist static energy associated with changes in convection to be approximately vertically uniform in the free troposphere. Because saturation moist static energy changes are largest in the upper troposphere, we hypothesise that these changes are primarily governed by cloud-radiative heating of the atmosphere.

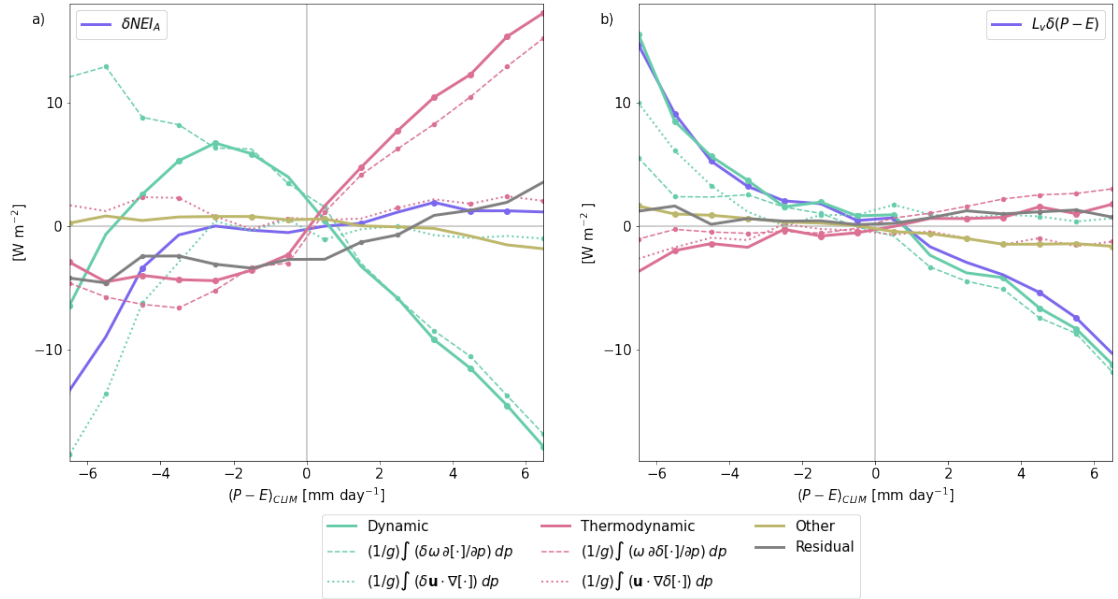


Figure 4.6: Annual-mean decomposition of the change in vertically integrated (a) moist static energy transport and (b) moisture transport into dynamic and thermodynamic components. ‘Other’ comprises nonlinear and density-related terms, and we also show the decomposition residual. We additionally show changes in NEI_A and $L_v(P-E)$ in panels (a) and (b), respectively, since in steady state these terms must be balanced by changes in vertically integrated transport (up to the residual). The cloud-radiative perturbation driving the changes is associated with CO_2 quadrupling and acts via the atmospheric/land pathway. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1). In the legend, $[\cdot]$ denotes h and $-L_v q$ for panels (a) and (b), respectively.

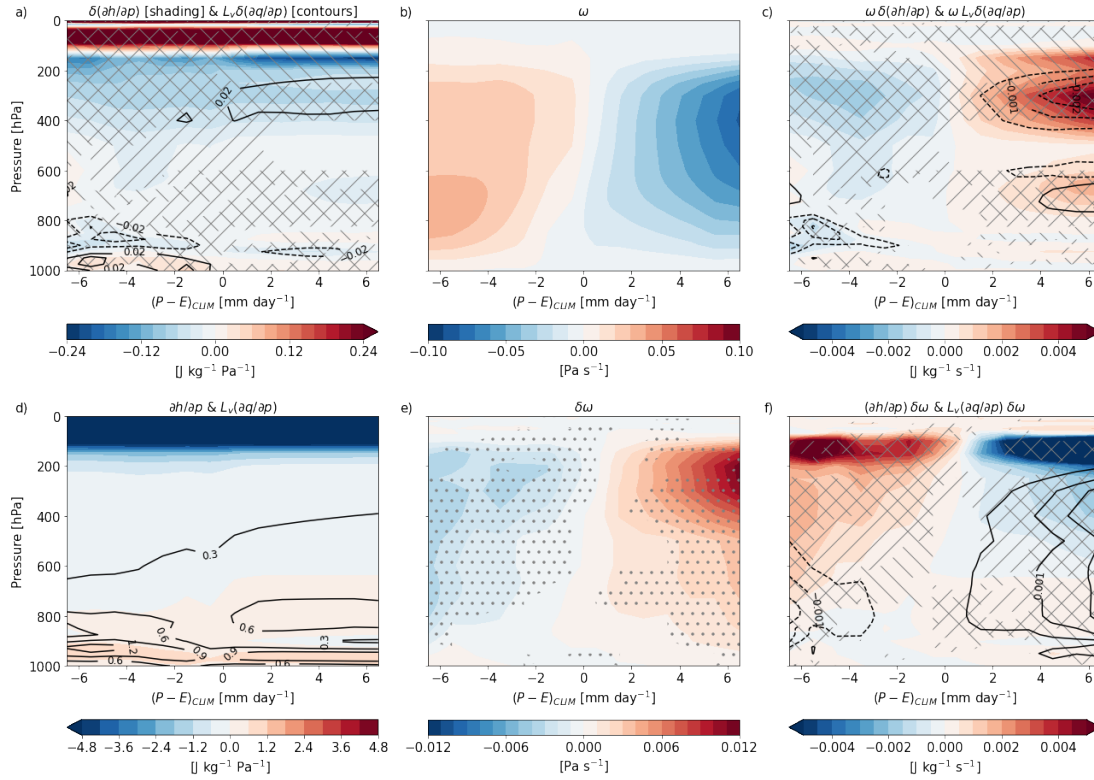


Figure 4.7: Annual-mean (a) change in vertical moist static energy gradient, (b) vertical velocity climatology, (c) change in the thermodynamic contribution to vertical moist static energy advection, (d) climatological moist static energy gradient, (e) change in vertical velocity, and (f) change in the dynamic contribution to vertical moist static energy advection. In panels (a) and (d), contours show the same for specific humidity; and in panels (c) and (f), the same for moisture transport, all multiplied by L_v . The cloud-radiative perturbation driving the changes is associated with CO₂ quadrupling and acts via the atmospheric/land pathway. The responses to the perturbation are calculated using radiation locking. In panels (a,c,f), forward- and backward-slanting hatching indicate moist static energy- and moisture-related responses, respectively, that meet the trustworthiness criteria (Section 3.3.1). In panel (e) stippling indicates changes that meet the trustworthiness criteria.

Dynamic component of moist static energy transport

The increase in upper-tropospheric saturation moist static energy (Fig. 4.4d) also provides valuable insight into the dynamical response to the cloud-radiative perturbation. Larger increases aloft cause rising parcels to reach neutral buoyancy earlier than in the control climate, resulting in shallower convection. Consistent with this mechanism, Figure 4.7e shows weakened ascent, particularly in the upper troposphere. Changes in ascent area are small, indicating that the response is dominated by a weakening of ascent strength rather than a change in the spatial

extent of ascent (Fig. D.1). The ascent weakening is therefore accompanied by weakened descent in dry regions (Fig. 4.7e), reflecting the overturning nature of the circulation in an approximately closed-mass region like the tropics, where changes in upward mass flux are balanced by changes in downward mass flux.

Weakening ascent in wet regions and descent in dry regions leads to a large dynamic contribution to the change in vertical advection of moist static energy (Figs. 4.7f, 4.6a). This is because the climatological moist static energy increases with altitude (Fig. 4.7d), driven by the geopotential term (Fig. 4.4b). While both the thermodynamic and dynamic contributions to vertical moist static energy advection are individually large, they largely cancel, so the net change in vertically integrated moist static energy transport across $(P-E)_{CLIM}$ regimes is small. Consistent with this, changes in NEI_A and the net transport requirement show only weak dependence on $(P-E)_{CLIM}$ (Fig. 4.6a).

Weakening of the circulation also reduces the dynamic contribution to meridional moist static energy advection, especially where $(P-E)_{CLIM} < -3 \text{ mm day}^{-1}$ (Fig. 4.6a). This is because the associated divergent winds also weaken. In particular, the near-surface branch of the Hadley circulation traverses strong moist static energy gradients over subtropical regions of the Indian and western Pacific oceans; when these winds weaken, up-gradient moist static energy advection decreases (Fig. 4.8). Accordingly, the largest deviations from zero in δNEI_A occur in the driest regimes, where the meridional advection contribution is non-negligible (Fig. 4.6a).

4.3.3 Moisture transport

We next examine how changes in moist static energy transport modify moisture transport and, in turn, $P-E$, using the moisture budget shown in Equation (3.8). The thermodynamic component of the moisture transport is small as the cloud-radiative perturbation does not drive substantial humidity changes (Figs. 4.4c, 4.6b). However, the cloud-driven weakening of the tropical overturning circulation affects the dynamic component of moisture transport.

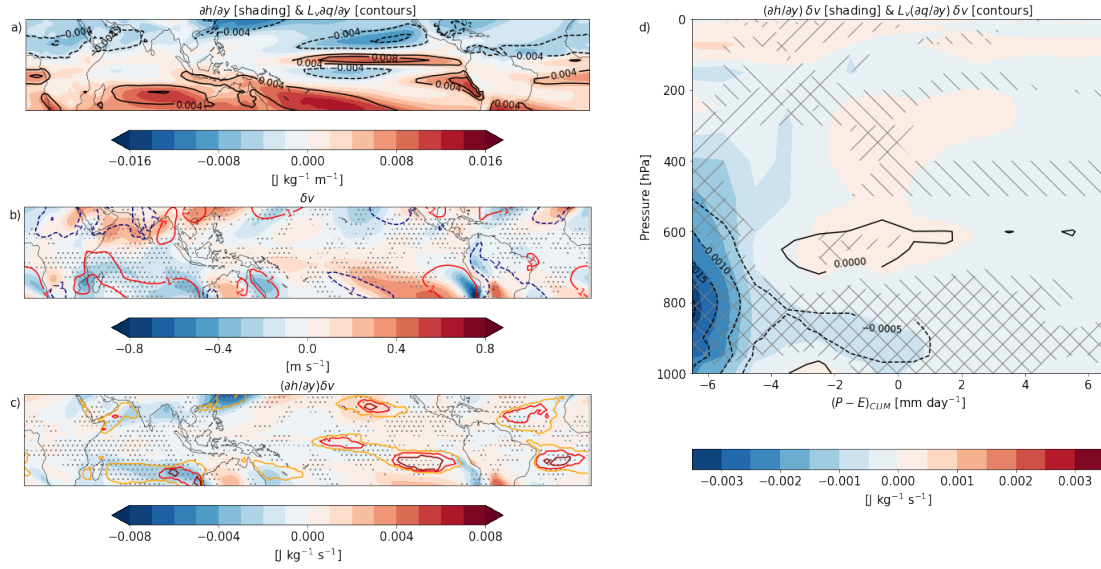


Figure 4.8: Annual-mean (a) meridional moist static energy gradient, (b) change in meridional wind, and (c) dynamic contribution to the change in meridional moist static energy advection, all averaged over 500–1000 hPa, and (d) vertically-resolved change in the dynamic contribution to the change in meridional moist static energy advection. In panels (a) and (d), contours show the meridional specific humidity gradient and the dynamic contribution to the change in meridional moisture advection, respectively, both multiplied by L_v . In panel (b), contours show the climatological meridional wind (-1 m s^{-1} , 1 m s^{-1}). In panel (c), contours show the number of months in which $(P-E)_{CLIM} \leq -4 \text{ mm day}^{-1}$ [3 (orange), 6 (red), 9 (dark red)]. In panel (d), the $0 \text{ J kg}^{-1} \text{s}^{-1}$ contour is removed above 400 hPa for clarity. The cloud-radiative perturbation driving the changes is associated with CO₂ quadrupling and acts via the atmospheric/land pathway. The responses to this perturbation are calculated using radiation locking. In panels (b,c), stippling indicates responses that meet the trustworthiness criteria (Section 3.3.1). In panel (d) forward- and backward-slanting hatching indicate moist static energy- and moisture-related responses, respectively, that meet the trustworthiness criteria.

How this circulation change affects moisture transport depends on the climatological moisture distribution. Unlike climatological moist static energy, which increases with altitude, moisture is most abundant lower in the atmosphere where temperatures are highest (black contours in Fig. 4.4c). This vertical gradient in atmospheric moisture (Fig. 4.7d) means that weakening vertical velocities produces a large dynamic contribution to changes in vertical moisture advection. (Figs. 4.7f). Noting the minus sign in Equation (3.8), this corresponds to reduced precipitation in wet regions (Figs. 4.1a, 4.6b).

Weakening of the tropical circulation also affects meridional moisture transport in the near-surface branch of the Hadley circulation. This is because the

climatological meridional moist static energy gradients have a substantial moisture contribution, which accounts for roughly half of the total gradient (Fig. 4.8b,d), and so weakening meridional winds reduce up-gradient moisture advection, particularly where $(P-E)_{CLIM} < -3 \text{ mm day}^{-1}$. This reduction in moisture transport is balanced by reduced evaporation (Figs. 4.1a, 4.6b). We hypothesise that this evaporation reduction occurs because weakening subsidence and near-surface winds cause the rate at which cold, dry air comes into contact with the ocean surface to be reduced. Evaporation increases over land (not shown), confirming over-ocean changes drive this response.

We note that the circulation-driven decrease in precipitation in wet regions reduces latent heating, which can influence atmospheric thermodynamics by modifying the vertical temperature structure (i.e., the lapse rate). While this does not significantly modify the moist static energy distribution, it is accompanied by an increase in atmospheric moisture (Fig. 4.5b), leading to a small thermodynamically driven change in moisture transport (Fig. 4.7c).

4.3.4 Achieving energetic balance

While we have documented how the moist static energy and moisture transports change, and how this affects $P-E$, we have not explained why the dynamic and thermodynamic contributions to transports change in the way they do. To address this, we explore how the changes in moist static energy transport contribute to restoring energetic balance within the budgets analysed here after the cloud-radiative perturbation. Recall that, because SSTs are fixed, the adjustments described here restore energetic balance within the atmospheric column and land surface, but do not represent a closed atmosphere–ocean energy equilibration.

