

Cloud Feedback -- A Forward-Looking Perspective on Needed Satellite Observations to Complement Suborbital Data and Models to Answer Important Questions Raised by the 2017-2018 Decadal Survey

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Artificial Intelligence (AI) Usage Disclosure

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1. Science Background

1.1 Method Behind This Document

In 2025, fifteen Subject Matter Experts (SMEs) in the Earth's aerosol, cloud, convection and precipitation fields at NASA GSFC (called Group 1) selected three "most important" science questions from the 2017-2018 Decadal Survey (National Academies of Sciences, 2018). These science questions were focused on aerosol total radiative forcing, cloud radiative feedbacks and the microphysics and dynamics of convective storms. Figure 1 illustrates the approach employed by the study team, with the one-year effort leading to three broad literature review papers; each paper focuses on one of the three science questions. Group 1 (a total of fifteen members from Goddard Space Flight Center (GSFC) separated in three sub-teams focused on aerosol, clouds, and convection) defined a common structure to these three papers and identified additional internal and external subject matter experts (SMEs) from national and international agencies and universities (Group 2, with 35 members across the three science themes). Group 1 asked Group 2 for input in their individual focus areas and Group 2 provided a total of ~430 relevant peer-reviewed papers and personal opinions via emails. The general content within this document is synthesized directly from artificial intelligence (AI)-based language informed by an AI/ Large Language Model (LLM), Google NotebookLM (<https://notebooklm.google/>). Group 1 developed AI/LLM questions to create the three literature review papers and asked questions to the AI/LLM, using three types of sources as input: (i) the peer-reviewed papers provided by Group 2, (ii) Group 2's email-based opinions (made anonymous) and (iii) chapters in the Intergovernmental Panel on Climate Change (IPCC) Assessment Report (AR6) related to each of the three science questions. This process was independently replicated by two co-authors in Group 1, after which a third person in Group 1 combined the inputs. Many co-authors from Group 1 and Group 2 then reviewed the papers, revised or reorganized sentences/paragraphs as necessary and added information (including text and citations) that was either missed by the AI/LLM or by the sources the AI/LLM used as input. The output of the AI/LLM was not checked for the extent to which the text may have been drawn directly from the cited source material or rewritten by the AI/LLM. It is recognized that some of the citations provided by the AI/LLM may include recursive references. **This document is intended primarily for reference purposes only and is not suitable for peer review publication.**

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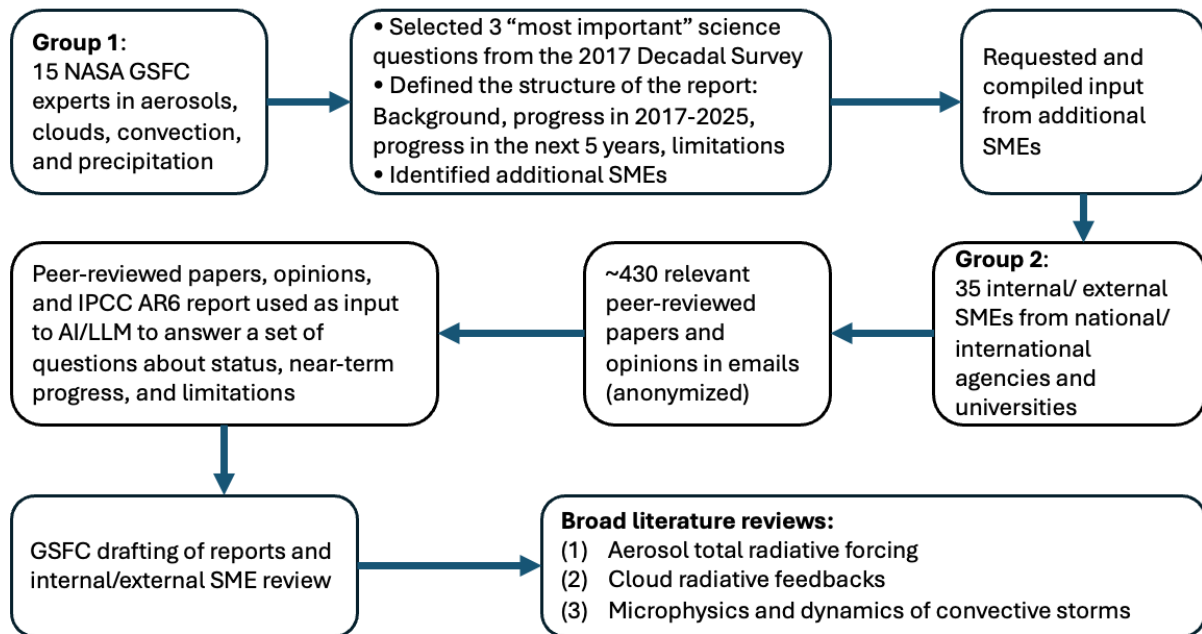


Figure 1: Illustration of the methodology used to develop this paper.

1.2 Science Objectives and Questions

The 2017-2018 Decadal Survey (National Academies of Sciences, 2018) identified several “most important” science questions, among them Question C-2, “How can we reduce the uncertainty in the amount of future warming of the Earth as a function of fossil fuel emissions, improve our ability to predict local and regional climate response to natural and anthropogenic forcings, and reduce the uncertainty in global climate sensitivity that drives uncertainty in future economic impacts and mitigation/adaptation strategies?” To address this science question, numerous specific objectives were identified, including the “most important” objective C-2a to **reduce the uncertainty in low and high cloud feedback by a factor of 2**. This objective involves determining the sensitivity of cloud properties to environmental factors, and characterizing the structure and properties of clouds of all phases (liquid, ice, mixed). The ultimate goal is to quantify cloud feedback in response to cloud controlling factors and aerosol-cloud interactions. Cloud feedback is defined as the change in radiative flux at top-of-atmosphere (TOA) due to cloud property changes per unit of global surface temperature change. Feedbacks associated with specific cloud properties can be separated using Cloud Radiative Kernels (CRK) or Partial Radiative Perturbation (PRP). Such a separation cannot be achieved with another cloud feedback estimation technique, the so-called “adjusted Cloud Radiative Effect (CRE)” method (Soden et al. 2008).

1.3 Importance

Clouds play a strong role in the Earth's radiation budget, simultaneously cooling the planet by reflecting sunlight (reducing the solar radiation reaching the surface by an average of $\sim 50 \text{ W m}^{-2}$ compared to clear-skies) and warming the planet by trapping longwave emission from the Earth's surface ($\sim$ adding 30 W m^{-2} on average more than clear skies) [Stephens et al., 2012] in the current climate. In the context of future climates, we would like to know how the enhancement of reflectance and trapping will change, i.e., to quantify the shortwave and longwave cloud feedback. Quantifying cloud feedbacks will reduce the **leading source of uncertainty in Earth's climate response to anthropogenic forcing** [Ceppi and Nowack, 2021; IPCC AR6 WGI, 2023; Raghuraman et al., 2024]. A large portion of the inter-model spread in equilibrium climate sensitivity (ECS) among general circulation models (GCMs) is largely dominated by differences in **low-latitude marine low-cloud feedbacks** [Cesana et al., 2023; Vial et al., 2013; Caldwell et al., 2016; Sherwood et al., 2020]. Still, extratropical low-cloud feedbacks have been shown to also contribute significantly to the increase in multi-model mean ECS between CMIP5 and CMIP6 models [Flynn & Mauritsen, 2020; Zelinka et al., 2020]. **High cloud feedbacks** are another key source of uncertainty [Sherwood et al., 2020; Raghuraman et al., 2024; Kemsley et al., 2024].

