A Survey of Mixed-Phase Clouds and Remote Sensing Technologies

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Abstract

This survey provides a comprehensive examination of mixed-phase clouds and the remote sensing technologies utilized in their study, emphasizing their significance in atmospheric science. Mixed-phase clouds, characterized by the coexistence of supercooled liquid droplets and ice crystals, present complexities in climate modeling due to intricate microphysical interactions and aerosol influences. The survey delves into the characteristics and formation of these clouds, highlighting their impact on climate feedback mechanisms and the challenges they pose in accurate climate predictions. Remote sensing technologies, such as polarized lidar and millimeter-wave cloud radar, are pivotal in atmospheric profiling, offering enhanced accuracy in cloud detection and phase classification. Recent advancements in these technologies, alongside innovative methodologies like multi-task learning frameworks, have refined cloud property retrieval and atmospheric profiling. The survey identifies current challenges, including technological and methodological hurdles in remote sensing, and proposes future research directions focused on expanding observational networks and improving data coverage. These efforts are crucial for advancing our understanding of cloud processes and their implications for climate systems, ultimately contributing to more accurate and reliable climate models. The integration of diverse datasets and sophisticated modeling techniques continues to push the boundaries of atmospheric research, enhancing predictive capabilities regarding weather and climate phenomena.

1 Introduction

1.1 Structure of the Survey

This survey provides a thorough exploration of mixed-phase clouds and the remote sensing technologies used in their investigation. Following the introduction, the paper is organized into several key sections, each addressing specific aspects of the topic. Section 2 offers background information and definitions, covering mixed-phase clouds, cloud phase, and microphysics, while defining critical terms such as polarized lidar and millimeter-wave cloud radar, underscoring their significance in meteorological research. Section 3 discusses the characteristics and formation of mixed-phase clouds, alongside the challenges they pose for climate modeling, supported by recent findings. The impact of cloud microphysics on climate feedback mechanisms is also examined. Section 4 focuses on remote sensing technologies, particularly polarized lidar and millimeter-wave cloud radar, detailing recent advancements and inherent limitations. Section 5 investigates cloud microphysics, emphasizing the optical and physical properties of cloud particles, microphysical processes related to ice formation, and the influence of aerosols and subpollen particles. Section 6 showcases applications and case studies that illustrate the practical use of remote sensing in atmospheric research. Section 7 addresses current challenges in studying mixed-phase clouds and remote sensing technologies, proposing future research directions and technological advancements. Finally, Section 8 concludes the survey by summarizing key points, reiterating the subject's importance, and highlighting the potential impact of future research in this domain.The following sections are organized as shown in Figure 1.