Figure 4.9 shows the equilibrated changes in the terms contributing to the moist static energy budget [Eq. (4.3)]. We recall that cloud radiative changes drive an increase in energy input to the atmospheric column, the magnitude of which is larger in wet regions. Although the cloud perturbation causes substantial dynamic and thermodynamic changes in moist static energy transport, cancellation between

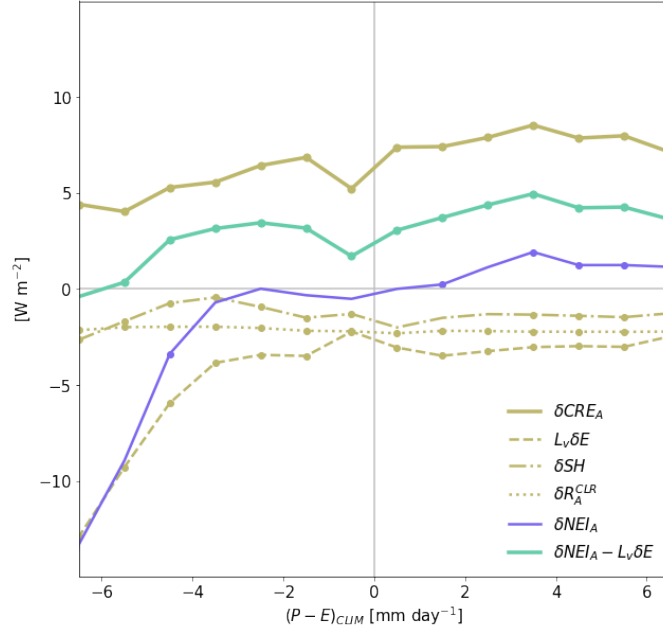


Figure 4.9: Annual-mean changes in the terms contributing to the moist static energy budget driven by cloud-radiative changes via the atmospheric/land pathway. The sum of changes in moist static energy transport and evaporative heating is also shown (green line). The cloud-radiative perturbation is driven by CO₂ quadrupling and the responses are calculated using radiation locking. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1).

these terms means the overall changes in vertically integrated moist static energy transport are small (Fig. 4.6a). Within individual hydrological regimes, overall transport changes are of similar magnitude to the decomposition residual, except where $(P - E)_{CLIM} < -3 \text{ mm day}^{-1}$ (Fig. 4.6a). There is also very little change in the tropical-mean net moist static energy transport convergence (30°S–30°N), with a tropical-mean anomaly of -0.41 W m^{-2} . These results are somewhat unexpected: previous studies highlight the important role of the Hadley circulation in poleward energy transport, so one might expect the circulation to respond to the cloud-radiative heating perturbation by exporting more energy to the subtropics or extratropics (e.g. Held & Hou, 1980).

Instead, the response of the system to this perturbation is complex, involving adjustments in all budget terms (Fig. 4.9). Clear-sky radiative cooling strengthens in response to the increased upper-tropospheric temperatures (Fig. 4.4a). Sensible heating weakens, linked to weakened near-surface winds (Fig. 4.8a), increased near-

surface air temperatures (Fig. 4.4a), and reduced land surface temperatures (not shown). However, these responses are relatively uniform across $(P-E)_{CLIM}$ regimes and so do not balance the spatial gradients in energy input to the atmosphere imposed by the CRE_A perturbation.

To interpret how energetic balance is restored, it is helpful to rearrange Eq. (4.3) as $\delta CRE_A = \delta NEI_A - \delta R_A^{CLR} - \delta SH - L_v \delta E$. Figure 4.9 shows that the structure of δCRE_A is balanced primarily by the combined effect of changes in evaporation and in moist static energy transport (green line), while δR_A^{CLR} and δSH make a comparatively small contribution to the spatial variations (up to the decomposition residual). Thus, while the net change in vertically integrated moist static energy transport is small due to cancellation between its thermodynamic and dynamic components (Fig. 4.6a), it acts together with reduced evaporation to restore energetic balance. Indeed, as shown in the previous section, reduced evaporation arises from weakened near-surface winds.

4.3.5 Mechanism of vertical velocity weakening

To complete the picture, we examine how the magnitude of the vertical velocity weakening is controlled. A useful starting point is the dry-region radiative-subsidence scaling used in prior work (e.g. Knutson & Manabe, 1995; Bony et al., 2016). This scaling is obtained by focusing on the free troposphere in dry regions, where we can assume that surface turbulent fluxes of latent and sensible heat are relatively small and horizontal energy transport is small compared to vertical energy transport due to the prevalence of weak temperature gradients. In this limit, the free-tropospheric moist static energy budget reduces to a local balance between radiative cooling and subsidence warming, giving

$$\langle \delta \omega \rangle_D = - \left\langle \delta \left(\frac{Q^R}{\partial s / \partial p} \right) \right\rangle_D, \quad (4.5)$$

where s is the dry static energy (so $\partial s / \partial p$ is the dry static stability), Q^R is the vertically resolved all-sky radiative heating, and $\langle \cdot \rangle_D$ denotes an average over climatologically dry regions. This approximation broadly captures the magnitude

and vertical structure of changes in vertical velocity in the dry free troposphere (Fig. 4.10, grey dashed line). Note that our use of this approximation differs slightly from earlier studies (e.g., Bony et al., 2016), which typically use clear-sky radiative heating only.

We next extend the analysis to the vertical velocity in wet regions. To do this, we assume that changes in vertical mass fluxes in ascending and descending regions balance across the tropics (a standard mass-budget constraint; e.g., Byrne & Schneider, 2016b, Eq. 1.3). This constraint is typically used in studies of tropical circulation and ITCZ width, its use here provides a simple way to extend the dry-region scaling (Eq. 4.5) to diagnose changes in ascent in wet regions. We additionally assume that the areas of wet and dry regions (α_W and α_D , respectively) remain unchanged under the cloud-radiative perturbation, that the air density is the same in wet and dry regions, and that changes in air density are small. Under these assumptions, we can write

$$\langle \delta\omega \rangle_W \approx -\frac{\alpha_D}{\alpha_W} \langle \delta\omega \rangle_D, \quad (4.6)$$

where $\langle \cdot \rangle_W$ denotes an average over wet regions (Fig. 4.10, grey line). Appendix D confirms that these assumptions are reasonable for our simulations.

Separating Equation (4.5) into contributions from changes in static stability and from changes in radiative heating, we find that the latter exerts only a limited influence on vertical velocity in our simulations. This likely reflects compensation between changes in clear-sky radiative cooling and cloud-radiative heating in dry regions. We therefore further simplify the dry-region vertical velocity response to

$$\langle \delta\omega \rangle_D \approx \langle \omega \rangle_D \left\langle \frac{\delta(\partial s / \partial p)}{\partial s / \partial p} \right\rangle_{trop}. \quad (4.7)$$

Here, we further approximate the fractional static stability change using the tropical-mean dry static energy profile (denoted $\langle \cdot \rangle_{trop}$), rather than the dry-region profile, consistent with the weak temperature gradient approximation (Sobel et al., 2001). Figure 4.10 shows the resulting approximation for dry regions (purple dashed line), as well as the corresponding wet-region response (purple solid line). The

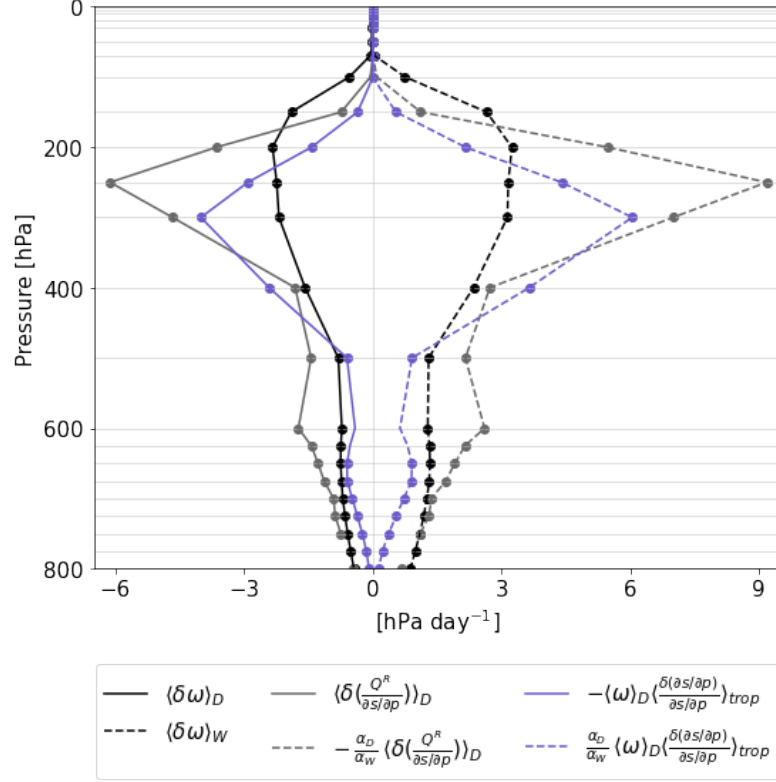


Figure 4.10: Annual-mean vertical velocity changes in dry regions [$(P-E)_{CLIM} < 0$ mm day $^{-1}$, solid line] and wet regions [$(P-E)_{CLIM} > 0$ mm day $^{-1}$, dashed line] driven by cloud-radiative changes via the atmospheric/land pathway (black line), and approximations for these changes based on Equations (4.5)-(4.6) (grey and purple lines). The cloud-radiative perturbation is driven by CO $_2$ quadrupling and the responses are calculated using radiation locking. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1).

picture that emerges is straightforward: increased cloud-radiative heating enhances tropical-mean static stability, which weakens the vertical velocity.

To connect these circulation changes to evaporation changes, we begin by assuming that precipitation changes only occur in climatologically wet regions (see Appendix D for validity check) and are determined by the dynamic component of changes in vertical moisture transport. This allows the tropical-mean precipitation change to be approximated as

$$\langle \delta P \rangle_{trop} \approx -\frac{\alpha_W}{g} \int_{p_t}^{p_b} \left\langle \frac{\partial q}{\partial p} \right\rangle_W \langle \delta \omega \rangle_W dp, \quad (4.8)$$

where we have additionally neglected correlations between $\partial q / \partial p$ and $\delta \omega$.

To link back to changes in evaporation, we assume that changes in precipitation and evaporation are balanced in the tropics (a standard large-scale moisture balance constraint; Appendix D):

$$\langle \delta E \rangle_{trop} \approx -\langle \delta P \rangle_{trop}. \quad (4.9)$$

Then, combining Equations (4.6)-(4.9) yields a combined scaling showing that changes in evaporation depend on changes in static stability and the sensitivity of this relationship is determined by climatological variables:

$$\langle \delta E \rangle_{trop} = -\langle \delta P \rangle_{trop} = -\frac{\alpha_D}{g} \int_{p_t}^{p_b} \left\langle \frac{\partial q}{\partial p} \right\rangle_W \langle \omega \rangle_D \left\langle \frac{\delta(\partial s / \partial p)}{\partial s / \partial p} \right\rangle_{trop} dp. \quad (4.10)$$

Crucially for the system's equilibration, changes in evaporation feed back on changes in static stability via changes in latent heat release. This, in turn, modifies the circulation and the evaporation itself. Through this adjustment mechanism, changes in evaporation are able to balance changes in CRE_A .

As a final check of the accuracy of our scaling, we estimate the tropical-mean evaporation change using Equation (4.10), obtaining a value of $-0.46 \text{ mm day}^{-1}$. The actual simulated change is $-0.12 \text{ mm day}^{-1}$. Thus, our scaling captures the sign and order of magnitude of the change, but does not capture the magnitude change accurately. The discrepancy is consistent with the substantial nature of the approximations made in Equation (4.5), and likely also reflects that the vertical component of moisture transport does affect evaporation. It may also reflect processes outside of the scope of the scaling, such as momentum constraints on the Hadley circulation.

4.4 Conclusions

Clouds play a major role in shaping atmospheric dynamics and thermodynamics through their influence on the atmospheric energy budget (e.g., Ceppi & Hartmann, 2016). Yet the mechanisms through which cloud-radiative changes affect the tropical $P-E$ response to CO_2 forcing remain poorly understood (Voigt et al., 2021). To address this gap, we apply the radiation-locking technique to simulations performed

with the ICON climate model to isolate the impact of changes in clouds on changes elsewhere in the climate system. We focus on how cloud changes influence $P-E$ via the ‘atmospheric/land’ pathway, i.e., independently of SST changes. To synthesise the large-scale responses of atmospheric dynamics and thermodynamics, we partition the tropics into regimes based on the climatological $P-E$ distribution.

We find that cloud changes induce a ‘wet-gets-drier, dry-gets-wetter’ annual-mean $P-E$ response in the tropics, characterised by reduced precipitation in wet regions and reduced evaporation in dry regions. These changes are primarily driven by increased upper-tropospheric cloud-radiative heating associated with rising high clouds (Voigt & Shaw, 2016). The resulting increase in static stability suppresses moist convection and ascent, reducing precipitation in regions that are climatologically wet. As the ascent area remains approximately constant, the entire tropical overturning circulation – including its near-surface branches – weakens. The reduced near-surface wind speed causes reduced evaporation, particularly in the near-surface branch of the Hadley cell, where climatological meridional moist static energy gradients are large. Analysis of the moist static energy budget reveals that, in tandem with changes in moist static energy transport, these changes in evaporation balance the spatial gradients in energy input to the climate system by the cloud-radiative perturbation. In contrast, changes in poleward energy transport are limited.

To understand how the system achieves energetic equilibrium in this way, we develop a scaling that links changes in static stability to the strength of the vertical velocity weakening and the associated evaporation response. This scaling suggests that static stability changes provide the dominant control on tropical mean evaporation in our simulations. The sensitivity of this relationship is controlled by both dynamic and thermodynamic elements of the climatology (namely the vertical velocity and the areal extent of dry regions, the moisture lapse rate in wet regions and the tropical-mean static stability). Importantly, this scaling highlights the regulatory role of changes in latent heating which allows changes in evaporation and precipitation to feed back on the stability, thereby modulating the slowdown of vertical motion required to restore energy balance.

Increasing cloud altitude and the associated increase in upper tropospheric cloud-radiative heating, is consistently simulated by global climate models (Voigt et al., 2024; McGraw et al., 2025), suggesting it is plausible that clouds could influence the circulation via this mechanism in other models too. Our results provide insight as to what might cause cloud-driven processes to contribute to inter-model spread in changes in the hydrological cycle. Alongside the cloud-radiative heating perturbation itself, accurate representation of the climatological controls highlighted by our scaling and the static stability response may also be needed. Notably, our results highlight the influence of interactions between cloud-radiative heating and latent heating on the static stability, a topic that has received limited attention thus far.