1.4 Parameters

The Aerosol Cloud Convection and Precipitation (ACCP) study, undertaken by NASA to explore mission concepts that address relevant 2017-2018 Decadal Survey priorities, directly mapped science question C-2 and objective C-2a (section 1.2) to specific ACCP science objectives focused on low cloud feedbacks (ACCP objective O1), high cloud feedbacks (ACCP objective O2), and aerosol-cloud interactions (ACCP objective O8). See the ACCP science narrative report ([https://aos.gsfc.nasa.gov/docs/ACCP_Science_Narrative-\(Mar2022\).pdf](https://aos.gsfc.nasa.gov/docs/ACCP_Science_Narrative-(Mar2022).pdf)) and the ACCP Science and Applications Traceability Matrix (SATM) (https://aos.gsfc.nasa.gov/docs/ACCP_SATM_Rel_Candidate_G.pdf) for more explanation on these science objectives. The ACCP study identified numerous key geophysical variables (GVs) that must be rigorously observed to adequately address ACCP objectives O1, O2, and O8; the subset of “threshold” (i.e., minimum required) GV is shown in Table 1.

Table 1 is adapted from the ACCP SATM. We emphasize that we have not modified any of the GV, their descriptions and their minimum desired capability since the making of this SATM (May 2021). The content of this paper was derived independently from the ACCP SATM (and consequently Table 1) with participation from different subject matter experts (SMEs). Table 1 in this document serves as the foundation for a broader discussion (workshop envisioned in later years) by the science community. The authors' consensus is that the current Program of Record (PoR) either shows more limited capability than the desired capabilities in Table 1 or does not provide these GV at all. This latter statement will be discussed further in a community forum.

Table 1: Adapted from the ACCP SATM (link provided above). The science question in this document can be traced back to ACCP objectives O1, O2 and O8. We only select the minimum set of GVs from ACCP SATM slide 12-33. We omit GVs "Scattering ratio" (i.e., the ratio of observed attenuated backscatter to molecular backscatter) and "Full attenuation altitude". GVs requiring profiles are denoted by (P). Aerosol GV requirements are defined for 65% of scenes with detectable aerosol and no overlying clouds. See the ACCP science narrative report ([https://aos.gsfc.nasa.gov/docs/ACCP_Science_Narrative-\(Mar2022\).pdf](https://aos.gsfc.nasa.gov/docs/ACCP_Science_Narrative-(Mar2022).pdf)) for more explanation on ACCP science objectives O1: Low clouds, O2: High clouds, O3: Convective storm systems, O4: Cold cloud and precipitation processes, O5: Aerosol Attribution and air quality, O6: Aerosol wet removal, vertical redistribution and processing, O7: Aerosol direct effects and absorption, and O8: Aerosol indirect effect.

GV	MINIMUM Desired Capability				
	Range	Uncertainty	XY	Z	Swath
Cloud liquid water path	0.02-0.5 kg m ⁻²	0.02 for < 0.1 kg m ⁻² ; 50% for > 0.1 kg m ⁻²	500m	N/A	Context Only
Cloud optical thickness (COT)	O1, O8: >0.1; O2: 0.1-50	O1, O8: 20%>10 Precip mode: 50%<10 No precip mode: 15%<10; O2: 100%	500m	N/A	Nadir
Hydrometeor vertical feature mask	Cloud top: 0.5-20km	Cloud top (CT): 100m	CT: 1 km	CT: 100-200 m	Nadir
Cloud top phase	Liquid, solid, mixed	N/A	O1, O8: 200m; O3: 3km	~1 OD	Nadir
Cloud radiative effects, SW & LW	0-1000 W m ⁻² (SW), 0-200 W m ⁻² (LW)	±20-40 W m ⁻² (SW), ±5-10 W m ⁻² (LW)	1km (SW), 2km (LW)	N/A (TOA)	>50 km
Ice Water Path	0.01-0.75 kg m ⁻²	100%	5 km	N/A	Nadir
(P) In-cloud vertical air velocity	0.5-3 m s ⁻¹ (above 5 km)	0.5 m/s	3km	N/A	Nadir

Cloud droplet effective radius	5-20 microns	For clouds with precip mode, 20%. For no precip mode, 10% for COT>2	1km	N/A	Nadir (lidar ratio technique), 100km (bi-and multispectral techniques)
Cloud droplet concentration	10-500 cm ⁻³	100%	2km	N/A	Nadir
Cloud areal extent/fraction	> 4 km ²	For COT > 0.3 [IR]	2 km	N/A	Wide
(P) Ice Water Content (*)	10 ⁻⁵ - 10 g m ⁻³	100%	2km	250m	Nadir
Cloud geometric-top temperature	>170	1%	2km	N/A	Nadir
Diurnally resolved cloud cover	0.05-1.00	5%	2 km	N/A	Wide
Diurnally resolved cloud top height	1-20 km	1km	2 km	N/A	Wide
Cloud lifecycle categories	≥ 3 phases	N/A	2 km	N/A	Wide
Cloud Albedo	0.1-0.8	5%	2km	N/A	100 km
(P) Aerosol-Cloud Feature Mask	N/A	1%, for COT > 0.1	foot-print	100 m	Nadir
(P) Precipitation phase profile	Liquid, Solid, Mixed	N/A	3 km	250m	Nadir
(P) Precipitation rate profile	0.1 - 2 mm hr ⁻¹	<100%	3km	250m	Nadir
(P) Aerosol extinction profile	0.01–5 km ⁻¹	Max of (0.02 km ⁻¹ , ±20%)	5km	30m	Nadir
Aerosol Optical Depth (AOD)	0.03 - 4	±0.02±0.05xAOD	5km	N/A	100km
Aerosol Single Scattering Albedo	0.6-1.0	±0.04	50km	N/A	100km
Aerosol Fine Mode Optical Depth	0.03-4	±0.02±0.05xAOD	50km	N/A	100km
Aerosol effective radius	0.1 to 1 mm	0.1 μm or 10%	50km	N/A	100km

(P) Aerosol non-spherical extinction fraction	0-2	$\pm 10\%$	50km	500m	Nadir
(P) Temperature	-85°C – 50°C	1.5°C	<25km	<25km	Global
(P) Humidity	0 - 100%	25%	<25km	<1km	Global
(P) Horizontal Wind	-80 - 80 m s ⁻¹	<2 m s ⁻¹	<25 km	<1 km	Global
(P) Vertical Wind	-50 – 50 cm s ⁻¹	2 cm s ⁻¹	<25km	<25km	Global
PBL Height	2-5 km	200m	5km	N/A	Nadir

2. Contemporary Satellites, Suborbital Observations and Models

The Program of Record (PoR) refers to contemporary spaceborne Earth-observing assets active sometime during the period 2017 to 2025 and includes national, international, and commercial assets that are currently flying or recently decommissioned. The PoR includes assets such as the A-Train, Terra, Plankton, Aerosol, Cloud, ocean Ecosystem (PACE), Earth Cloud Aerosol and Radiation Explorer (EarthCARE), among others. While the focus here is on satellite-based sensors, we acknowledge the necessity of suborbital observations and models to address the science objectives. In this section, we first describe the progress made on addressing the science question using contemporary PoR and models since the 2017-2018 Decadal Survey (section 2.1). We then assess the potential progress achievable in the next five years using current methods (section 2.2) and we finish this section by describing key limitations that cannot be addressed using contemporary satellites (section 2.3).

2.1. Progress Made Using the Contemporary PoR and Models from 2017 to 2025

The period of 2017-2025 is specifically called out because we want to focus on science and technology improvements/updates after the last NASA Earth Science 2017-2018 Decadal Survey (published in 2018) and IPCC AR6 (published in 2021-2023).

2.1.1. Relevant Findings

While cloud feedback, the radiative response of clouds to global surface temperature changes, ultimately affects the global temperature itself [IPCC AR6 WGI, 2023], its global value is uncertain and is dependent on cloud type [Chao et al., 2024] and many other cloud properties. In the modern satellite era, global spaceborne observational datasets have revealed key insights about clouds, their temporal responses to a changing climate, and their impacts on the Earth's radiation budget. Multi-decadal zonal cloud trends derived from independent datasets indicate an expansion of the sub-tropical zones in recent years [Tselioudis et al., 2024]. And recent global temperature

increases have been tied to a reduction in the planetary albedo resulting from a reduction in global cloud cover [Goessling et al., 2025].

Cloud feedbacks are often constrained using so-called Cloud Controlling Factor (CCF) analysis which estimates cloud radiative responses to large-scale meteorological drivers. Typical CCFs for low marine and boundary layer clouds include local surface temperature (T_{sfc}) or sea-surface temperature (SST), estimated boundary layer inversion strength (EIS), vertical velocity (e.g., ω_{700}), relative humidity (e.g., RH_{700}), temperature advection (T_{adv}), and near-surface wind speed (W_s) [Qu et al., 2015; Scott et al., 2020; Cesana & Del Genio, 2021; Kemsley et al., 2024; Tan et al., 2024]. Observational analyses using CCFs generally have shown evidence of a positive low-cloud feedback [Cesana & Del Genio, 2021; Ceppi et al., 2024; Ceppi & Nowack, 2021]. For subtropical low clouds, increased SST yielding reduced low cloud amount ($-2.4\text{ \%}/\text{K}$ average from satellite products) and enhanced inversion strength yielding increased low cloud amount ($1\text{ \%}/\text{K}$ average from satellite products) have been found to be dominant factors [IPCC AR6 WGI, 2023; Cesana et al., 2023]. An analysis of CCFs using ridge regression of satellite observations suggests a moderately positive global low-cloud feedback of $0.45\text{ W m}^{-2}\text{ K}^{-1}$, or roughly twice the mean value ($0.22\text{ W m}^{-2}\text{ K}^{-1}$) found from 16 CMIP general circulation models (GCMs) [Ceppi et al., 2024]. This difference is attributed to an underestimation of present-day tropical marine low-cloud amount by GCMs, as low-cloud sensitivity to warming is proportional to this amount [Ceppi et al., 2024]. While GCMs have long been evaluated with satellite observations as benchmarks, recent evidence suggests that such observations of short-term cloud feedbacks are likely inappropriate for evaluating long-term feedbacks [Chao et al., 2024].

The CCF approach has been applied primarily to marine low clouds, with less focus on high clouds despite their significant contribution to uncertainty [Grise & Tselioudis, 2024, and references therein; Kemsley et al., 2024]. Nevertheless, candidate CCFs for high clouds, such as upper tropospheric static stability, sub-cloud moist static energy, convective available potential energy (CAPE), convective inhibition (CIN), and upper-tropospheric wind shear have recently been explored [Kemsley et al., 2024].

2.1.2. Satellite Sensors and Analysis Methods

Successful remote sensing of clouds requires observations with sufficient inherent information to determine cloud parameters, and analysis algorithms that can successfully extract that information. Sensors can be either *passive*, measuring signals for which the sun is the source of electromagnetic radiation, or *active* measuring signals for which they themselves provide the source of radiation. Remote sensing system designs are characterized by seven types of resolutions defining the information gathered by a measurement system:

1. horizontal spatial resolution, the horizontal size of the observational ‘footprint’,
2. vertical resolution, the number of layers the atmospheric column corresponding to the horizontal ‘footprint’ is being resolved into.

3. temporal resolution, the frequency of observations
4. spectral resolution, the distinct parts of the electromagnetic spectrum that can be observed,
5. geometric resolution, the number of different vantage points geometries the footprint can be viewed from (many sensors have just one view-angle),
6. polarimetric resolution, sensitivity to the electromagnetic radiation's polarization state.
7. radiometric resolution, the number of bits/counts the signal can be discretized into

Ultimately, what is important is the “coverage” of the measurements – how much of the Earth's area, atmospheric vertical column, time period, spectral range, geometry (angles), and dynamic range can be measured at once or aggregated. A sensor is likely to always observe some signals with “high” resolution, but sacrifice coverage for others. For example, one sensor might provide detailed vertical, spectral, angular and/or polarimetric information at one point once a year, while another might provide only multispectral information, but over a large portion of the globe every few minutes. Sufficiently characterizing the accuracy, precision and uncertainties of the observed signals is critical, and guides the resolution at which the GV is retrieved. Thus due to engineering, technological, cost and/or other limitations, we must choose among these ‘resolutions’ appropriately for the intended purpose – in this case cloud remote sensing. Table 2 lists several types of satellite instruments that have been used for cloud remote sensing.

Table 2: Satellite instruments that have been used for cloud remote sensing, and their respective seven “resolutions” (see bullet list above). P& CCM: Prelaunch and continuous calibration monitoring.

Horizontal spatial	Vertical spatial	Temporal/ coverage	Spectral	Geometric	Polarimetric	Instruments	Radiometric
Moderate (1-10km) horizontal	Column averaged*	<3 day revisit, global	VIS-SWIR, IR multispectral	Single view	n/a	MODIS, VIIRS, EarthCARE MSI	P&CCM
Coarse (>10km)	Column averaged	<3 day revisit, global	IR/MW sounders/imagers	One view	n/a	AIRS, CRIS, AMSU, AMSR, ATMS	P&CCM
Moderate (1-10km)	Column averaged	<3 day revisit, global	UV-SWIR, hyperspectral	One view	n/a	OCI, TROPOMI	P&CCM
Moderate (1-10km)	Column averaged	<3 day revisit, global	VIS-NIR multispectral	2-9 views	n/a	MISR, SLSTR	P&CCM
Moderate (1-10km)	Column averaged	<3 day revisit, global (varies)	VIS-NIR multispectral or hyperspectral	2-60 views	Linear (I,Q,U)	POLDER, HARP2, SPEXone	P&CCM
Moderate (1-10km)	Vertically resolved, depends on product	~30 day revisit, global	UV, VIS channel (varies)	One view	Depolarization	ICESat-2, CATS, CALIOP, ATLID	P&CCM
Moderate (1-10km)	Vertically resolved, depends on product	~30 day revisit, global		One view	n/a	CloudSat CPR; EarthCare Doppler CPR	P&CCM
Moderate (1-10 km)	Column averaged	~10 mins (e.g. 144 x day) revisit, geostationary	VIS-IR multispectral	One view	n/a	ABI, AHI, AML, FCI	Prelaunch
Coarse (~ hundred km)	Limb, vertically resolved	~ 16 days revisit, global	MW, sub-mm	One view	Polarized	MLS, SMILES	P&CCM

*: the “column-integrated” or “top layer of the column” are omitted to save space, but should be considered in addition when “column-averaged” is written.

The satellite sensors listed in Table 2 and their observations have been used to study cloud feedbacks. Synergistic retrievals combine active (lidar/radar) and passive sensors (spectroradiometer, polarimeter) for more comprehensive global distributions and radiative impacts of clouds [Tan et al., 2023; SK, personal communication].