However, previous results suggest that competing mechanisms may dominate in other models. Voigt and Shaw (2015) reported that the cloud-radiative response to CO₂ forcing strengthened Hadley cell vertical velocities in one aquaplanet model while weakening them in another, and Harrop and Hartmann (2016) found that climatological cloud-radiative heating strengthens Hadley cell vertical velocities on aquaplanets. If the scaling we identify were the sole control on these changes, vertical velocity strengthening would result from reduced static stability. Yet models consistently simulate cloud-radiative heating anomalies that peak in the upper troposphere (Voigt et al., 2019, 2024; McGraw et al., 2025), which should stabilise the column; indeed, Harrop and Hartmann (2016) noted that Equation (4.5) could not account for their results. A possible starting point for exploring why the scaling does not explain changes in other models could be identifying which scaling assumptions – e.g., weak free-tropospheric temperature gradients, unchanging area coverage of wet/dry regions – do not hold in these cases. We also note that the ICON configuration used here underestimates low-cloud fraction (Crueger et al., 2018, Section 3.4.1) and shows negligible lower-tropospheric cloud-radiative heating changes (Figs. 3.4); changes in low-cloud radiative effects may therefore play a larger role in other models (e.g., Fermepin & Bony, 2014). Furthermore, ICON exhibits regional biases in longwave cloud radiative effects within the atmosphere,

which may influence the magnitude and spatial structure of the cloud-radiative heating perturbation that drives the circulation response.

A valuable extension to this analysis would be developing a deeper understanding of the role of changes in the land surface budget. Understanding the extent to which this affects $P-E$ changes in oceanic regions would increase confidence in the mechanism we propose. Furthermore, $P-E$ changes over land are distinct from those over ocean, and it would be very interesting to understand why. We note that the parallel dependence of CRE_A and moist static energy transport on $(P-E)_{CLIM}$ for $-1 < (P-E)_{CLIM} < 6 \text{ mm day}^{-1}$ suggests a possible direct role for changes in moist static energy transport (Fig. 4.9). Initial exploration of this relationship hints at a role for changes over land (not shown). Similarly, it would be valuable to further explore the extratropical influence on the tropics. This could be driven by extratropical cloud changes, or result from two-way couplings between climate changes in the tropics and extratropics.

Both of these questions can be explored via deeper analysis of our existing simulations. However, further targeted locking studies could also be valuable. To isolate the role of the extratropics, we could apply regional radiation-locking to the tropics and extratropics separately to measure each region's one-way influence on the other (Albern et al., 2020). Similarly, to isolate the role of land, we could run simulations with locked land surface temperatures and moisture.

Finally, a central element of the mechanism identified here is the reduction in evaporation. However, because these simulations use fixed SSTs, the evaporation response is artificially constrained: SSTs cannot adjust and, over oceans, any surface energy imbalance is implicitly offset by a residual sink/source of energy that maintains the imposed SSTs. In reality, changes in both SSTs and their spatial patterns can influence surface sensible and latent heat fluxes, as well as atmospheric circulation and dynamics, potentially leading to substantially different responses. In Chapter 5, we investigate how our results are modified when a slab ocean is included in the experimental setup.



Magdalen Bridge, 28 Nov 2024

5

Cloud-radiative influences on $P - E$ via the SST-mediated pathway

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5.1 Introduction

In Chapter 4, we showed that, in the absence of sea surface temperature (SST) changes, the cloud-radiative response to CO₂ quadrupling produces a ‘wet-gets-drier, dry-gets-wetter’ pattern in tropical precipitation-minus-evaporation, $P - E$. Here, we assess how surface-atmosphere coupling modifies this cloud-radiative influence on the tropical hydrological cycle.

Tropical SSTs exert a fundamental control on the dynamics and thermodynamics of the tropical atmosphere, shaping the spatial pattern of $P - E$. Through moist convection, SSTs regulate free-tropospheric temperatures, which in turn strongly influence atmospheric humidity (Emanuel et al., 1994; Held & Soden, 2006). Spatial variations in SST affect convective instability and drive changes in the large-scale overturning circulation (Neelin & Held, 1987; Xie et al., 2010). Consequently, uncertainty in projected SST patterns contributes substantially to uncertainty in future changes in the hydrological cycle (Ma & Xie, 2013; Kent et al., 2015; Good et al., 2021; Zhang et al., 2023). Because SSTs anchor the surface energy balance, any radiative perturbation that alters surface fluxes can modify SST gradients, thereby influencing large-scale energy and moisture transport and the distribution of $P - E$.

Clouds are an important source of such radiative perturbations. Although their ability to modify surface temperatures is well established, their influence on the hydrological cycle remains less well explored. Previous studies (e.g., Previdi, 2010; McGraw et al., 2025) have shown that changes in cloud radiative effects contribute to inter-model spread in global- and tropical-mean precipitation sensitivity to warming. Because cloud changes are spatially heterogeneous, they can also affect regional SST patterns (Andrews et al., 2015; Hartmann & Dygert, 2022), with corresponding impacts on energy and moisture transport. For example, Ceppi and Hartmann (2016) demonstrated that cloud-driven SST anomalies can induce meridional shifts of the midlatitude jet.

In this chapter, we investigate how the cloud-radiative response to quadrupled CO₂ influences tropical (30°N–30°S) $P - E$ via changes in SSTs, i.e., via the ‘SST-mediated pathway’. As in Chapter 4, we use simulations from Huber (2022)

performed with the ICON global climate model (GCM; Giorgetta et al., 2018), which include realistic continents, sea ice, and a seasonal cycle. We again employ the radiation-locking technique to isolate the influence of cloud-radiative changes on other components of the climate system (Wetherald & Manabe, 1988; Ceppi & Hartmann, 2016; Voigt et al., 2019, 2021).

Here, however, we analyse a further set of simulations that incorporate a slab-ocean model, alongside the fixed-SST experiments. The slab ocean includes prescribed, seasonally varying q -fluxes representing the climatological convergence of ocean heat transport. This set up allows SSTs to respond to changes in the surface energy budget while ocean heat transport remains fixed. By comparing cloud-driven changes in the slab-ocean and fixed-SST simulations, we isolate processes operating through the SST-mediated pathway.

As in Chapter 4, we analyse how cloud-radiative perturbations modify energy flows through the climate system to establish a new energetic equilibrium and thus drive changes in $P-E$. We also partition the tropics by climatological $P-E$ and apply the same trustworthiness criteria as in Chapters 3 and 4 to evaluate the radiation-locking results (Section 3.3.1).

The remainder of the chapter is structured as follows. We first revisit the $P-E$ changes driven by clouds via the SST-mediated pathway introduced in Chapter 3. We then examine how the cloud-radiative perturbation modifies the surface energy budget and thus drives adjustments in atmospheric energy and moisture transport, before presenting our conclusions.

5.2 Model and methods

The model simulations used here are the same as in Chapter 3, and are described in Section 3.2. The radiation-locking method is employed following Section 3.3.1.

We use the partial radiative perturbation (PRP) analysis conducted by Huber (2022) and described in Section 4.2.1 to quantify the changes in atmospheric heating rates and surface radiative fluxes resulting from the cloud response to CO₂ quadrupling.

To understand how the cloud radiative radiative perturbation affects the broader climate system, we use the atmospheric moisture budget (outlined in Section 3.3.2) in combination with the atmospheric moist static energy budget (outlined in Section 4.2.2) and the surface energy budget, which we introduce below.

5.2.1 Surface energy budget

The surface energy budget is

$$NEI_S = CRE_S + R_S^{CLR} + SH + L_v E, \quad (5.1)$$

where NEI_S is the net energy input to the surface, CRE_S is the surface cloud radiative effect, R_S^{CLR} is the clear-sky radiative flux into the surface, SH is the sensible heat flux, and $L_v E$ is the latent heat flux (with L_v the latent heat of vaporisation and E the moisture flux). All fluxes are defined positive downward. In contrast, all fluxes are defined positive into the atmospheric column for the atmospheric moist static energy budget (Eq. 4.3).

In the slab-ocean framework, the same net surface energy input can also be written in terms of the prescribed ocean heat flux convergence, Q^{flux} , and the tendency of surface heat storage, $Q^{storage}$, as introduced in Chapter 3,

$$NEI_S = Q^{flux} + Q^{storage}. \quad (5.2)$$

We can then combine these expressions to yield the perturbation surface energy budget,

$$\delta CRE_S + \delta R_S^{CLR} + \delta SH + L_v \delta E = \delta Q^{flux} + \delta Q^{storage}. \quad (5.3)$$

Because Q^{flux} is prescribed as the climatological ocean heat flux convergence, $\delta Q^{flux} = 0 \text{ W m}^{-2}$. At seasonal timescales, $\delta Q^{storage}$ can be non-zero over ocean. Over land, $\delta Q^{storage} \approx 0 \text{ W m}^{-2}$, because the land surface has a small effective heat capacity and any perturbation is rapidly balanced by adjustments in surface fluxes.

As noted in Section 3.2, the interpretation of energy budgets depends on the imposed lower boundary condition. This chapter analyses experiments using both

fixed-SST and slab-ocean configurations. In the SLAB simulations, anomalies in net surface energy input are accommodated by mixed-layer heat storage (up to the prescribed ocean heat transport convergence, Q^{flux}), allowing SSTs to adjust as part of a coupled surface-atmosphere energy response. In contrast, in the fixed-SST simulations SSTs are constrained, and surface energy anomalies over ocean are balanced by an implied ocean heat uptake that maintains the prescribed SSTs.

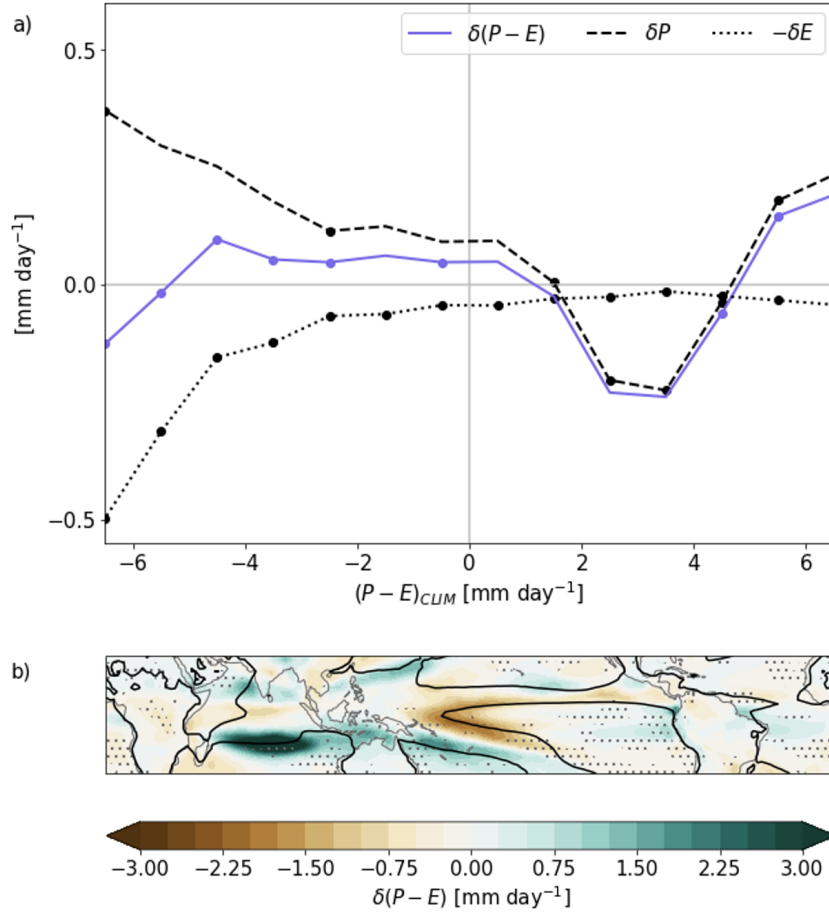


Figure 5.1: Annual-mean changes in (a) $P-E$ (purple solid line), P (black dashed line) and $-E$ (black dotted line) driven by cloud-radiative changes via the oceanic pathway and shown as a function of climatological $P-E$, and (b) a map of the $P-E$ changes. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. In panel (b), black contours denote where the climatological annual-mean $P-E = 0 \text{ mm day}^{-1}$. Dots and stippling indicate changes which meet the trustworthiness criteria defined in Section 3.3.1 in panels (a) and (b), respectively.

5.3 Results

When the SST-mediated pathway is isolated, the $P-E$ response to cloud-radiative changes is relatively muted when expressed as a function of the climatological $P-E$, $(P-E)_{CLIM}$ (Fig. 5.1a). The response comprises small increases across most regimes and a reduction where $2 < (P-E)_{CLIM} < 4 \text{ mm day}^{-1}$. The perturbation enhances both precipitation and evaporation in climatologically dry regions, with the largest increases in the driest areas, while in wetter regions evaporation changes are minimal and the $P-E$ reduction arises mainly from decreased precipitation. Notably, the enhanced evaporation in dry regions counteracts the decrease that occurs via the atmospheric/land pathway discussed in Chapter 4. In Figure 5.1 and throughout, cloud-driven changes are denoted using $\delta[\cdot]$.

These changes reflect a spatial reorganisation of $P-E$ (Fig. 5.1b), characterised by poleward shifts of the $P-E$ maxima over the Indian Ocean and the western Pacific. Smaller shifts occur over the eastern Pacific and the Atlantic. Locally, the influence of the SST-mediated pathway exceeds that of the atmospheric/land pathway despite its comparatively muted signature in $(P-E)_{CLIM}$ space (Fig. 5.1b versus Fig. 4.1b).

5.3.1 Achieving energetic balance at the surface

To understand the $P-E$ response, we first examine the surface energy budget. In the slab-ocean simulations, surface flux anomalies drive mixed-layer heat storage and SST adjustment, whereas in the fixed-SST simulations, the same anomalies correspond to an implied ocean heat uptake required to maintain the prescribed SSTs.

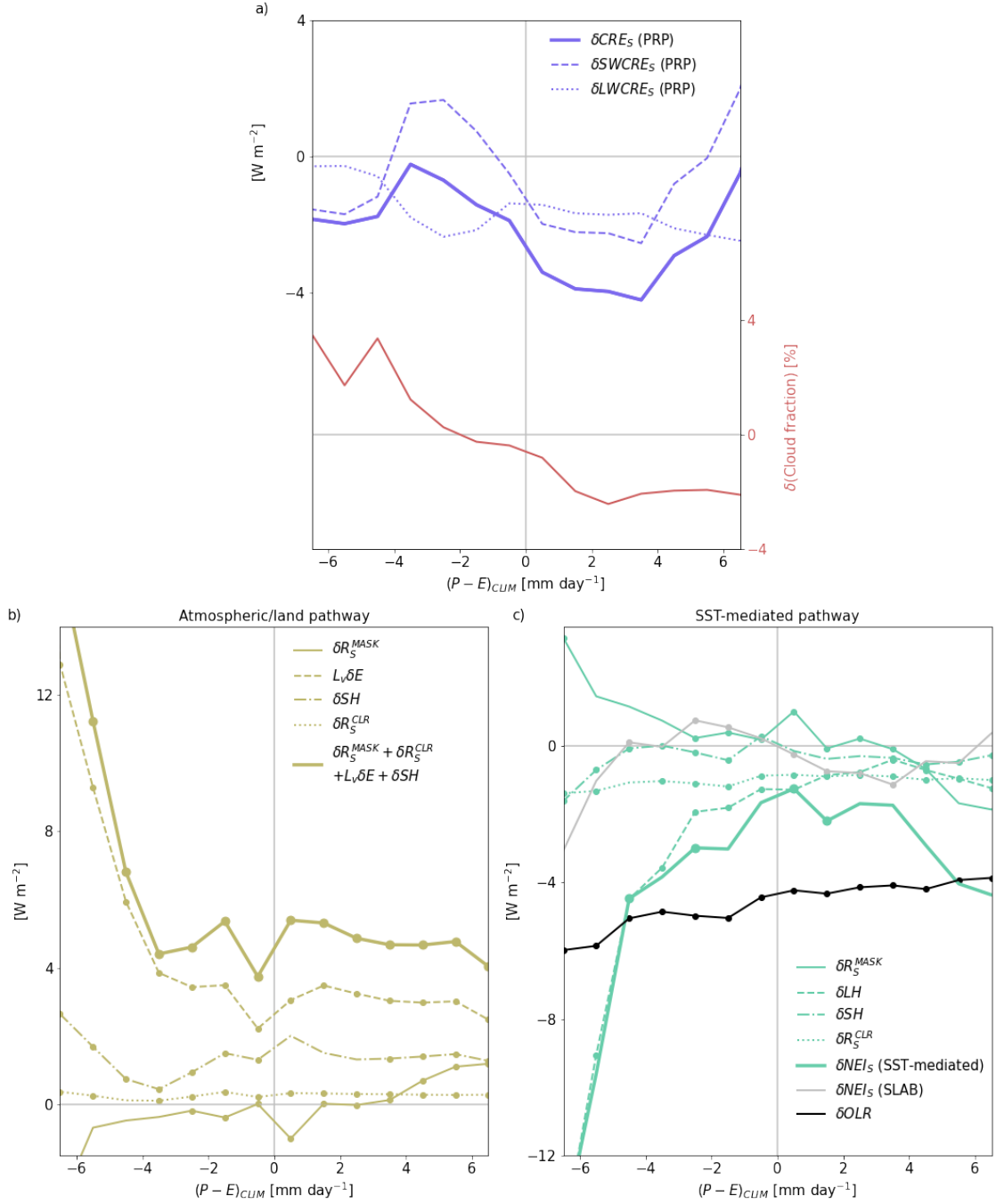


Figure 5.2: Annual-mean changes in (a) surface cloud radiative effects, calculated using PRP and using radiation locking (i.e., from the difference between all-sky and clear-sky surface radiative fluxes); and in the terms contributing to the surface energy budget driven by cloud-radiative changes (b) via the atmospheric/land pathway; and (c) via the SST-mediated pathway, both calculated using radiation locking. Recall that, for the surface budget, fluxes are defined as positive downwards. In panel (a), changes in column-mean cloud fraction are also shown and in panel (c), changes in outgoing longwave radiation, OLR , are shown as is the change in NEI_S for the SLAB simulations i.e. the sum of the atmospheric/land and SST-mediated changes are shown; both driven by cloud radiative changes. The cloud-radiative perturbation is driven by CO_2 quadrupling. Dots indicate responses calculated using radiation locking that meet the trustworthiness criteria (Section 3.3.1).

We begin by characterising δCRE_S (Fig. 5.2a) diagnosed using PRP. Across the tropics, surface cloud radiative effects become increasingly negative, with the largest changes occurring in climatologically wet regions (Fig. 5.2a). This response generally follows changes in cloud fraction, although the relationship is less straightforward when shortwave and longwave changes are considered separately and in very wet and very dry regions. This indicates that, while cloud fraction changes are important, variations in other cloud properties – such as albedo and altitude – also play a key role. These δCRE_S changes may partly reflect the under-representation of low clouds in our ICON configuration. By contrast, CMIP3 and CMIP5 models typically simulate positive surface cloud-radiative changes across the subtropics, linked to reductions in low-cloud amount (Figs. 1.8c, 3.3c). Note that in the surface energy budget, δCRE_S is defined as the difference between all-sky and clear-sky surface radiative fluxes and therefore includes a non-cloud contribution (R_S^{MASK}), which we separate into components associated with the atmospheric/land pathway and the SST-mediated pathway (Fig. 5.2b,c).

In addition to the changes in CRE_S , the surface budget responds to flux perturbations driven by cloud-radiative effects acting through the atmospheric/land pathway. As discussed in Chapter 4, these include reduced evaporation across the tropics, with the largest decreases occurring in the climatologically driest regions, and decreased sensible heating throughout the tropics. The resulting flux anomalies, and their combined influence on the surface budget, are shown in Figure 5.2b.

Together, δCRE_S and the flux perturbations associated with the atmospheric/land pathway lead to an overall increase in energy input to the surface across the tropics. This enhanced downward energy flux peaks in the climatologically driest regions where δCRE_S is weaker and evaporation changes dominate the response. In climatologically wet regions, the overall change in NEI_S appears closely related to the SST-mediated component of the change in R_S^{MASK} .

Overall, the coupled slab-atmosphere system adjusts toward a new steady state through surface warming, as higher SSTs intensify evaporation and clear-sky radiative cooling (Fig. 5.2c). Although the radiative adjustments are complex, the

changes in outgoing longwave radiation (black line) indicates that SST warming is largest in dry regions, coincident with the strongest evaporation increases.

The spatial distribution of surface temperature changes is shown in Figure 5.3, and shows warming across most of the globe. At most longitudes, temperature increases peak in the midlatitudes of both hemispheres, with the largest warming occurring over the southern Indian Ocean and the northern Pacific. Over land, temperatures also rise but with greater longitudinal variability than over the ocean. In the tropics, the SST increase is concentrated in climatologically dry regions, consistent with the surface energy budget response described above and with the co-located peak in evaporation (Fig. 4.8c).

Finally, we note that, in the slab ocean simulations, the system does not equilibrate such that $\delta NEI_S = 0 \text{ W m}^{-2}$ within individual $(P-E)_{CLIM}$ regimes (Fig. 5.2c). Because the location of these regimes shifts seasonally, this reflects changes in mixed-layer heat storage over the seasonal cycle.

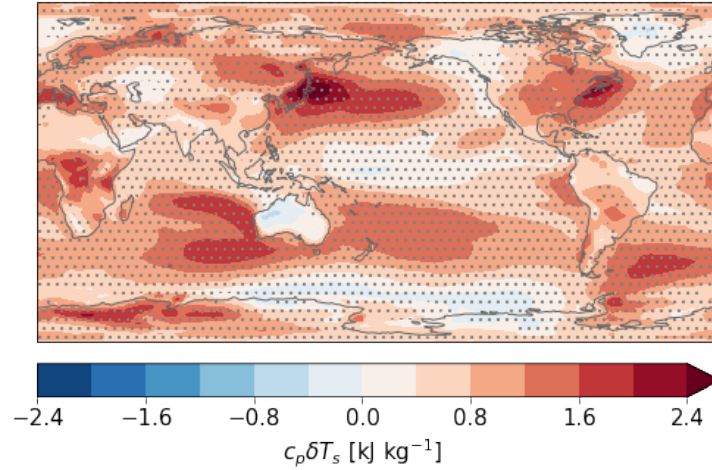


Figure 5.3: Annual-mean changes in surface sensible heat driven by cloud-radiative changes via the SST-mediated pathway. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Stippling indicates changes which meet the trustworthiness criteria defined in Section 3.3.1.

5.3.2 Moist static energy transport

To understand how changes in the surface energy budget affect atmospheric energetics, we turn to the vertically integrated moist static energy budget [Equation (4.4)].

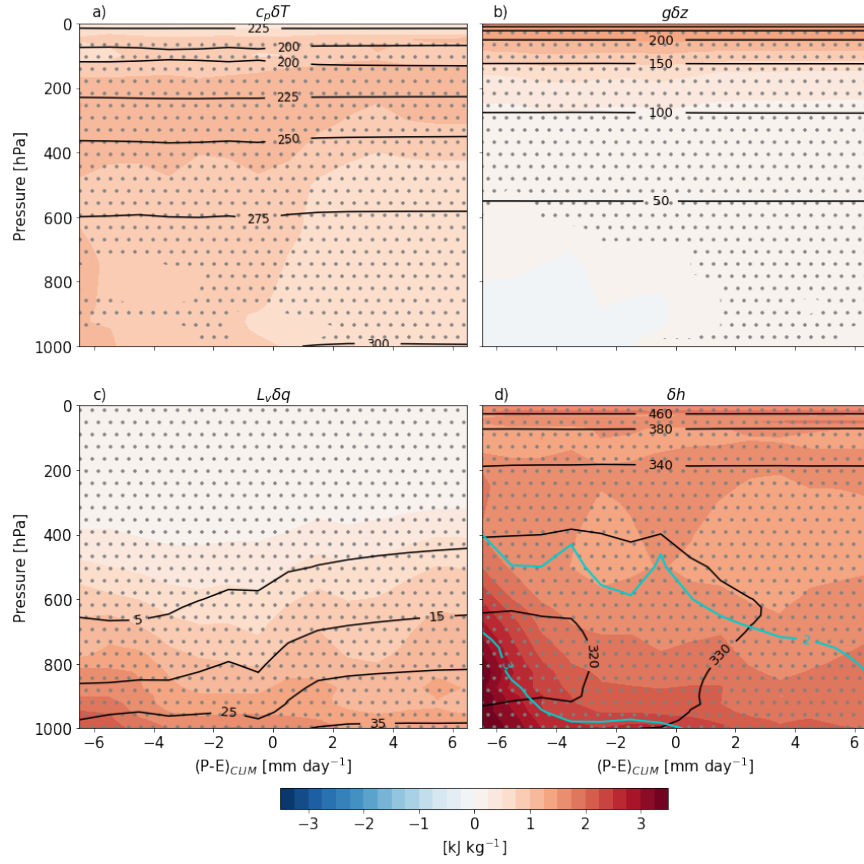


Figure 5.4: Annual-mean changes in (a) sensible heat, (b) geopotential, (c) latent heat, and (d) moist static energy (shading) and saturation moist static energy (blue contours) driven by cloud-radiative changes via the SST-mediated pathway, all in kJ kg^{-1} . The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Stippling indicates responses that meet the trustworthiness criteria (Section 3.3.1). In all panels, black contours show the climatological distribution of each variable.

Thermodynamic component of moist static energy transport

Tropical atmospheric temperatures rise across all $(P-E)_{CLIM}$ regimes (Fig. 5.4a). Near-surface warming is strongest in dry regions, where surface temperature increases are largest. In wet regions, temperature increases peak in the upper troposphere. The vertical uniformity of the associated changes in free-tropospheric saturation moist static energy suggests that frequent convection maintains a moist-adiabatic lapse rate in these regions (Emanuel et al., 1994). This enhanced upper-tropospheric warming extends into dry regions, consistent with the weak temperature-gradient constraint in the tropical free troposphere (e.g., Sobel et al., 2001), and produces a

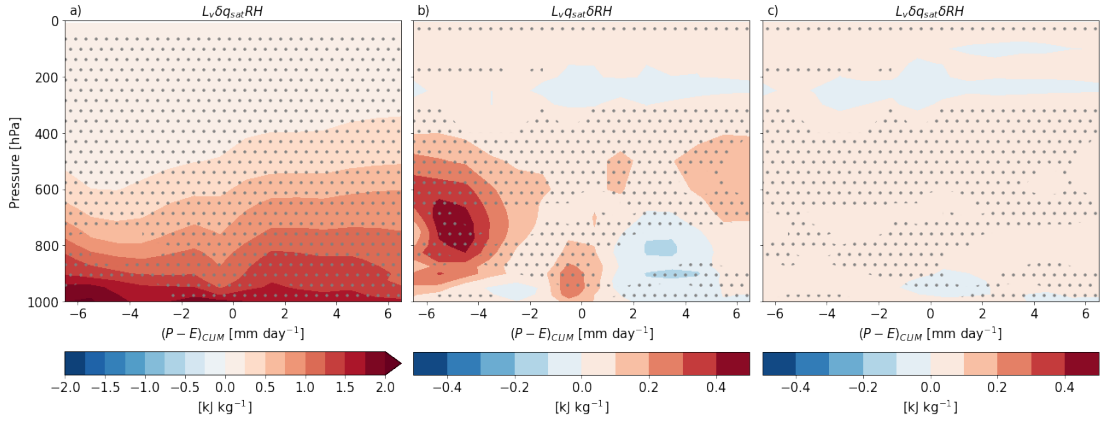


Figure 5.5: The (a) thermodynamic, (b) dynamic, and (c) nonlinear components of the annual-mean changes in latent heat driven by cloud-radiative changes via the SST-mediated pathway. The cloud-radiative perturbation is driven by CO₂ quadrupling and the responses are calculated using radiation locking. Stippling indicates responses that meet the trustworthiness criteria (Section 3.3.1).

modest rise in tropopause height throughout the tropics (Fig. 4.4b).

Atmospheric warming increases the saturation specific humidity (Fig. 5.5a) and, consequently, atmospheric moisture (Fig. 5.4c). The increase is much larger than that driven through the atmospheric/land pathway (Fig. 4.5a) because the lower troposphere, where baseline temperatures are higher, experiences stronger warming. Under these conditions, the nonlinear Clausius–Clapeyron relationship yields a larger increase in saturation specific humidity per degree of warming.

In most $(P-E)_{CLIM}$ regimes, surface-driven changes in atmospheric temperature and moisture have limited impact on moist static energy transport (Fig. 5.6a), particularly compared with changes driven by the atmospheric/land pathway (Fig. 4.6a), because the associated moist static energy gradient changes are comparatively small (cf. Figs. 5.4d, 4.4d).