The methodological approaches of these studies vary and depend on datasets used and/or the science question at hand:

- A variety of statistical approaches are used, including:
 - Coupling cloud radiative kernels (CRKs) with anomalies of cloud property histograms retrieved from satellites to estimate cloud feedbacks in investigate cloud radiative effects [Soden et al., 2008; Zelinka et al., 2012; Chao et al., 2024; Raghuraman et al., 2024; Myers et al., 2021; Cesana et al., 2023; Chao et al., 2024; Raghuraman et al., 2024; Tan et al., 2024], coupling retrieved cloud property histograms with cloud radiative effects (CREs) derived from satellite observations of broadband radiances to evaluate cloud representation in GCMs [Schuddeboom & McDonald, 2021], combining satellite retrieved cloud property histograms and scalar statistics with model fields to estimate effective radiative forcing due to aerosol-cloud interactions (ERFaci) [Wall et al., 2022a; Duran et al., 2024] and effective climate sensitivity (ECS) [Sherwood et al., 2020; Wall et al., 2022a] (with several studies leveraging satellite datasets designed specifically for global model evaluations, such as MODIS MCD06COSP [Pincus et al., 2023]); Using CRK methods to study aerosol-cloud interactions [Wall et al., 2022a; Duran et al., 2024].
 - Comparing scalar statistics (means, variances) of satellite retrievals and/or models [Grosvenor et al., 2018; Kahn et al., 2023a];
 - Investigating correlations between satellite cloud retrievals and meteorological variables [Coopman & Tan, 2023]; performing regression analyses of satellite retrievals and/or models [Dessler & Forster, 2018; Mace et al., 2021];
 - Using cloud controlling factor (CCF) analysis to investigate cloud changes and feedback mechanisms [Zelinka et al., 2020; Wall et al., 2022a; Myers et al., 2023; Ceppi et al., 2024; Grise & Tselioudis, 2024; Kemsley et al., 2024; Tan et al., 2024];
 - Employing clustering algorithms to investigate changes and feedbacks associated with specific cloud mixtures/morphologies [Schuddeboom & McDonald, 2021; Tselioudis et al., 2021; Grise & Tselioudis, 2024; Tan et al., 2024; Cho et al. 2024], including Self-Organizing Map (SOM) clustering [Schuddeboom & McDonald, 2021];
 - Using analyses of time series of satellite retrieved cloud and model derived properties and radiative quantities to understand changes in cloud radiative effects, feedbacks, and climate sensitivity [Andrews et al., 2022; Raghuraman et al., 2023];
 - Exploiting active sensor statistics to investigate cloud-precipitation processes, including Contoured Frequency by Optical Depth Diagrams (CFODD) [Suzuki et al., 2024];
 - Using statistical sampling methods, including Monte Carlo [Dessler & Forster, 2018] and bootstrapping [Kemsley et al., 2024], as a means to interrogate large datasets;

- **Mathematical approaches** such as Taylor Series approximation and decomposition have been used to provide observational constraints on cloud feedbacks by partitioning contributions from individual cloud types [Myers et al., 2021; Myers et al., 2023; Chao et al., 2024; McKim et al., 2024]
- **Opportunistic experiments** like volcanic emissions and ship tracks have been used to investigate aerosol-cloud interactions and estimate their radiative forcing [e.g., Yuan et al., 2022; Yuan et al., 2023; Yuan et al., 2024].
- **A variety of ML/AI methods** have been used to enable 3D cloud reconstruction from passive imagery [e.g., Haynes et al., 2021; Noh et al., 2022; Wang et al., 2025], create derived datasets and counterfactual scenarios for aerosol-cloud interactions [e.g., Yuan et al., 2022; Yuan et al., 2023; Yuan et al., 2024; Chen et al., 2024], classify cloud types [Ceppi et al., 2024; Wang et al., 2020], retrieve cloud properties [Cheng et al., 2024], and retrieve aerosol and raindrop properties [Tan et al., 2024].
- **A wide range of models** have been used at various spatial/temporal scales:
 - General Circulation Models (GCMs), including CMIP5 [e.g., Sherwood et al., 2020; Ceppi & Nowack, 2021; Ceppi et al., 2024; Kemsley et al., 2024], CMIP6 [e.g., Sherwood et al., 2020; Ceppi & Nowack, 2021; Cesana and Del Genio 2021; Cesana et al., 2022; Wall et al., 2022a; Myers et al., 2023; Ceppi et al., 2024; Duran et al., 2024; Kemsley et al., 2024], GISS-ModelE3 [e.g., Cesana et al., 2021], and LMDZ5A/CAM5/ECHAM-6.1.05 [Bony et al., 2016]; specific uses include investigating impacts of improvements in simulating warm rain probability on cloud lifetime feedback [Mulmenstadt et al., 2021], evaluating simulated cloud and precipitation properties against satellite [e.g., Tselioudis et al., 2021] and ground-based [Stanford et al., 2023] observations, coupling with satellite-derived cloud radiative kernels to investigate marine low cloud response to changes in SST patterns and meteorology [Myers et al., 2023], and investigating the dependence of radiative feedback on SST change patterns from multi-decadal simulations [Andrews et al., 2022].
 - Cloud resolving models, or large eddy simulations (LES), to investigate cloud life cycle and net radiative effects [e.g., Hartmann et al., 2018]
 - Analytical models derived from satellite meteorological and cloud observations to simulate cloud coverage changes [Elsaesser et al., 2022].

2.1.3. Remaining Science Gaps

- **Cloud Feedback as the Largest Source of Uncertainty:**
Clouds remain the leading source of uncertainty in Earth's climate response to anthropogenic forcing and a major source of uncertainty in global climate projections [Ceppi and Nowack, 2021, Grise et al., 2024, IPCC AR6 WGI Chapter07, Kemsley et al., 2024, Liu, 2022, Loveridge 2024,

Mulmenstadt et al., 2021, Suzuki et al., 2024, Tan et al., 2023, Tan et al., 2024, Wang et al., 2021, Yuan 2023]. This uncertainty is often expressed via the wide range of modeled and observed ‘cloud feedback,’ namely the temperature-mediated response of cloud properties and radiative fluxes to a global surface -temperature increase caused by the radiative energy imbalance of the climate system [Mulmenstadt et al., 2021]. The diversity of cloud feedback is the primary source of the spread in projected surface temperature responses to anthropogenic forcing and has persistently been identified as the largest source of inter-model spread in effective climate sensitivity (ECS) across several generations of climate models [He 2021]. While a synthesis of existing evidence suggests cloud feedback is likely positive [IPCC AR6], amplifying global warming, constraining the values of feedback within a narrow range remains elusive [Ceppi and Nowack, 2021, Kemsley et al., 2024, Mulmenstadt et al., 2021, Tan et al., 2023, Suarez et al., 2023]. The uncertainty in cloud feedback stems from our limited capability in observing and simulating the diversity of cloud types, multiscale turbulent interactions, microphysics of phase changes, interactions with large-scale circulations, and observational difficulties [Suarez et al., 2023].

- Persistent Uncertainties in Low Cloud Feedbacks:

The response of low clouds to warming constitutes a key uncertainty for climate projections [Ceppi et al., 2024, Cesana and Del Genio, 2021]. Tropical low-cloud feedbacks dominate the spread among Earth system model (ESM) estimates of equilibrium climate sensitivity (ECS) [Cesana et al., 2023]. While recent research shows a positive low-cloud feedback and this component is no longer the largest source of uncertainty in total cloud feedback [IPCC AR6 WGI Chapter07], the magnitude of the tropical low-cloud feedback still exhibits substantial uncertainty, with values in models ranging roughly from $-1 \text{ W m}^{-2} \text{ K}^{-1}$ to $2 \text{ W m}^{-2} \text{ K}^{-1}$ (e.g., Cesana et al., 2023, Cesana & Del Genio, 2021; Klein et al., 2017). Observational analyses and high-resolution models suggest tropical marine low clouds exhibit a positive feedback, driven by increasing sea surface temperature, but the response of trade cumulus may be weaker than stratocumulus [Tan et al., 2024, Suarez et al., 2023]. Uncertainties remain regarding the mesoscale organization of low clouds and interactions with the underlying ocean surface, which are important factors modifying the low-cloud response [Tan et al., 2024, Suarez et al., 2023]. How regional low-cloud feedbacks differ across timescales and between ocean basins and their relationship to ocean dynamics are emerging topics requiring more investigation [Suarez et al., 2023]. Some models systematically underestimate present-day tropical marine low-cloud amounts, a bias that leads to underestimation of low-cloud response to warming [Ceppi et al., 2024].