However, thermodynamically driven changes in moist static energy transport become larger where $(P-E)_{CLIM} < -3 \text{ mm day}^{-1}$ (Fig. 5.6a). The nature of this response reflects the nonlinear dependence of saturation specific humidity on temperature: (1) near-surface moist static energy gradient changes are dominated by moisture variations; and (2) because the magnitude of moisture changes follows the climatological temperature profile, vertical moist static energy gradient changes

tend to exceed horizontal ones. Given that these regions are characterised by climatological descent (Fig. 5.7, contours), the $\omega \delta(\partial h / \partial p)$ term in Equation (4.4) acts to increase moist static energy export from these very dry regions

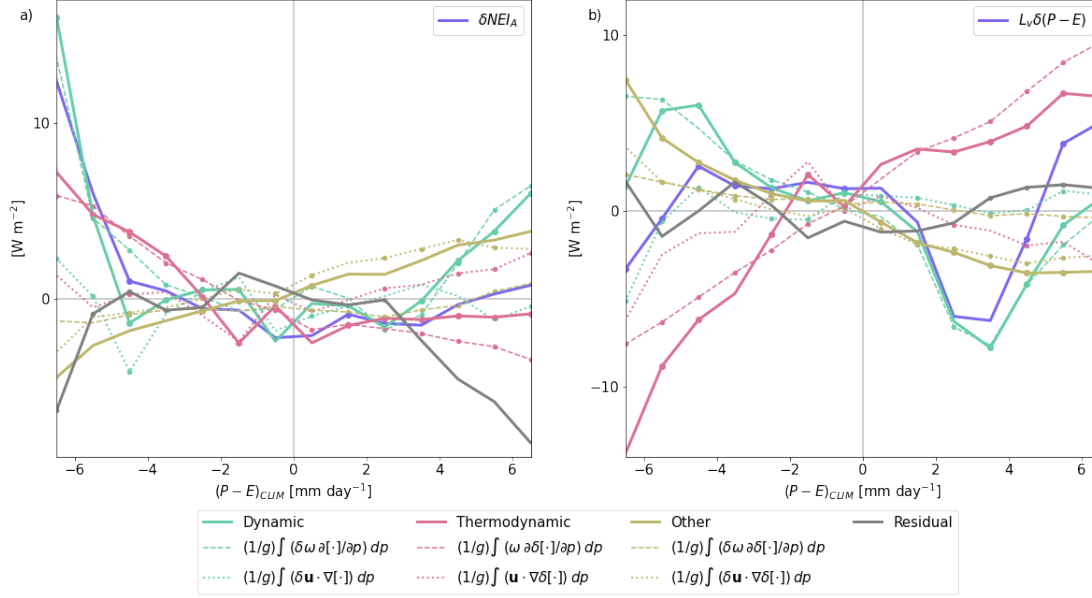


Figure 5.6: Annual-mean decomposition of the change in vertically integrated (a) moist static energy transport and (b) moisture transport into dynamic and thermodynamic components. ‘Other’ comprises nonlinear and density-related terms, and we also show the decomposition residual. We additionally show changes in NEI_A and $L_v(P - E)$ in panels (a) and (b), respectively, since in steady state these terms must be balanced by changes in vertically integrated transport (up to the residual). The cloud-radiative perturbation driving the changes is associated with CO_2 quadrupling and acts via the SST-mediated pathway. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1). In the legend, $[\cdot]$ denotes h and $-L_v q$ for panels (a) and (b), respectively. Recall that, for the moist static energy budget, fluxes are defined as positive into the atmospheric column.

Dynamic and nonlinear components of moist static energy transport

Changes in vertical velocity across $(P - E)_{CLIM}$ regimes exhibit a complex structure (Fig. 5.7). Descent weakens in very dry regions, while ascent weakens in moderately wet regions. The ascent weakening is approximately uniform throughout the free troposphere, whereas the reduction in descent peaks in both the boundary layer and the upper troposphere. In addition, upper-tropospheric ascent strengthens in very wet regions.

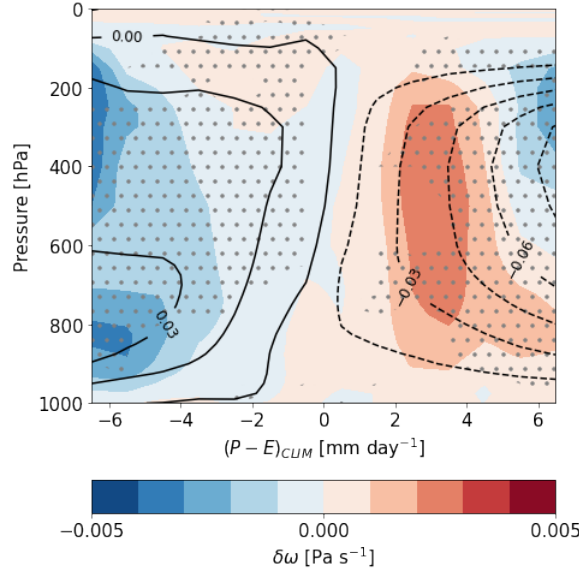


Figure 5.7: Annual-mean changes in vertical velocity driven by cloud-radiative changes via the SST-mediated pathway. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1). Black contours show the climatological vertical velocity distribution.

When viewed in $(P-E)_{CLIM}$ space, this pattern resembles a general weakening of the climatological vertical velocities. However, it more accurately reflects a regional reorganisation of ascent and descent linked to increases in near-surface moist static energy in dry regions. Ascent shifts toward these regions (Privé & Plumb, 2007), with the strongest changes occurring over the Indian Ocean and the western Pacific, where surface temperature – and hence near-surface moist static energy – increases most (Fig. 5.3). The latitudinal distributions of near-surface moist static energy and column-mean vertical velocity changes (Fig. 5.8) support the interpretation that ascent shifts poleward.

The vertical structure of the vertical velocity changes suggests that, in very dry regions, convection driven by increased SSTs is relatively shallow. We therefore hypothesise that the anomalous upper-tropospheric ascent in dry regions is driven by latent heat release associated with this shallow convective precipitation (Figs. 5.4a, 5.7).

Because climatological moist static energy increases with height, changes in ω project strongly onto the vertical advection term $\delta\omega (\partial h / \partial p)$ (Fig. 5.6a).

A nonlinear component of the moist static energy transport response also emerges, associated with changes in horizontal transport. Anomalous poleward meridional winds, linked to the shift in ascent location, align with changes in the near-surface meridional moist static energy gradient, enhancing moist static energy export from climatologically wet regions (Figs. 5.9, 5.6a). We note that this nonlinear term accounts only for interactions among cloud-driven changes. However, cloud perturbations may also modify total moist static energy transport through nonlinear interactions with water vapour- or CO₂-driven changes (Section 3.7).

Finally, the decomposition residual contributes substantially to changes in NEI_A in some $(P-E)_{CLIM}$ regimes, particularly where $(P-E)_{CLIM}$ is large and positive, making the results more difficult to interpret. This residual may indicate an important role for sub-monthly transient eddies in modulating energy transport.

We note that the energy flux equator (EFE) framework is often used to explore latitudinal ITCZ shifts (e.g., Kang et al., 2008), and Figure 5.8 suggests that it could be relevant in our case. However, Figure 5.1b indicates that the spatial distribution of $P - E$ changes is more complex than a simple ITCZ displacement, and may instead be characterised as a poleward shift of tropical oceanic precipitation more broadly (including the SPCZ). A detailed EFE-based analysis would therefore require a more nuanced regional approach, perhaps following Adam et al., 2016 or Boos and Korty (2016).

5.3.3 Moisture transport

To assess how changes in moist static energy transport influence the hydrological response, we consider the vertically integrated moisture budget [Eq. (3.8)].

The thermodynamic component of the response, characterised by enhanced lower-tropospheric moisture associated with surface warming, increases the amount of water vapour transported by the climatological circulation, thereby strengthening moisture exchange between wet and dry regions [Fig. 5.6b;](Held & Soden, 2006). However, nonlinear changes in moisture transport – arising from the same mechanism as the nonlinear moist static energy transport response – substantially dampen this

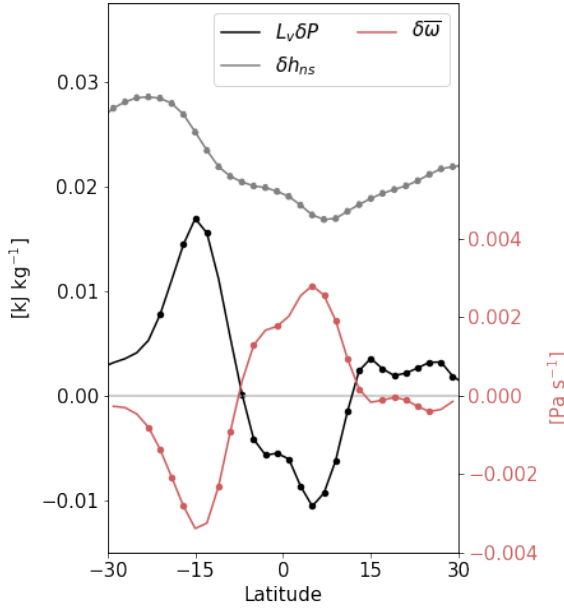


Figure 5.8: Annual-mean changes in near-surface moist static energy (h_{ns}), precipitation ($L_v \delta P$) and column-mean vertical velocity ($\bar{\omega}$) driven by cloud-radiative changes via the SST-mediated pathway. Each field has been multiplied by $\cos(\text{latitude})$ to account for the decreasing area per degree latitude toward the poles. Near-surface moist static energy is defined as the moist static energy at the lowest atmospheric model level. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1).

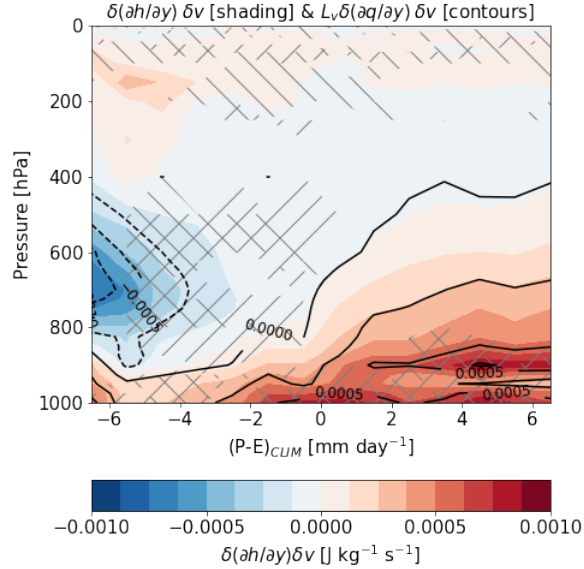


Figure 5.9: Annual-mean, vertically-resolved changes in the nonlinear component of the meridional moist static energy transport driven by cloud-radiative changes via the SST-mediated pathway. Contours show the same for moisture transport, multiplied by L_v . The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. The $0 \text{ J kg}^{-1} \text{ s}^{-1}$ contour is removed above 400 hPa for clarity. Forward- and backward-slanting hatching indicate moist static energy- and moisture-related responses, respectively, that meet the trustworthiness criteria (Section 3.3.1).

increase (Fig. 5.9). As a result, the overall change in moisture transport is dominated by the dynamic component. Because climatological specific humidity decreases with

height, weakened subsidence reduces moisture export (i.e., $(\partial q/\partial p) \delta\omega$ is negative), while weakened ascent enhances it. Accounting for the minus sign in Equation (3.8), this pattern implies a shift in precipitation consistent with the displacement of the ascent region (Fig. 5.6b). The precipitation response is also reflected in relative humidity changes, which peak between 600–800 hPa in dry regions (Fig. 5.5b).

5.3.4 Achieving energetic balance in the atmosphere

Finally, we assess how the adjustments in moisture and moist static energy transport contribute to restoring the coupled system’s energetic balance following the cloud-radiative perturbation, and how this equilibrium differs from that in the fixed-SST configuration. The resulting changes in the terms of the moist static energy budget [Eq. (4.3)] are shown in Figure 5.10b.

In contrast to the fixed-SST configuration, where evaporation decreases as part of a circulation-driven adjustment, allowing SSTs to respond produces enhanced evaporation in climatologically dry regions. The enhanced evaporative heating is balanced primarily by increased clear-sky radiative cooling and by changes in moist static energy transport, reflecting the circulation reorganisation associated with the SST pattern (Fig. 5.10b).

Interestingly, the coupled ocean-atmosphere system still equilibrates such that spatial gradients in δCRE_A are balanced by a combination of changes in moist static energy transport and evaporation (Figs. 5.10a,c). However, the SST adjustment enables moist static energy transport changes to play a larger role in restoring energetic balance than in the atmosphere-only configuration.

5.4 Conclusion

Tropical SSTs exert a fundamental control on atmospheric circulation and the spatial pattern of precipitation-minus-evaporation, $P - E$ (e.g., Xie et al., 2010; Ma & Xie, 2013). However, the extent to which cloud-radiative changes influence this coupling remains poorly understood. In this chapter, we investigate how CO₂-driven cloud-radiative perturbations affect the tropical hydrological cycle via their

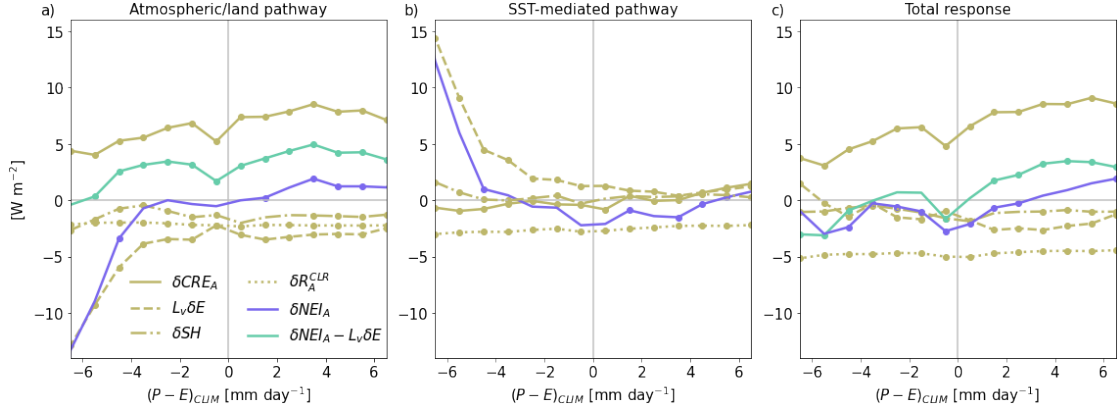


Figure 5.10: Annual-mean changes in the terms contributing to the moist static energy budget driven by cloud-radiative changes (a) via the atmospheric/land pathway; (b) via the SST-mediated pathway; and (c) the total response. In panels (a) and (c), the sum of changes in moist static energy transport and evaporative heating is also shown. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses are calculated using radiation locking. Dots indicate responses that meet the trustworthiness criteria (Section 3.3.1).

influence on SSTs. Using radiation-locking experiments with the ICON model in a slab-ocean configuration, we isolate how cloud radiative changes alter the surface energy balance and examine how the resulting SST changes modify atmospheric moisture and moist static energy transports, thereby shaping changes in $P-E$.