- High (Anvil) Cloud Feedbacks as a Major Uncertainty Source:

Uncertainty from high cloud types combined is approximately equal to that of low-cloud types combined [Sherwood et al., 2020]. Anvil cloud feedbacks are still leading sources of uncertainty in quantifying climate sensitivity [McKim et al., 2024, Sullivan & Voigt, 2021]. Uncertainty

remains regarding how high cloud properties – amount, altitude, and optical depth – respond to warming [Raghuraman et al., 2024]. The mechanism underlying a thinning of high clouds is unclear, including whether it is induced by precipitation efficiency changes [Raghuraman et al., 2024]. Simulating the growth of the precipitating stratiform anvil region is challenging for GCMs due to crude parameterization of de-trained ice [Elsaesser et al., 2022]. How tropical anvil areal extent will change and modulate radiation as the climate warms is one of the largest uncertainties in recent cloud feedback assessments [Elsaesser et al., 2022]. Determining how high clouds respond to their cloud controlling factors requires further work [Chao et al., 2024]. Upper-tropospheric static stability (SUT) is highlighted as an important CCF for high clouds and longwave cloud feedback, and its inclusion in observational constraint frameworks may reduce uncertainty associated with changes in anvil cloud amount as a function of climate change [Kemsley et al., 2024].

- **Mixed-Phase Clouds and Cloud Phase Feedback Uncertainty:**

Representing mixed-phase clouds (consisting of both liquid droplets and ice crystals) in numerical models is one of the largest sources of uncertainty in predicting our future climate [Coopman and Tan, 2023, Murray et al., 2021]. Climate models often assume liquid droplets and ice crystals are uniformly mixed, contrary to observations showing separate pockets [Coopman and Tan, 2023]. This difference impacts cloud lifetime and the role of mixed-phase clouds in climate change [Coopman and Tan, 2023]. The Wegener-Bergeron-Findeisen (WBF) process, where ice crystals grow rapidly at the expense of liquid droplets, is physically well-understood but challenging to represent in ESMs due to scale differences and the inability to adequately resolve cloud phase heterogeneity [Burrows et al., 2022, Suzuki et al., 2024].

The magnitude of the negative cloud-phase feedback (i.e., feedback due to the transition from ice to more reflecting liquid clouds as the climate warms) depends on poorly known factors such as the amount and nature of INPs, their sources, concentration, and seasonal cycles. Their rudimentary treatment in climate models leads to substantial uncertainties [Coopman and Tan, 2023, Murray et al., 2021, Zamora et al., 2018] and possibly overestimates of the magnitude of the cloud-phase feedback [Murray et al., 2021].

- **Challenges in Representing Cloud Processes in Models:**

General circulation models (GCMs) are unable to explicitly represent small-scale cloud processes on their coarse spatial grids, resulting in a large spread in their simulation of cloud feedback and contribute partially to the uncertainty of cloud feedback uncertainties [Ceppi and Nowack, 2021, Grise et al., 2024]. Even in high-resolution models like cloud-resolving models, subgrid-scale processes, including cloud microphysics, must still be parameterized, some of which involve coupling with aerosol as cloud condensation nuclei (CCN) or ice nuclei (IN), and the associated uncertainties propagate to larger-scale values like cloud feedback parameters (e.g., microphysical schemes that are coupled with large-scale thermodynamics or aerosols) [Sullivan & Voigt, 2021,

Tan et al., 2023]. The diversity in model cloud feedbacks arises partly from the parameterization of clouds and their coupling to other sub-grid-scale processes [IPCC AR6 WGI Chapter07]. Structural parameterization errors are rarely tuned away in GCMs and manifest as biased regional rainfall distributions, tropical variability modes, and cloud feedbacks [Elsaesser et al., 2022].

- **Uncertainties in Cloud Controlling Factor (CCF):**

The cloud controlling factor approach, which estimates temperature-mediated cloud response based on observed relationships between clouds and large-scale meteorological variables, has been used to constrain cloud feedback [IPCC AR6 WGI Chapter07, Grise et al., 2024, Kemsley et al., 2024, Naud et al., 2023]. However, the choice of meteorological CCFs is crucial for a meaningful constraint, and there is less research explicitly targeting high clouds compared to low clouds [Kemsley et al., 2024, Grise et al., 2024]. While this approach allows estimation of cloud response without relying on uncertain simulated cloud properties, it assumes other feedback processes are unbiased [IPCC AR6 WGI Chapter07]. A fundamental unknown in climate science is whether mechanisms operating over shorter timescales (like interannual variability), which inform CCF analyses, are also the dominant mechanisms behind feedbacks that occur on longer timescales relevant to climate change [Stephens et al., 2023].

- **Aerosol-Cloud Interactions (ACI) and Ice Nucleating Particles (INPs):**

ACI is one of the dominant sources of uncertainty in projections of future climate change [Loveridge et al., 2024, Yuan et al., 2023]. Uncertainty in ACI dominates the overall uncertainty in knowledge of radiative forcing of Earth's climate [Tan et al., 2023]. The complex microphysical pathways through which aerosols influence clouds (directly and indirectly) and limitations in modeling/measuring these processes contribute to uncertainty [Loveridge et al., 2024]. While some studies suggest ACI affects cloud cover via precipitation inhibition, new findings show cloud cover can increase even as rainfall strengthens, proposing alternative mechanisms that require further testing [Chen et al., 2024]. Despite recent advances, uncertainties in how aerosols affect precipitation and ice nucleation rates contribute to large uncertainties in model cloud fraction and phase [Zamora et al., 2018]. Understanding the effect of small-scale mixing including its potential to reduce cloud lifetime and affect cloud cover, requires more studies [Suarez et al., 2023]. Atmospheric ice-nucleating particles (INPs) are required to initiate ice formation in clouds and play a critical role in cloud freezing processes with implications for precipitation and radiative properties [Burrows et al., 2022]. The efficiency of black carbon as an INP is currently highly uncertain [Suzuki et al., 2024].

- **Uncertainties Across Different Regions and Cloud Types:**

Extratropical low-altitude clouds are a significant contributor to uncertainty in climate sensitivity [Mulmenstadt et al., 2021]. Extratropical cloud feedback, particularly the shortwave feedback, bears further investigation as shifts in this quantity between climate model generations can lead to

substantial differences in ensemble ECS [Suzuki et al., 2024]. The scientific understanding of processes underpinning extratropical SW cloud feedback remains elusive, including ice nucleation and the representation of the WBF process [Suzuki et al., 2024]. Arctic clouds are especially poorly represented in climate models, and a better process-level understanding is needed to reduce the spread in model representations [Suzuki et al., 2024]. Supercooled clouds over polar regions also exert substantial radiative impacts, but major uncertainties in their representation in models arise from knowledge gaps concerning processes affecting cloud life cycles [Silber et al., 2021]. It is quite possible that CCFs and their relationships identified for tropical clouds will not hold in the dynamically different extratropics [Naud et al., 2023].