Allowing SSTs to adjust produces a hydrological response that differs qualitatively from the fixed-SST case discussed in Chapter 4. In the slab ocean configuration, the cloud-radiative perturbation generates widespread surface warming, strongest in climatologically dry regions. Surface cloud radiative effects, δCRE_S , become more negative in wet regions and change little in dry regions, whereas changes in atmospheric cloud radiative effects, δCRE_A , increase the net downward surface energy flux primarily by reducing evaporation, particularly in dry regions. These δCRE_A -driven changes exceed those in δCRE_S , leading to warmer SSTs, enhancing evaporation and clear-sky radiative cooling and establishing a new energetic equilibrium at the surface.

A key consequence of this SST adjustment is that evaporation increases in dry regions, counteracting the dynamically-driven evaporation reduction that occurs via the atmospheric/land pathway. Enhanced SSTs in dry regions raise near-

surface moist static energy, drawing ascent toward these locations and increasing precipitation in dry regions while reducing it in wetter ones. Notably, the vertical structure of the anomalous ascent suggests that latent heating from this additional convection helps sustain the new circulation pattern. Unlike the cloud-driven $P-E$ changes via the atmospheric pathway, these adjustments are spatially confined, occurring primarily over the Indian Ocean and western Pacific. We noted in Chapter 3 that changes in $P-E$ in the region $0-4 \text{ mm day}^{-1}$ do not meet our trustworthiness criteria. However, given changes in P and E individually do, and that we find mechanistically consistent and reliable changes in other variables, we argue that the radiation locking decomposition can be considered broadly reliable in this case.

Changes in moist static energy transport driven via the SST-mediated pathway are small in most $P-E$ regimes owing to compensating thermodynamic, dynamic, and nonlinear contributions. Nonetheless, when viewed in the context of the full atmospheric energy budget, allowing SSTs to respond enables changes in moist static energy transport to play a more prominent role in balancing the cloud-driven radiative perturbation than in the fixed-SST configuration. There is also a substantial decomposition residual which suggests that unresolved transient eddies may play an important role.

The magnitude and pattern of the $P-E$ response are sensitive to model characteristics and to the idealisations of our experimental set up. The slab ocean employs a prescribed ocean heat flux convergence, which constrains dynamical ocean feedbacks and limits SST pattern changes. In addition, ICON under-represents low clouds. While biases in atmospheric longwave cloud radiative effects may affect the stability response, uncertainty in shortwave cloud radiative effects is likely more consequential for the SST-mediated pathway since these directly shape the surface energy budget and hence the SST adjustment. Moreover, in our simulations the circulation shift is tightly linked to where evaporation increases, with enhanced evaporation occurring preferentially in regions of large climatological evaporation; accurately representing this spatial structure is therefore also important.

Further investigation could extend these results in several directions. Dynamic changes dominate the moisture transport response because thermodynamic and nonlinear contributions largely cancel. It would be valuable to clarify why this cancellation occurs and, thus, whether it could also occur in other models. Examining how the precipitation shifts identified here vary over the seasonal cycle would also be interesting, particularly given indications that changes in mixed-layer heat storage affects the response. Beyond potential further analysis of the present simulations, future work should assess the influence of interactive ocean heat transport and of the representation of low-cloud feedbacks on these results.



Medley Bridge, 25 Jun 2024

6

Conclusions and outlook

While it has long been recognised that clouds and their radiative effects are tightly coupled to the large-scale circulation, the fundamental role of this coupling in the climate response to CO₂ forcing has received increasing attention in recent decades (Bony et al., 2015). This thesis explores two complementary approaches to developing insight into this interaction and its role in tropical climate change. First, we assess how circulation changes have influenced cloud feedbacks estimated from observed trends, using a method based on the empirical relationship between cloud radiative effect (CRE) and vertical velocity introduced by Bony et al. (2004). Second, we use global climate model (GCM) experiments with artificially modified CREs to examine how cloud-radiative changes shape the circulation and hydrological responses to CO₂ forcing. This chapter summarises our main findings and identifies potential avenues for future research by revisiting the research questions set out in the introduction.

Q1: How do circulation changes contribute to tropical cloud feedbacks estimated from observed trends?

In the second chapter of this thesis, we examined what long-term observational trends can reveal about the influence of circulation on changes in CREs. To do this, we combined DEEP-C all-sky radiative flux observations (Liu & Allan, 2022) with the ERA5 reanalysis (Hersbach et al., 2020) to estimate tropical cloud feedbacks from multi-decadal trends in CRE and surface temperature over 1985 – 2020. Following Bony et al. (2004), we decomposed feedbacks into dynamic and non-dynamic components, and developed a novel extension of this method to estimate the spatial distributions of the components.

Our results showed that narrowing and strengthening of tropical ascent has produced substantial local dynamic feedbacks, comparable in magnitude to non-dynamic feedbacks. When averaged over the tropics, however, the net, shortwave and longwave dynamic components were small compared to the non-dynamic components. This is consistent with results from high- and low-resolution climate models (Byrne & Schneider, 2018; Mackie & Byrne, 2023), and can be explained by the quasi-linear relationship between CRE and vertical velocity, together with the atmospheric mass budget linking dynamic feedbacks across circulation regimes (Wyant et al., 2006; Byrne & Schneider, 2018). Because this result depends on the climatological relationship between CRE and vertical velocity rather than on the nature of circulation changes, we suggest it will also hold in future. This implies that isolating the non-dynamic component of the feedback may be more informative for estimating cloud type-specific feedbacks relevant to climate sensitivity. This may also make it possible to use shorter time series to identify trends, because much of the internal variability will be captured by the dynamic component.

We also found that both dynamic and non-dynamic feedbacks estimated using multi-decadal trends differ from those estimated using interannual variability. For the dynamic component, we showed explicitly that this arises because circulation changes are driven by different mechanisms on the two timescales: ENSO dominates

interannual variability, whereas multi-decadal trends reflect longer-term circulation changes. This result indicates that variability-derived feedback estimates should be interpreted with caution.

In their assessment of equilibrium climate sensitivity, Sherwood et al. (2020) highlighted the combined anvil area and albedo feedback as particularly uncertain. They relied exclusively on a variability-based estimate from Williams and Pierrehumbert (2017) adopting a value of $-0.20 \pm 0.20 \text{ W m}^{-2}\text{K}^{-1}$. To provide an alternative, we calculated new estimates of the total and non-dynamic components of this feedback using observed trends: -0.30 ± 0.16 and $-0.28 \pm 0.14 \text{ W m}^{-2}\text{K}^{-1}$, respectively (errors are twice the standard error). Our result contrasts with neutral estimates by Sokol et al. (2024) and Raghuraman et al. (2024). Our fairly blunt approach of considering all feedbacks in ascending regions to be associated with anvil clouds likely contributes to this discrepancy. However the estimates of Sokol et al. (2024) and Raghuraman et al. (2024) rely on limited-domain cloud resolving models and observed variability, respectively, meaning they may not capture important components of forced anvil cloud changes. The ‘cloud controlling factor’ methodology, recently applied to the anvil area feedback by Wilson Kemsley et al. (2025), may provide an alternative method for estimating this feedback from observations.

An important limitation of our study is the uncertainty over how well feedbacks inferred from recent trends represent CO_2 -forced feedbacks, given the confounding influences of aerosols and natural variability. Moreover, we do not remove the contribution of rapid adjustments to CRE trends, which may be substantial (Raghuraman et al., 2023). Extending our analysis to account for rapid adjustments would therefore be a valuable step forward. We also rely on relatively simple regression techniques to estimate the observed trends, and sensitivity tests suggest our results depend on the choice of dataset and time period. Extending our treatment of uncertainty to include these methodological choices would help strengthen confidence in trend-derived feedbacks.

In recent years, there has been renewed interest in characterising tropical circulation regimes using sub-cloud buoyancy rather than vertical velocity. First

proposed by Williams and Pierrehumbert (2017), sub-cloud buoyancy captures both the large-scale circulation and its thermodynamic environment, enabling clearer separation between shallow and deep clouds. Its renewed appeal stems from its dependence on sub-cloud and free-tropospheric moist static energy, which provides a simple framework – grounded in convective quasi-equilibrium and weak temperature gradient theory – for assessing how circulation changes influence clouds indirectly (Williams et al., 2023a; Mackie et al., 2025). In doing so, it addresses a key limitation of the Bony et al. (2004) decomposition, where non-local dynamic feedbacks are not captured.

An interesting future application of this method could be clarifying how changes in the large-scale circulation contribute to the individual tropical cloud feedbacks outlined in Section 1.4.2. For example, decreases in high cloud fraction have been linked to dynamic and non-dynamic drivers across scales ranging from narrowing of the ITCZ and changes in tropics-wide tropospheric stability to changes in convective organisation and cloud microphysics (e.g., Lindzen et al., 2001; Su et al., 2014; Byrne & Schneider, 2018; Seeley et al., 2019a; Wing, 2019; Schiro et al., 2022). Application of tools such as the Bony et al. (2004) decomposition, or its sub-cloud moist static energy analogue, to global cloud-resolving simulations offers a promising route to unify these perspectives, by tracing how processes from convective to planetary scales combine to shape cloud feedbacks.

Q2: How do radiative changes in clouds, water vapour and CO₂ contribute to changes in tropical $P - E$?

In the subsequent chapters, we examined how cloud–radiative changes influence the tropical circulation and hydrological cycle under a quadrupling of atmospheric CO₂. To do this, we applied the radiation-locking technique, which separates the individual influences of radiative changes in CO₂, clouds, and water vapour, to ICON GCM simulations from Huber (2022).

Whereas previous radiation-locking studies focused on aquaplanets (Voigt & Shaw, 2015; Ceppi & Hartmann, 2016; Byrne & Zanna, 2020), we asked whether clouds exert a similarly strong influence on the annual-mean hydrological cycle in a more realistic setup with continents and a slab ocean. To our knowledge, this is the first study to apply radiation locking to the tropical $P-E$ response in a configuration with more complex surface boundary conditions. Using the moisture and moist static energy budgets, we diagnosed how cloud-driven radiative changes shape tropical precipitation-minus-evaporation, $P-E$. To facilitate this, we express the $P-E$ changes as a function of the climatological $P-E$. This allows a simplified perspective on the hydrological cycle, analogous to the vertical-velocity framework used in Chapter 2. It also enabled comparison with the thermodynamic scaling of Held and Soden (2006). Second, by comparing slab-ocean and fixed-SST simulations, we separated cloud influences into an atmospheric/land pathway (independent of SST changes) and an SST-mediated pathway.

A limitation of the Huber (2022) simulations was the availability of output data: only monthly means were archived, preventing explicit closure of the moisture and moist static energy budgets at sub-monthly timescales (Inoue et al., 2024). However, this archival frequency is typical for radiation-locking experiments, given the large number of simulations conducted. In addition, the vertical velocity field was corrupted and therefore had to be reconstructed from horizontal convergence (Appendix C).

In Chapter 3, we quantified the relative contributions of radiative changes in CO_2 , water vapour, and clouds to tropical $P-E$ changes. We found that cloud-radiative changes play a pivotal role, driving a ‘wet-gets-drier, dry-gets-wetter’ $P-E$ response that opposes the ‘wet-gets-wetter, dry-gets-drier’ response associated with water vapour radiative changes. As a result, the total $P-E$ change most closely resembles the comparatively weak CO_2 -driven pattern, characterised by drying in both wet and dry regions and slight moistening where climatological $P-E \sim 0 \text{ mm day}^{-1}$. The Held and Soden (2006) thermodynamic scaling fails to capture the total change in the $P-E$ distribution, or the contributions to this change driven by CO_2 -, water

vapour-, and cloud-radiative changes. While it is well established that the total $P-E$ response to CO_2 forcing reflects a balance between dynamic and thermodynamic influences (e.g., Held & Soden, 2006; Chadwick et al., 2013), our results show that circulation changes shape the response to each individual radiative perturbation.

To further disentangle the contributions to cloud-driven $P-E$ changes, we separated the response to the cloud-radiative perturbation into components occurring via the atmospheric/land pathway and via the SST-mediated pathway. The robust wet-gets-drier, dry-gets-wetter response arises mainly via the atmospheric/land pathway. In contrast, ocean-mediated changes exert a limited influence on $P-E$ when viewed as a function of the climatological $P-E$ distribution, only driving a small drying signal in climatologically wet regions. Decomposing these $P-E$ changes into dynamic and thermodynamic components using the moisture budget showed that circulation changes dominate in both pathways: thermodynamic contributions are small in the atmospheric/land pathway, and are largely cancelled by nonlinear circulation–moisture interactions in the SST-mediated pathway.

Q3: How do cloud-radiative changes affect tropical $P-E$ via the atmospheric/land pathway?

In Chapter 4, we examined the mechanism through which clouds drive changes in $P-E$ via the atmospheric/land pathway. To develop our understanding, we focused on how the atmosphere restores energetic balance following the cloud-radiative perturbation. We found that the radiative perturbation warms the upper troposphere, increasing static stability. This inhibits ascent and suppresses precipitation in climatologically wet regions. The resulting weakening of ascent weakens winds throughout the tropics including near the surface, leading to reduced evaporation. This effect is particularly pronounced in the lower branch of the Hadley circulation, where climatological meridional moist static energy gradients are large.

To interpret these results, we developed a scaling which shows that evaporation changes are directly controlled by the static stability response to cloud-radiative

heating. Importantly, precipitation changes feed back on stability through latent heat release, providing a path to energetic equilibration. The sensitivity of the relationship between static stability and evaporation depends on climatological factors including the strength of dry-region descent, the fractional area of wet versus dry regions, the vertical moisture gradient in wet regions, and the tropical-mean static stability.

Cloud-driven radiative heating of the upper troposphere is a robust response to CO₂ forcing in GCMs, linked to the rise in cloud altitude with warming (Sherwood et al., 2020; Voigt et al., 2024; McGraw et al., 2025). It is therefore plausible that the mechanism identified here also operates in other models. However, the vertical structure of the heating response varies across models, reflecting differences in both simulated cloud changes and the climatological distribution and properties of high clouds (Voigt et al., 2024; McGraw et al., 2025). In this context, our scaling could be a useful tool for understanding how this diversity contributes to spread in projected hydrological cycle changes. At the same time, the scaling underscores the role of other elements of the climate system in mediating the interaction between clouds and $P - E$, which may also contribute to inter-model spread.

That said, previous aquaplanet studies suggest other cloud radiative changes may dominate in other models (Voigt & Shaw, 2015; Harrop & Hartmann, 2016). Notably, our ICON configuration under-represents tropical low clouds, meaning their radiative changes could exert a competing influence in other models. In cases where our scaling does not capture the dominant mechanism, it may still be useful to identify which scaling assumptions are violated, thereby helping to clarify why models differ in their hydrological cycle responses.