2.2. Potential Progress in the Next Five Years

- **New Satellite Missions and Sensor Capabilities:**

Numerous recent and forthcoming satellite missions are expected to provide significant contributions towards addressing the cloud-related science objectives of the 2017-2018 Decadal Survey. Multi-angle/multi-spectral shortwave polarimeters, such as SPEXone and HARP2 on the PACE observatory (launched February 2024), 3MI on METOP-SG (launch date: August 2025), and PolCube (proposed; partnership between NASA LaRC and the Korea Astronomy and Space Science Institute), are expected to provide enhanced information content on cloud and aerosol microphysics, aerosol typing, etc., that can inform on aerosol-cloud interactions. The collective passive and active payload of EarthCARE (launched May 2024), including a single-wavelength HSRL (ATLID), single-frequency Doppler radar (CPR), multi-spectral shortwave imager (MSI), and broadband SW/LW radiometer (BBR), is expected to provide new insights into clouds, aerosols, and the interactions between them and with atmospheric radiation [e.g., Lamer et al., 2020; Silber et al., 2021; Suzuki et al. 2024; Tan et al. 2023]; likewise for the envisioned active/passive payload, and dual orbits (polar, inclined), of the Atmosphere Observing System (AOS), the mission concept that emerged out of the 2017-2018 Decadal Survey ACCP Study [e.g., Lamer et al., 2020; Tan et al. 2023]. Observations of far-infrared emission, to date not systematically obtained from spaceborne platforms, from PREFIRE (launched May 2024) and FORUM (expected launch in 2026) are expected to provide new insights into the optical properties and microphysics of thin ice clouds [L'Ecuyer et al., 2021]. The radiometer and three Ka-band radars of INCUS ([link](#); launch date 2027) will enable a new time-differencing approach that can provide insight into the convective processes influencing high anvil clouds. Sub-mm radiometers (e.g., AWS, ICI, PolSIR) are expected to help improve anvil modeling and bettering our understanding and modeling of CCP processes. Libera will build on CERES heritage with improved radiometric accuracy and a new “split-shortwave” channel partitioning the reflected solar irradiance into visible and NIR contributions (van den Heever et al., 2025).

- **Advanced Analytical and Observational Methods:**

- **Cloud Controlling Factors (CCF) Analysis:** This method helps understand and constrain cloud variability and trends by exploiting observed relationships between satellite cloud observations and meteorological variables [Kemsley et al., 2024]. It is advantageous for climate models as it does not rely on cloud parameterizations or satellite simulator output [Grise et al., 2024]. While widely applied to low clouds, more systematic application to high clouds is a focus for future research [L. Oreopoulos, pers. comm., Kemsley et al., 2024].
- Artificial Intelligence (AI)/Machine Learning (ML):
 - **Cloud Detection and Properties:** ML-based methods (e.g., random forest, neural networks) have improved low-level cloud detection in multilayer scenes, increasing the probability of detection (PoD) from **0.685 to 0.815** [Haynes et al., 2021]. ML can potentially convert 2D passive cloud fields into 3D fields using collocated active sensor data [L. Oreopoulos, pers. comm., Wang 2025]. ML is also being explored for improved nighttime and multilayered cloud retrievals using Day/Night Band (DNB) data [Noh et al., 2022].
 - **Aerosol-Cloud Interactions (ACI):** AI/ML is used to create "counterfactual worlds" in natural experiments (e.g., volcanic eruptions, ship tracks) to compare clouds with and without aerosol perturbations, providing robust new constraints for climate models [Chen et al., 2022, L. Oreopoulos, pers. comm.].
 - **Aerosol Properties:** An ML-based paradigm is proposed for retrieving aerosol light absorption (ABS) and Cloud Condensation Nuclei (CCN) concentrations from satellite lidar measurements, providing vertically resolved CCN to within **30% uncertainty** in 85% of retrievals when trained with airborne HSRL-2 data and reanalysis. Simulating EarthCARE ATLID observations with noise-added UV lidar data yielded CCN within **50% uncertainty** in 83% of retrievals, a performance noted as "far beyond any published physics-based lidar retrievals" [Redemann and Gao, 2024]. ML could also be a promising route for complex ice microphysics [Sullivan et al., 2023].
- **Double Decomposition Method for Cloud Feedback:** This novel method combines cloud radiative kernels and cloud regime concepts to decompose interannual cloud feedback into contributions from changes *within* and *shifts between* cloud morphologies [Zelinka et al., 2023].
- **Synergistic Active and Passive Remote Sensing:** The combination of active and passive satellite observations (as was done with observations from the A-train) is powerful for understanding cloud processes, vertical profiles, and some microphysical properties, and has improved cloud type discrimination, leading to more accurate cloud feedback inferences [Cesana et al., 2023, S. Kato, pers. comm.]. These analyses, including atmospheric cloud radiative effect, need to continue with future collocated active and passive observations [S. Kato, pers. comm.].

- **Trajectory-Enhanced Soundings:** This methodology extends snapshots of low-Earth-orbiting (LEO) soundings up to **6 hours** into the future using parcel forward-trajectory calculations. This approach fills temporal gaps in thermodynamic fields, enabling the study of trends in conditions favorable for convection from stable, single-instrument records [Kahn B. et al., 2023b, Richardson et al., 2023].
- **Suborbital (airborne and ground-based) observations:** Ground-based observations, while spatially sparse, provide high-temporal-resolution, long-term statistics and direct measurements (e.g., from balloon soundings) that complement satellite data and are crucial for validation of satellite retrievals [McKenna et al., 2023, Wang et al., 2024]. Miniaturizing instruments for Uncrewed Aerial Systems (UASs) and tethered balloons can facilitate more regular profiling to validate and enhance satellite/reanalysis products (Zamora et al., 2025). In addition, extensive datasets from recent field campaigns such as ARCSIX, PACE-PAX, and WH2yMSIE, along with upcoming campaigns such as NURTURE and INSPYRE, each having (or expected to have) suites of advanced in situ and remote sensing instrumentation, can be expected to provide new insights into cloud processes and radiation interactions, and can enable development/evaluation of new synergistic retrieval techniques.
- **Methods Not Yet Fully Utilized/Under Development:**
 - **Cloud Tomography:** Further development of cloud tomography techniques using 3D radiative transfer to include microwave measurements will help to self-consistently measure the cloud particle size spectrum [Loveridge et al., 2024].
 - **Polarimetric Retrievals in Heterogeneous Clouds:** The performance of polarimetric techniques in heterogeneous clouds for satellite sensors is still underexplored, with effects of resolution and co-registration uncertainty yet to be examined [Loveridge et al., 2024].
 - **Inferring Convective and Large-Scale Mass Fluxes:** Combining cloud-top dynamics diagnosis with analysis approaches that add a time dimension to satellite observations to infer convective and large-scale mass fluxes separately [Kikuchi et al., 2023].
 - **New Multi-Sensor Synergies:** Nascent efforts towards new multi-sensor synergies are being explored, for instance combining stereo cloud heights (MISR) and single-view IR radiances (MODIS) to retrieve the properties of multi-layer clouds, an approach demonstrated on limited datasets but not yet applied systematically [Mitra et al., 2023].
- **Improvements and Better Uses of Models**
 - **Satellite Simulators:** Satellite simulators (e.g., CFMIP Observational Simulator Package, COSP) are crucial for robustly comparing model output with satellite retrievals by accounting for observational biases and algorithm differences [McCoy et al., 2023, Kikuchi et al., 2023]. They allow for "scale-aware and definition-aware" evaluations [Kikuchi et al., 2023]. Ground-based simulators in COSP have been implemented to facilitate

comparisons with ground-based observations [McCoy et al., 2023]. It is important for modeling centers to implement these simulators and make their output publicly accessible [Tan et al., 2024].