Our results highlight the importance of interactions between changes in latent heating and CREs, and how these combine to influence the static stability and, in turn, the circulation. This coupling has received relatively little attention, although several studies suggest that non-radiative heating changes play a key role in controlling ascent area and explaining inter-model spread in this quantity in RCE simulations (Jenney et al., 2020; Mackie & Byrne, 2023). In addition, the

maintenance of weak temperature gradients, and consequent limitation of horizontal moist static energy transport, is critical to how the climate system equilibrates in ICON. However, upper-tropospheric temperature gradients are not necessarily negligible (e.g., Williams et al., 2023a), so a deeper exploration of the processes controlling these gradients would be valuable.

Q4: How do cloud-radiative changes affect tropical $P-E$ via the SST-mediated pathway?

Chapter 5 examines the SST-mediated pathway, which quantifies the influence of cloud radiative changes on the tropical hydrological cycle through their effect on SSTs. Cloud-radiative perturbations modify the surface energy balance both directly, through changes in surface CREs, and indirectly, because changes in atmospheric CREs alter other surface fluxes. Changes in surface CREs reduce the net energy input to the surface, particularly in climatologically wet regions. However, this effect is outweighed by reduced evaporation associated with changes in atmospheric CREs - an influence strongest in climatologically dry regions. To restore surface energy balance, SSTs warm, with the largest anomalies occurring in these dry regions. The warming enhances evaporation, largely offsetting the reduction driven by atmospheric CRE changes. It also raises near-surface moist static energy, which draws ascent and precipitation toward drier areas while suppressing these processes in climatologically wet regions.

The vertical structure of the anomalous ascent indicates that latent heating reinforces the circulation anomalies, helping to sustain the new equilibrium. Thus, as in Chapter 4, our results suggest that coupled interactions between changes in cloud radiative effects and latent heating are important in shaping circulation changes. However, a key distinction from Chapter 4 is that the $P-E$ changes arising through the SST-mediated pathway are spatially confined, occurring primarily over the Indian Ocean and western Pacific, where SST increases are greatest.

Changes in moist static energy transport driven via the SST-mediated pathway are small in most $P-E$ regimes. Nonetheless, the SST changes and subsequent

atmospheric adjustments allow changes in moist static energy transport to contribute more substantially to restoring energetic balance than in the fixed-SST configuration. However, a large decomposition residual limits insight into how exactly this happens and suggests that unresolved transient eddies may play a role. In addition, the use of prescribed climatological q -fluxes likely constrains ocean–atmosphere coupling, reducing the realism of the simulated energy adjustments.

Consistent with Chapter 4, the under-representation of low clouds by our ICON configuration must be taken into account when interpreting these results. In particular, other climate models typically simulate positive low cloud feedbacks in subtropical regions, suggesting the changes in surface CREs simulated by ICON are too negative.

Overall, the results from Q2–Q4 demonstrate that cloud-radiative changes play a fundamental role in shaping the tropical $P-E$ response to CO_2 forcing in the ICON model. A natural next step is to assess whether these mechanisms operate similarly across other models. The intensive nature of the radiation-locking methodology makes its application to large model ensembles impractical, but it could feasibly be applied to a limited subset of models that span the range of cloud-radiative responses observed across the ensemble. Alternatively, a sensitivity study could be conducted in which idealised cloud-radiative perturbations, designed to reflect inter-model differences, are imposed within a single model framework. A promising candidate for such an approach is the Isca model (Vallis et al., 2018), which allows for varying degrees of idealisation in the representation of atmospheric physics, including moisture and the associated latent-heating response to imposed perturbations.

Beyond testing the robustness of mechanisms across models, it would be valuable to examine the extent to which climatological variables identified here as influencing the $P-E$ response contribute to inter-model spread. Where the mechanistic basis of their influence is well understood, observations of these variables could potentially be used to constrain projections of $P-E$ changes.

There remain many interesting avenues to explore in understanding how cloud-radiative changes influence the tropical circulation and hydrological cycle. In our

analysis, results are largely shaped by $P-E$ changes over the ocean, but a key next step is to better understand the influence of cloud changes on $P-E$ over land. Although the radiation-locking technique becomes less reliable at small spatial scales, our findings suggest that, to first order, the cloud influence on $P-E$ over tropical land can be interpreted in aggregate. It would also be interesting to explore how cloud-radiative changes affect over-land $P-E$ at seasonal timescales, building on the aquaplanet study of Byrne and Zanna (2020). Another potential approach is to apply radiation locking in simulations with a single idealised continent of simplified geometry and properties, which could help isolate the fundamental mechanisms at play. The analysis could also be refined by decomposing the divergent circulation into its meridional and zonal components, allowing assessment of how clouds compete with other circulation drivers that may differ between the two cases.

Future work should also consider methodological refinements. Given the central role of high clouds in our results, it may be valuable to use temperature, rather than model levels, as the vertical coordinate in future radiation-locking studies. In the current approach, when a cloud field from one simulation is imposed onto another, the positioning is based on cloud altitude. However, aligning clouds by temperature may be more physically meaningful, since longwave CREs depend strongly on temperature.

Finally, our results highlight that radiative changes in clouds, water vapour and CO_2 all contribute to changes in tropical circulation strength. Building on the conclusions of Merlis (2015), we suggested that the influence of water-vapour and CO_2 radiative changes on circulation strength may arise from cloud masking: by modifying the radiative perturbation in cloudy ascending regions, clouds alter spatial gradients in atmospheric energy input and thereby weaken vertical velocities. A valuable direction for future work would be to test this hypothesis and assess the extent to which the tropical circulation slowdown depends on the mean-state cloud climatology.

Contribution of thesis to addressing outstanding questions

In the Introduction, we highlighted several outstanding questions regarding how cloud–circulation interactions shape the tropical climate response to anthropogenic forcing. These were: (i) the extent to which cloud–circulation coupling influences tropical temperature and hydrological change; (ii) the mechanisms through which clouds and circulation interact to shape these responses; (iii) whether such interactions contribute to uncertainty in projections of tropical warming, circulation, and hydroclimate; and (iv) how best to combine observations, reanalyses, and model hierarchies to address these questions. This thesis contributes towards addressing these questions in several ways.

First, our results show that cloud–circulation coupling plays a central role in both observed cloud-radiative changes and modelled tropical hydroclimate responses. For Q1, circulation changes were found to strongly influence regional CRE trends over recent decades, even though tropical-mean dynamic feedback contributions remain small compared to non-dynamic components. For Q2–Q4, radiation-locking experiments show that cloud-radiative changes play a fundamental role in shaping the tropical $P-E$ response to CO_2 forcing in ICON, and can oppose the water-vapour-driven changes in the spatial distribution of $P-E$.

Second, the thesis develops mechanistic insight into how these cloud–circulation interactions shape tropical climate changes. For Q1, we showed that mass-budget constraints and the climatological CRE– ω relationship explain why circulation changes generate large local dynamic feedbacks but weak tropical-mean dynamic contributions. For Q2–Q4, we demonstrated how cloud-radiative perturbations reshape $P-E$ through energetically constrained atmospheric/land and SST-mediated pathways involving changes in stability, surface fluxes, and the strength and spatial distribution of ascent.

Third, the results facilitate plausible hypotheses linking the cloud–circulation coupling to uncertainty in projections. For Q1, the contrast between trend- and variability-derived feedback estimates highlights the sensitivity of observational

estimates to timescale, aerosols, and rapid adjustments. Our results also demonstrate that key feedbacks associated with high clouds, including the anvil area and albedo feedback, remain difficult to constrain using either observations or conventional GCMs alone. For Q2–Q4, the mechanisms we identified suggest that inter-model diversity in cloud-radiative heating, surface energy adjustments, and the climatological state of clouds and circulation, could all translate into spread in circulation weakening and the redistribution of tropical $P - E$.

Finally, the thesis makes targeted methodological choices: a CRE- ω decomposition to unpick observed CRE trends, radiation locking to isolate the role of radiative drivers in a GCM, and simplified tropical frameworks to interpret the resulting circulation and hydrological responses.

Fully addressing the outstanding questions will require strategic use of the tools available to us. A particularly promising direction is the use of newly-developed high-resolution simulations to connect large-scale changes, such as those diagnosed in this work, to the smaller-scale cloud and convective processes that generate them. Coordinated intercomparison efforts such as DYAMOND3 provide an opportunity to study anvil feedback mechanisms and their coupling to large-scale circulation change in a setting that reduces reliance on convective parameterisations.

At the same time, lower-resolution models with idealised physics or boundary conditions remain valuable for identifying robust mechanisms linking changes in clouds, circulation and the hydrological cycle. Used within model hierarchies, such experiments can clarify which mechanisms persist in more realistic configurations and help explain why models differ in their responses. Similar hierarchies could also be developed at high resolution.

Finally, observations remain essential for evaluating these modelling results. Extending trend-based analyses to better account for aerosols, internal variability and rapid adjustments, and applying emerging observational diagnostics based on sub-cloud buoyancy or cloud-controlling factors, may help constrain forced cloud feedbacks and the role of circulation within them.



Port Meadow, 26 Oct 2024

Appendices



Estimation of DEEP-C instrument uncertainty

Liu et al. (2020) estimate the uncertainty on the global- and annual-mean net radiative flux change between 1985 – 2000 to be $\pm 0.61 \text{ W m}^{-2}$ at the 90% confidence level. This uncertainty is associated with gaps in the observational record in 1993 and 1999 – 2000. Johnson et al. (2016) estimate the uncertainty on the change in radiative flux over the CERES period (2000 – 2020) to be $\pm 0.10 \text{ W m}^{-2}$, also at 90% confidence level. Uncertainty on the CERES data is based on uncertainty in ocean heat uptake measured by Argo (Roemmich & Argo Steering Team, 2009), which is used to validate and anchor the satellite data (Loeb et al., 2012).

To estimate the instrument uncertainty on the cloud feedback, we begin by estimating the uncertainty on the change in net all-sky radiative flux to be $\sqrt{(0.61)^2 + (0.10)^2} = 0.62 \text{ W m}^{-2}$. Ignoring uncertainty associated with the ERA5 clear-sky fluxes, the instrument uncertainty on the change in cloud radiative effect (CRE) is also 0.62 W m^{-2} . Assuming that the data are normally distributed, we convert this to a standard error (1σ) of 0.38 W m^{-2} . To convert to an error on the feedback, we divide by the number of years and then by the tropical-mean surface temperature trend over the same period, producing an error of $0.66 \text{ W m}^{-2}\text{K}^{-1}$.

We assume that this error is independent of the area it covers as it depends on global factors that affect the satellite calibration equally in all regions.

Consequently, we add (in quadrature) an instrument error of $0.66 \text{ W m}^{-2}\text{K}^{-1}$ to the existing error on the linear regression for feedbacks associated with individual vertical velocity regimes (e.g., Fig 2d,e) or gridpoints (e.g., Fig. 5a-c). We add (in quadrature) an instrument error of $0.66 \text{ W m}^{-2}\text{K}^{-1} \times P(\omega)$ to the non-dynamic component of the contribution of each vertical velocity regime to tropical-mean cloud feedbacks and an instrument error of $0.38 \text{ W m}^{-2} \times (dP(\omega)/d\bar{T})$ to the nonlinear component (e.g., Fig 4). To calculate the instrument error on tropical-mean feedback values we sum (*not* in quadrature) the thermodynamic and nonlinear component instrument errors over vertical velocity regimes and then add together (in quadrature) the totals of these sums. This leads to an instrument error marginally larger than $0.66 \text{ W m}^{-2}\text{K}^{-1}$ because we use $d\text{CRE}(\omega)$ twice in our calculation method. Note that we would expect the total thermodynamic and nonlinear component instrument errors to be related but, for simplicity, we add them in quadrature. This decision has limited impact because the instrument error on the nonlinear component is much smaller than that on the thermodynamic component. Also note that (in contrast to the instrument errors) we sum the linear regression errors over vertical velocity regimes in quadrature. To calculate the overall error on tropical-mean feedback values we add the tropical-mean regression error and the tropical-mean instrument error in quadrature.

B

Comparison of feedback calculation methods

		DEEP-C		ERA5	
		CRE in ω -regimes	Tropical-mean CRE	CRE in ω -regimes	Tropical-mean CRE
Tropical-mean cloud feedback (W m ⁻² K ⁻¹)	Net	+0.21 (0.20)	+0.31 (0.27)	−1.30 (0.21)	−1.22 (0.22)
	LW	+1.17 (0.22)	+1.78 (0.20)	+1.87 (0.19)	+2.26 (0.18)
	SW	−0.96 (0.37)	−1.47 (0.34)	−3.17 (0.36)	−3.48 (0.31)

Table B.1: Net, longwave (LW) and shortwave (SW) tropical-mean cloud feedbacks estimated from trends between January 1985 and July 2020 using DEEP-C and ERA5. Feedbacks denoted ‘CRE in ω -regimes’ are calculated following Equation (2.2). Feedbacks denoted ‘Tropical-mean CRE’ are calculated by computing a separate linear trend in tropical-mean cloud radiative effect (CRE) anomalies for each calendar month, dividing this by the corresponding calendar-month trend in tropical-mean surface temperature anomalies, and then taking the average over months. Errors are the standard error (1σ) of the regression error only (i.e. do not include instrument error) to allow comparison of calculation methods.



Vertical velocity reproduction

Method

Almost all vertical velocity data from Huber (2022) were found to be corrupted. To address this, we recalculated vertical velocities using a simplified form of the mass continuity equation. We work on ICON’s native vertical levels, which we express in terms of their height, z . Although $\omega = Dp/Dt$, we treat $\omega(z)$ as a diagnostic field evaluated on height levels. Using hydrostatic balance to rewrite the continuity equation in height coordinates gives

$$\nabla \cdot \mathbf{u} - \frac{1}{\rho g} \frac{\partial \omega}{\partial z} = 0, \quad (\text{C.1})$$

where $\mathbf{u} = (u, v)$ is the horizontal wind, ρ is the air density, $g = 9.81 \text{ m s}^{-2}$ is the gravitational acceleration, ω is the vertical pressure velocity (hereafter ‘vertical velocity’) and z is the height. From this, vertical velocity at each model level can be calculated using

$$\omega(\text{lat}, \text{lon}, z, t) = -g \int_z^{z_T} \rho(\text{lat}, \text{lon}, z', t) \nabla \cdot \mathbf{u}(\text{lat}, \text{lon}, z', t) dz', \quad (\text{C.2})$$

where z_T is the height of the top level of the atmospheric model and we impose the boundary condition $\omega(z_T) = 0$.

For best results, this calculation should be performed on the original model grid, at the native time-step, and using the same numerical integration and differentiation

methods as the model itself (Seager & Henderson, 2013). Even then, discrepancies may arise because vertical velocities can be modified by physical parametrisations, meaning the continuity equation does not necessarily hold at each time-step (Inoue et al., 2024). In our case, we use the original vertical levels, but we do not use the original horizontal grid (although we maintain a similar resolution) and we only have monthly mean data. Furthermore, ICON is not hydrostatic so the use of this approximation may introduce further errors in the reproduction.