- **Calibrated Physics Ensembles (CPE):** The GISS model is incorporating "aerosol" into its CPE, which aims to consider a wide range of cloud properties relevant to cloud feedback (e.g., stratocumulus and shallow cumulus diagnostics) beyond just cloud radiative effects [A. Fridlind, pers. comm., Elsaesser et al., 2025]. This involves using observation-constrained large perturbed parameter ensembles enabled by emulators [A. Fridlind, pers. comm.].
- High-Resolution Modeling:
 - **Cloud-Resolving Models (CRMs) and Large Eddy Simulations (LES):** These models are advancing the understanding of physical mechanisms and improving the prediction of low-cloud feedbacks [Myers et al., 2023, Sherwood et al., 2020]. Resolving sub-kilometer scales improves cloud representation and reduces precipitation biases [Myers et al., 2023]. Longer simulations with finer resolution and larger domains in LES will allow the simulation of mesoscale circulations' impact on feedbacks [Sherwood et al., 2020].
 - **Global Convection-Permitting and Storm-Resolving Models:** With horizontal grid-spacings of a few kilometers, these models are becoming feasible and are expected to provide further insights into Mesoscale Convective Systems (MCSs) and their response to climate change [Chakraborty et al., 2023, Sullivan et al., 2023, Sherwood et al., 2020].
 - **Addressing Model Biases:** Better process-level understanding of Arctic mixed-phase clouds is needed to reduce model spread [Zelinka et al., 2021; Tan et al., 2023]. Model biases in warm rain formation significantly impact cloud feedbacks and climate sensitivity, highlighting the need for improvement [R. Wood, pers. comm.; Mülmenstädt et al., 2021]. Cloud cover bias across CMIP6 models result in a low-bias in CCF, which can be constrained using satellite observations [Ceppi et al., 2024].
- **Paleoclimate Data Assimilation:** Using paleoclimate data, such as proxies for rain and convective-stratiform cloud ratios, helps constrain model skill and identify optimal parameter choices that best match historical records. This can, in turn, better constrain Equilibrium Climate Sensitivity (ECS) [G. Elsaesser, pers. comm., Ramos et al., 2022, T. Yuan., pers. comm.].
- **Process-Oriented Evaluation:** A strong emphasis should be placed on understanding cloud and precipitation properties from a process-oriented perspective. This involves using a simulator approach to account for observational limitations and ensure consistency with model physics [McKenna et al., 2023, Stanford et al., 2023]. Future analyses should simultaneously evaluate thermodynamic and cloud conditions across multiple sites to

establish robust process-based mechanisms and address biases [McKenna et al., 2023, Stanford et al., 2023].

- **Integrated Approaches:** Advancing the "cloud problem" requires simultaneous progress in understanding water vapor, precipitation, thermodynamics, dynamics, radiation, turbulence, and microphysics, as these aspects are interconnected [B. Khan, pers. comm.].
- **Connecting Observing System Requirements to Process Questions:** This can be achieved within a climate Observing System Simulation Experiment (OSSE) framework by using observation-constrained large perturbed parameter ensembles [A. Fridlind, pers. comm.].

- **Modeling Capabilities Not Yet Fully Utilized/Under Development:**

- **Prognostic Ice Nucleating Particle (INP) Capability:** Most regional and global models currently lack this capability, which is necessary to distinguish the impacts of cloud processes (activation and removal) on existing aerosol populations and avoid biases [Burrows et al., 2022].
- **Improved Ice Cloud Microphysics:** Further progress in understanding cold clouds requires improved representations of ice cloud microphysics within models [Sherwood et al., 2020].
- **Expanded Precipitation Diagnostics and Simulators:** Future expansion of these tools in large-scale GCMs is critical, as many cloud-related mechanisms depend on accurate precipitation characterization [McCoy et al., 2023].
- **Convective Ice Outflow and Warm Conveyor Belt Dynamics:** Improving the representation of these processes remains a very long-term goal for climate models, including storm-resolving models [A. Fridlind, pers. comm.].

2.3. Limitations that Cannot be Addressed Using Contemporary Observations

2.3.1. Profiles of aerosol microphysical, optical and chemical properties

- Satellites have provided global insights into atmospheric aerosols, but they have not yielded sufficient data to notably reduce uncertainties in aerosol climate forcing due to limitations in accuracy, spatiotemporal resolution, and coverage [Redemann and Gao, 2024].
- Only lidar observations provide the crucial vertically resolved aerosol information needed to address the most uncertain aerosol climate interactions [Redemann and Gao, 2024].
- Current satellite measurements and physics-based retrieval approaches struggle to constrain aerosol light absorption (ABS) and cloud condensation nuclei (CCN), but global vertical distribution observations are urgently needed to constrain Earth System Models (ESMs) [Redemann and Gao, 2024].

- Space-borne remote sensing instruments cannot reliably retrieve CCN and ice-nucleating particle (INP) concentrations at a spatial resolution sufficient for cloud process modeling, especially for very small aerosol particles ($<0.1\ \mu\text{m}$) [Tan et al., 2023].
- Satellites also cannot provide chemical information about CCN or INPs [Chakraborty et al., 2023].
- The source term for CCN in the remote Southern Ocean is still poorly understood [McCoy et al., 2023].

2.3.2. Aerosols near clouds

- Passive satellite sensors are often unable to see through clouds, preventing them from providing information on overlapping layers of aerosol and cloud [Chakraborty et al., 2023].
- Information about aerosol properties near cloud boundaries is unreliable [Marshak et al., 2021; Chakraborty et al., 2023].
- Passive satellite aerosol retrievals are more uncertain in cloudy regions, and cloud retrievals are more uncertain in environments with abundant aerosols. This makes it challenging to clearly quantify how aerosol and cloud changes independently influence trends in absorbed solar radiation (ASR) [Marshak et al., 2021; Loeb et al., 2024b].
- It is challenging to define clouds accurately and distinguish them from aerosols embedded in seemingly clear-sky regions. The local radiative effect of clouds on their surroundings can be very large, with clouds significantly enhancing the aerosol radiative effect in the solar spectrum [Eytan, 2025; Marshak et al., 2021].

2.3.3. Cloud optical/microphysical properties

- Ice Water Path (IWP) retrievals are basically too uncertain to be widely useful, and total Liquid Water Path (LWP) from MAC-LWP is not available at the pixel level and has crude uncertainty estimates [A. Fridlind, pers. comm.].
- Precipitating ice and drizzle are very poorly observed by CloudSat due to a lack of sensitivity, especially over the sparsely observed Southern Ocean [A. Fridlind, pers. comm.].
- Quantifying ice clouds from satellite instruments is difficult due to the physics of atmospheric ice. While optical and infrared sensors can detect ice clouds, signal attenuation often limits observations to cloud-top information [Duncan & Eriksson 2018]. Note that PREFIRE radiometers are expected to be highly sensitive to low optically thin clouds, especially when they are primarily composed of ice crystals [L'Ecuyer et al., 2021].
- Satellite-derived cloud column droplet number concentration (Nd) estimates have high uncertainties: 78% for pixel-level retrievals and 54% for 1x1 degree averages. This uncertainty is primarily driven by errors in effective radius (re) retrievals [Grosvenor 2018]. Observations are substantially worse for cumulus clouds [Grosvenor 2018].

- Bi-spectral retrievals, like those from MODIS, make strong assumptions (e.g., Independent Pixel Approximation, Plane-Parallel Homogeneous Assumption), leading to errors. For moderately oblique solar zenith angles ($<45^\circ$) in heterogeneous clouds, cloud optical depth is typically underestimated by -35% , and effective radius is overestimated by $\sim 20\%$, resulting in a large underestimate of droplet number concentration (implied error of -67.5%) [Loveridge, 2024].
- MODIS cloud-top height (CTH) retrieval precision is impacted by forward-modeling uncertainty, with a bias of approximately -540 ± 690 m [Cheng et al., 2024]. For previous data versions, MODIS CTHs showed a deviation from CALIPSO results of approximately -1.4 ± 2.9 km [Cheng et al., 2024]. Multi-layer clouds pose significant challenges for MODIS CTH due to limited vertical detectivity [Cheng et al., 2024].
- Satellite observations underestimate the occurrence of mixed-phase clouds over the Southern Ocean [Wang et al., 2024; Ahn et al., 2018]. CALIPSO slightly underestimates the thickness of the mixing region in mixed-phase clouds. Microphysics assumptions could result in discrepancies in retrieving the same cloud parameter using the same Level-1 observation (e.g., CloudSat significantly overestimates it, and DARDAR underestimates it [Wang et al., 2024]). Algorithms for differentiating supercooled liquid water from ice particles at lower temperatures still have large uncertainties [Wang et al., 2024].
- From modeling perspective, mixed-phase clouds are often crudely represented in global models, oversimplifying complex microphysical processes like nucleation and secondary ice formation [Matus and L'Ecuyer 2017].