Evaluation of reproduced vertical velocities

Through comparison to the ERA5 reanalysis (Hersbach et al., 2020), we determined that the final ~ 100 months of the free-running P-SST (i.e., fixed-SST) simulations are likely not corrupted. Therefore, by comparing the reproduced vertical velocities to the original data over this period, we were able to evaluate the reproduced vertical velocities.

Figure C.1 compares the reproduced and original spatial distribution of annual-mean, column-mean vertical velocity for the CTRL and PERT simulations over this period. There are regional errors which, given their structure, appear to be related to orography and horizontally re-gridding the data (Fig. C.1c,d). These errors are very large in polar regions, but are generally small compared to the simulated vertical velocities in the tropics. Figure C.2 makes the same comparison, but for the difference in vertical velocity between PERT and CTRL. Because some of the reproduction errors are time-invariant, their magnitudes are smaller here than for the climatologies. Finally, Figure C.3 compares the reproduced and original values of the vertically-resolved vertical velocity metrics for each $(P-E)_{CLIM}$ regime.

Overall, these results indicate that the reproduced vertical velocity field is sufficiently accurate for our purposes.

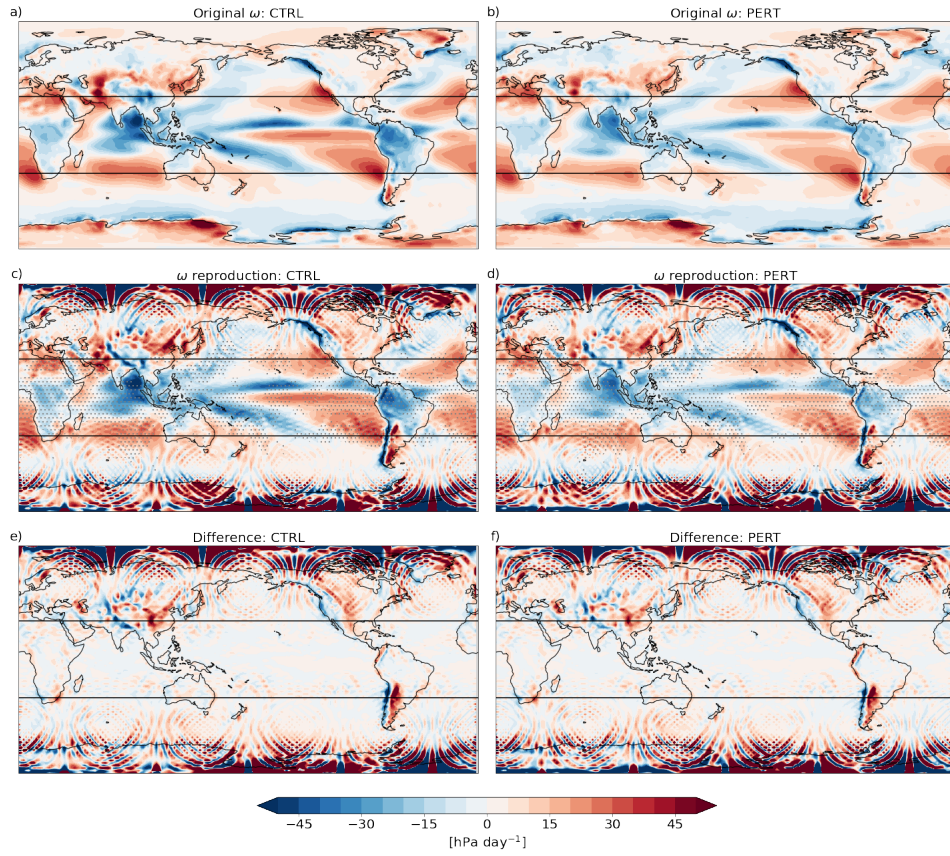


Figure C.1: Annual-mean spatial distribution of column-mean vertical velocity for the period when the original data are uncorrupted. Panels (a,b) show results from the original CTRL and PERT data, respectively. Panels (c,d) show the reproduction, and panels (e,f) the differences. Black horizontal lines demarcate 30°N-30°S. In (c,d), stippling marks regions where the reproduction is within 50% of the original.

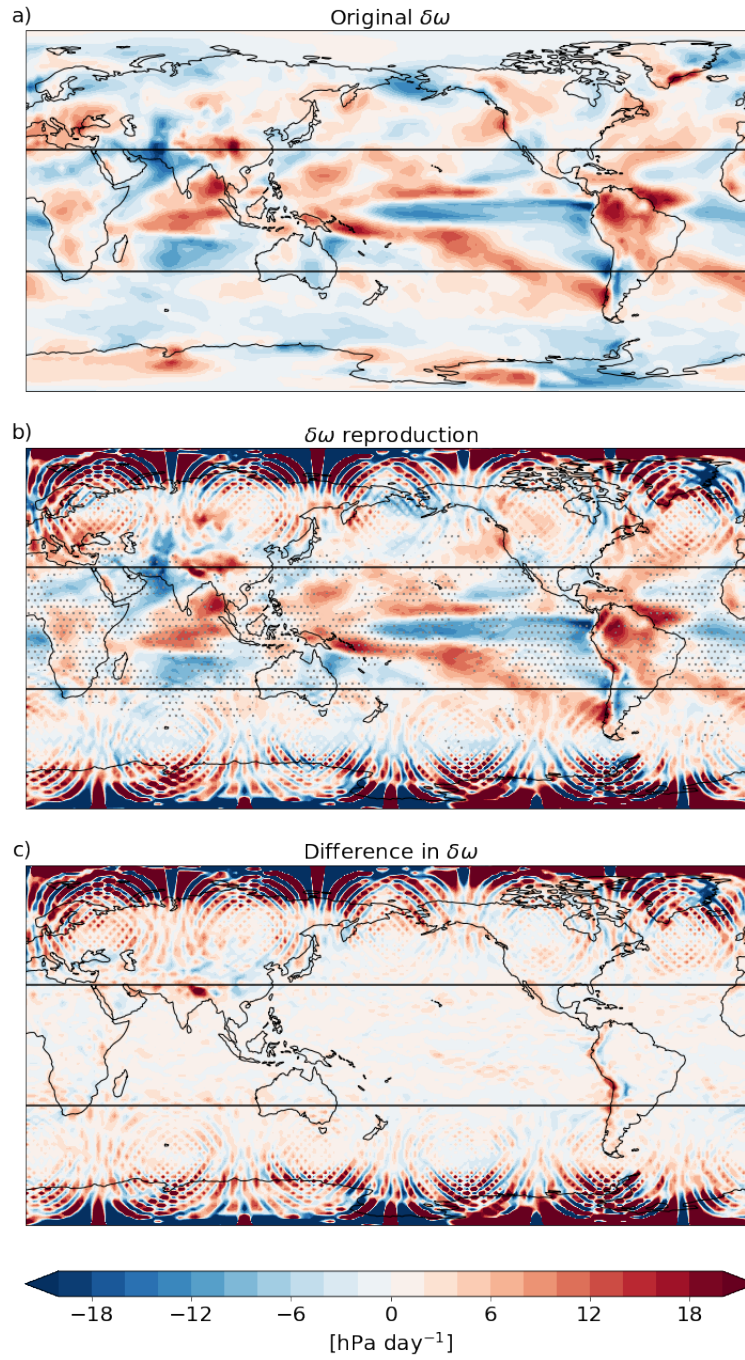


Figure C.2: Annual-mean spatial distribution of the PERT–CTRL difference in column-mean vertical velocity for the uncorrupted period. Panel (a) shows the original data, (b) the reproduction, and (c) their difference. Black horizontal lines demarcate 30°N–30°S. In (b), stippling marks regions where the reproduction is within 50% of the original.

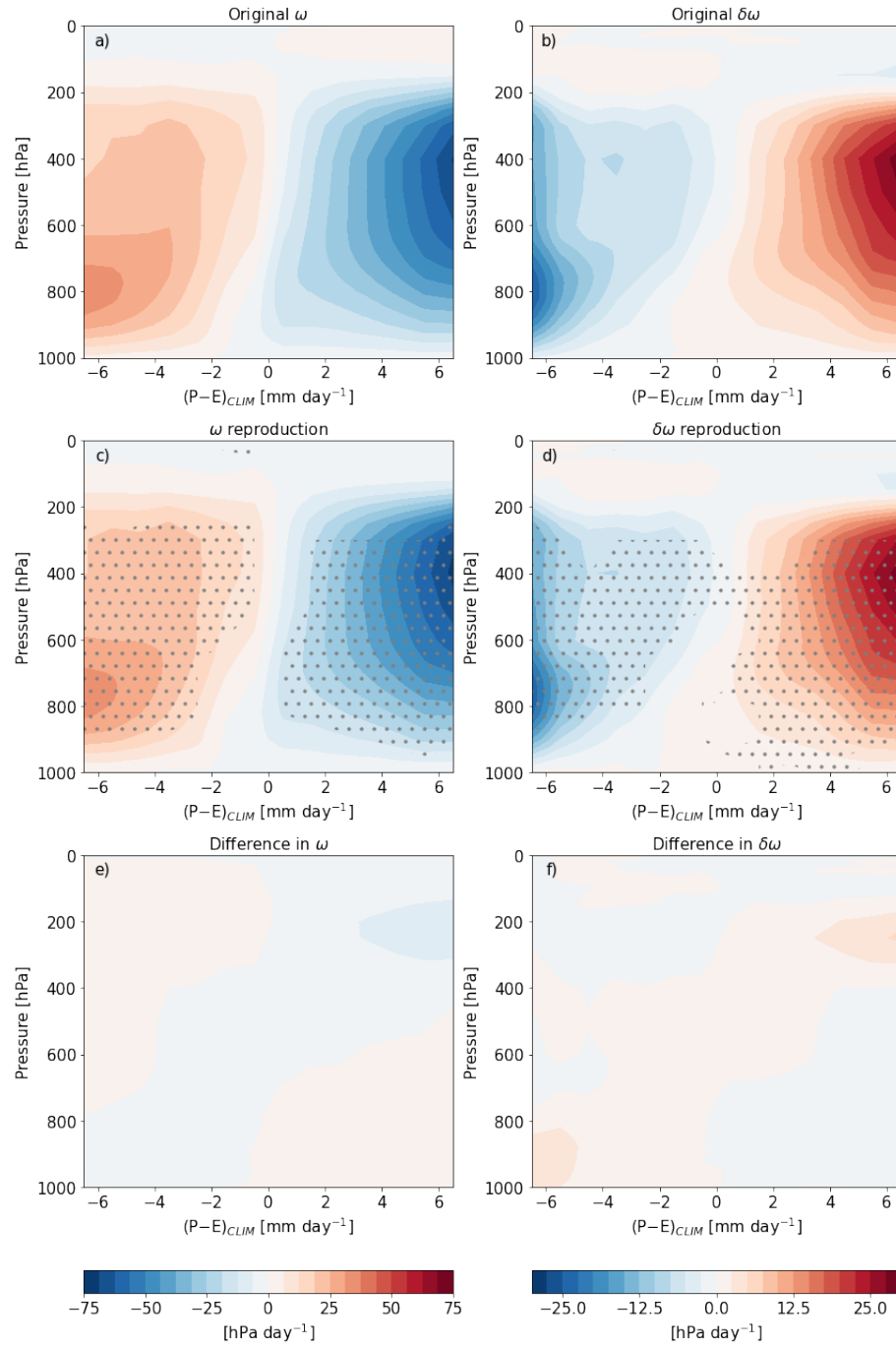


Figure C.3: Annual-mean vertical velocity for the uncorrupted period. Panels (a,b) show results from the original data: (a) vertical velocity at $1\times\text{CO}_2$ and (b) the $4\times\text{CO}_2 - 1\times\text{CO}_2$ change as a function of $(P-E)_{CLIM}$. Panels (c,d) show the reproduction, and (e,f) the differences. In (c,d), stippling marks regions where the reproduction is within 25% of the original.

D

Assumption validation

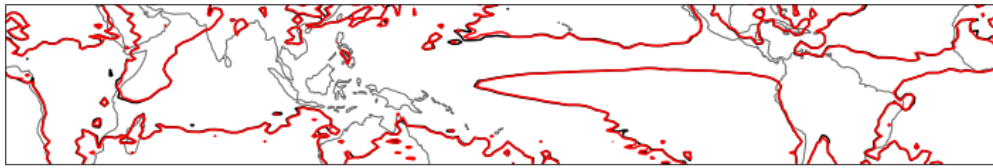


Figure D.1: Black contours denote where the climatological column-average annual-mean $\omega = 0 \text{ hPa day}^{-1}$ and red contours show how this is modified by cloud-radiative changes via the atmospheric/land pathway. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses to the perturbation are calculated using radiation locking.

	Tropical-mean change
Column-mean ω	$0.02 \text{ hPa day}^{-1}$
$P - E$	0.02 mm day^{-1}

Table D.1: Changes in annual-mean tropical-mean precipitation-minus-evaporation, $P - E$, and column-mean vertical velocity, ω , driven by cloud-radiative changes via the atmospheric/land pathway. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses to the perturbation are calculated using radiation locking.

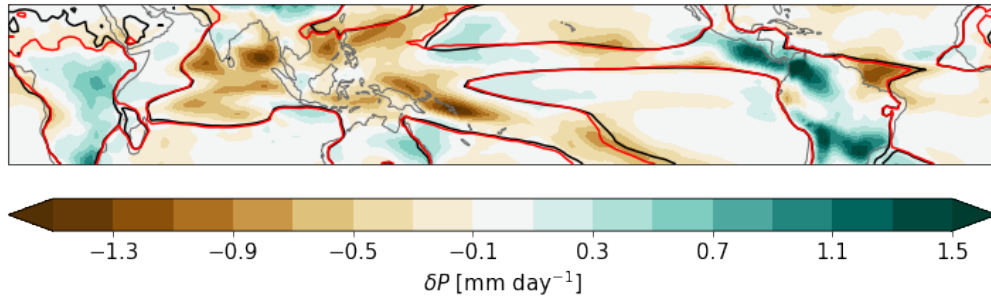


Figure D.2: Changes in annual-mean precipitation, P , driven by cloud-radiative changes via the atmospheric/land pathway. Black contours denote where the climatological annual-mean $P-E = 0 \text{ mm day}^{-1}$ and red contours show how this is modified by cloud-radiative changes via the atmospheric/land pathway. The cloud-radiative perturbation is driven by CO_2 quadrupling and the responses to the perturbation are calculated using radiation locking.



Walton Well, 4 Apr 2025

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