2.3.4. Spatial and temporal sampling

- The highly limited spatio-temporal sampling of CloudSat–CALIPSO leaves many open questions regarding the variability of atmospheric ice, from diurnal to intraseasonal timescales [Duncan & Eriksson 2018; Stubenrauch et al., 2024].
- Space-based radar and lidar products have relatively limited spatial coverage compared to passive satellite sensors [Liu, 2022].
- Studies using simulated cloud fields have typically examined small domains (on the order of 10 km), failing to resolve the full range of spatial and microphysical structures in clouds [Loveridge, 2024].
- Satellite cloud observations for radiation budget analyses rely mainly on two polar-orbiting satellites (Terra and Aqua) separated by 3 hours, which are insufficient to observe cloud diurnal cycles and daily mean radiation budget [S. Kato, pers. comm.]. Geostationary data has started to be used to fill-in the diurnal gaps (e.g., GEO used in the CERES new products). While future observations may only come from one afternoon orbit, they are generally deemed sufficient to monitor changes [S. Kato, pers. comm.; NOTE: EBAF has already transitioned to NOAA-20 because of the Aqua and Terra orbit drifts].

- Subgrid distribution of satellite cloud fraction (e.g., CERES FBCT, MODIS COSP) is only available during daytime [Chao et al., 2024].

2.3.5. Coverage in challenging regions

- Low-altitude clouds over the Southern Ocean are poorly represented in global climate models and reanalysis products, leading to persistent biases in the energy budget [Ahn et al., 2018]. These clouds frequently contain ice, which complicates MODIS optical property retrievals and leads to high failure rates (42% with the 3.7- μm channel) [Ahn et al., 2018].
- Estimates at the poles are particularly challenging due to long periods of darkness, low sun angles, high likelihood of overcast, and the prevalence of ice-containing clouds (Duncan et al., 2020) .
- Space-based active lidar and radar detect 25%–40% fewer clouds below 0.5 km and 0%–25% fewer between 0.5–1.0 km compared to surface observations over the Arctic land area [Liu, 2022]. These detection limitations result in uncertainties in monthly mean cloud radiative effect (CRE) of up to 2.5 W m^{-2} at the surface and 3.4 W m^{-2} at the TOA, and up to 30 W m^{-2} for individual cases [Liu, 2022].
- Active space-borne lidar cannot penetrate entire cloud layers with optical thicknesses greater than approximately 5 [Tan et al., 2023]. The synergistic use of radar and lidar still fails to observe the lowest kilometer of the atmosphere due to radar ground clutter and lidar beam attenuation [Tan et al., 2023].
- Retrievals in the visible wavelengths are impossible during high-latitude winter and challenging when the sun is low in the sky [McCoy et al., 2023].

2.3.6. Disentangling aerosol, cloud effects from meteorological influences

- A major challenge in quantifying aerosol-cloud interactions (ACIs) is that aerosols often co-vary with meteorological factors that control clouds, making it difficult to disentangle direct causal relationships from meteorological variability [Oreopoulos et al., 2020; Chen et al., 2022; Chen et al., 2024; Malavelle 2017; Wall C. et al., 2022a; Tan et al., 2023].
- Climatological analyses of ACI correlations, while suitable for large-scale models, can be contaminated by meteorological co-variability [Chen et al., 2024].
- The causality behind correlations between aerosol proxies and mesoscale convective system (MCS) properties cannot be established from remote sensing alone [Chakraborty et al., 2023]; however, recent advances in statistical methods make it possible to gain some insight into ACI causality when satellite data are used in conjunction with models and reanalysis products (e.g., Zamora and Kahn, 2020; Zamora and Kahn, 2024).

2.3.7. *Disentangling cloud feedbacks*

- The Cloud Radiative Effect (CRE) is not equivalent to cloud feedback because CRE includes clear-sky fluxes that may also be changing [L. Oreopoulos, pers. comm.]. Cloud feedback is specifically defined as the change in radiative flux due to changes in cloud properties, *while everything else remains constant* [L. Oreopoulos, pers. comm.]. Hence, the adjusted CRE method is proposed in some literature (e.g., Soden et al., 2008).
- CRE is a poor proxy for cloud feedback as it is a convolution of forcing, cloud masking, and cloud feedbacks [Raghuraman et al., 2023].
- A key limitation of relying solely on observations is the difficulty in isolating underlying processes that contribute to TOA radiation changes [Loeb et al., 2024a]. Changes in cloud cover in response to SST increases imply a feedback, but a contribution from radiative forcing or internal variability cannot be ruled out [Loeb et al., 2024b].
- Uncertainty in how clouds respond to anthropogenic forcing is the primary difficulty in estimating climate sensitivity [Pincus et al., 2023].
- Observations alone are insufficient to understand cloud feedback because changes with and without radiative forcing are needed [S. Kato, pers. comm.].
- The cloud feedback in response to short-term climate fluctuations may differ from the long-term feedback relevant to equilibrium climate sensitivity (ECS) [Chao et al., 2024].
- Model skill in simulating short-term cloud feedbacks is not correlated with skill in simulating long-term cloud feedbacks [Chao et al., 2024]. Therefore, feedbacks quantified on observable timescales are not interchangeable with the long-term feedbacks that largely determine ECS [Chao et al., 2024].
- Mechanisms observed over shorter time spans may not be the dominant mechanisms for feedbacks that operate on longer timescales [Stephens et al., 2023]. For example, observed thickening and brightening of anvil clouds on interannual timescales are not reflected in climate model responses [Stephens et al., 2023].
- Observational estimates of cloud feedback (using cloud-controlling factors) are based on the assumption that long-term feedbacks can be inferred from shorter-timescale (daily-interannual) cloud responses to temperature [McCoy et al., 2023].

2.3.8. *Integrating satellite, suborbital, and model data*

- A multi-platform approach integrating satellite measurements with ground-based and in situ observations is critical for understanding the context [B. Khan, pers. comm.] and making further progress on MCS-microphysics and -aerosol interactions [Chakraborty et al., 2023].
- Satellite simulators (e.g., CFMIP Observational Simulator Package - COSP) are necessary to address sampling and retrieval limitations and enable consistent comparisons between model output and satellite retrievals [McCoy et al., 2023; Stanford et al., 2023; Pincus et al., 2023;

Kikuchi et al., 2023; Tan et al., 2023]. In particular, the Earth Model Column Collaboratory (EMC2) radar and lidar instrument simulator is used to account for instrument sensitivities and ensure coherent comparison of model output with observations [Stanford et al., 2023].

- Machine learning (ML) models trained with lidar data and in situ measurements can predict higher-level aerosol properties like aerosol light absorption (ABS) and CCN, which are difficult to constrain with current satellite measurements and physics-based retrieval approaches [Redemann and Gao, 2024]. Similarly, ML models trained with radar data can help extract vertical information of cloud embedded in the passive wide-swath measurements [e.g., Noh et al., 2021].
- Observational campaigns using ground-based instruments provide unique detailed insights into cloud processes that space-based instruments cannot resolve, particularly near the surface where ground clutter affects radar and signal attenuation affects lidar [Liu et al., 2022].

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