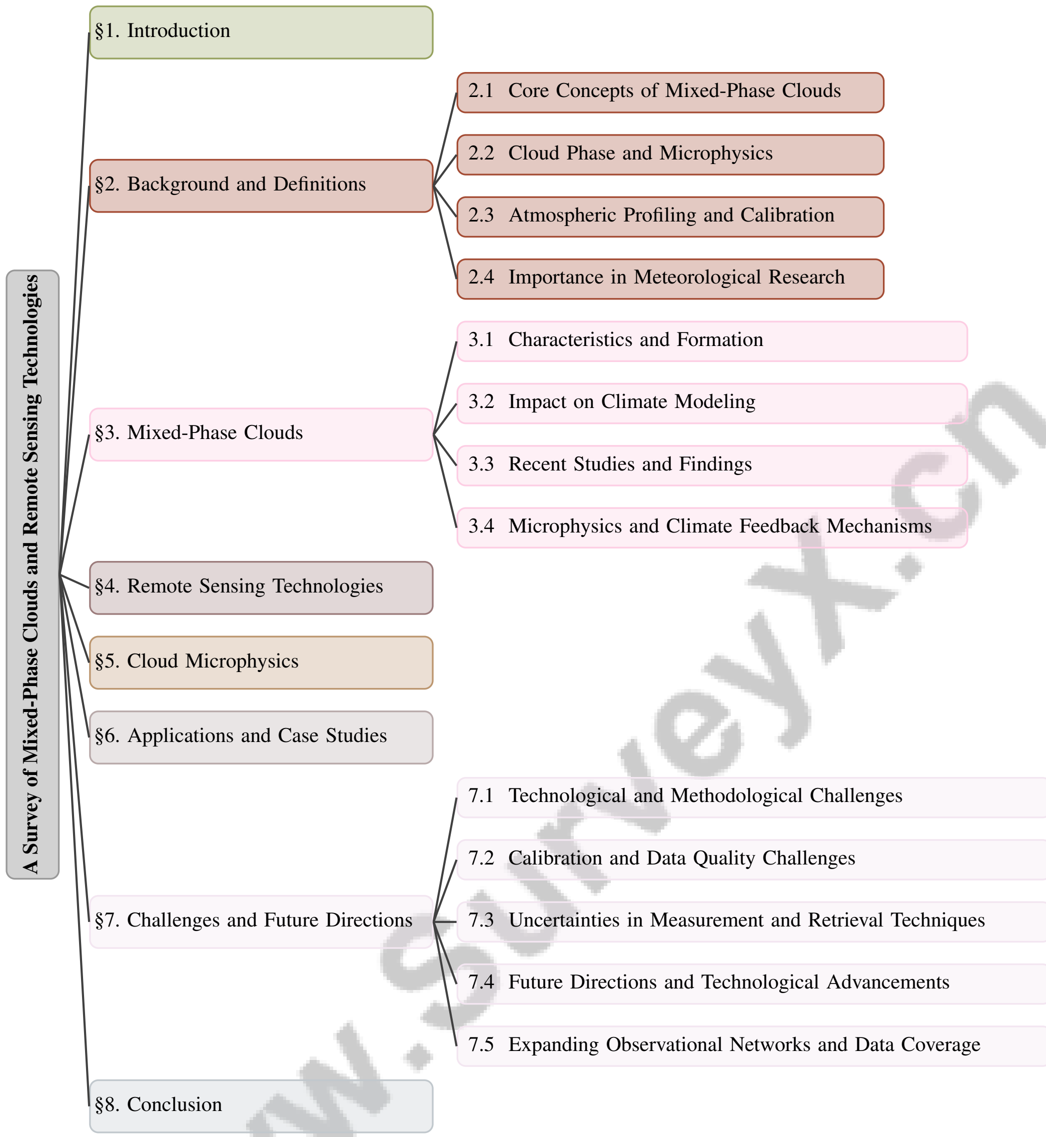

Figure 1: chapter structure

2 Background and Definitions

2.1 Core Concepts of Mixed-Phase Clouds

Mixed-phase clouds, characterized by the coexistence of supercooled liquid droplets and ice crystals, are crucial to atmospheric dynamics and significantly influence the Earth's climate. These clouds are prevalent during marine cold-air outbreaks (MCAOs) in the Arctic, contributing to unique climatic conditions [1]. The coexistence of liquid and ice phases complicates cloud modeling and atmospheric predictions, necessitating precise classification of cloud types within the mixed-phase temperature regime to comprehend glaciation processes and their climate implications [2].

A significant challenge in studying mixed-phase clouds is accurately retrieving cloud properties such as masking, phase classification, and cloud optical thickness (COT) from satellite data [3]. Misidentification, especially between liquid and mixed-phase clouds, often arises due to systematic biases in lidar systems' ability to measure backscattered signals, leading to substantial errors in climate modeling and weather predictions [4].

The formation of primary ice particles in mid-level stratiform mixed-phase clouds is influenced by aerosols, which act as ice nucleating particles (INPs) and cloud condensation nuclei (CCN), affecting

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ice nucleation processes [5]. Understanding aerosol effects on stratiform, orographic, and deep convective mixed-phase clouds is essential for elucidating the microphysical processes governing cloud dynamics and precipitation patterns [6].

Microphysical interactions within mixed-phase clouds, such as the seeder–feeder mechanism, are crucial for precipitation initiation and development, influenced by thermodynamic conditions like supersaturation distributions. A comprehensive understanding of cloud dynamics and their radiative feedback mechanisms is vital for refining climate models and enhancing predictive accuracy for weather and climate phenomena. Recent advancements in turbulence-resolving simulations and observational techniques have illuminated the complexities of mixed-phase clouds, a significant source of uncertainty in climate projections. Accurately representing these clouds and their interactions is essential for better estimating future warming and anticipating climate change impacts [7, 2, 8].

2.2 Cloud Phase and Microphysics

The phase state of clouds—liquid, ice, and mixed-phase—is pivotal in determining cloud dynamics and their atmospheric impacts. Mixed-phase clouds, with supercooled liquid droplets and ice crystals, exhibit complex microphysical interactions influenced by local dynamics and environmental conditions, affecting their persistence and properties [9].

A critical aspect of cloud microphysics is the activation of cloud condensation nuclei (CCN), which shapes the droplet size spectrum and precipitation potential. The supersaturation budget within a cloud is vital in this activation process, dictating droplet formation [10]. This process is further complicated by aerosols acting as both CCN and INPs, thereby influencing microphysical properties and radiative forcing [6].

The transition between cloud phases, such as from stratocumulus to cumuliform, is often driven by ice formation, impacting cloud morphology and dynamics [1]. Ice crystals modify the cloud's radiative properties and precipitation efficiency, influencing broader atmospheric conditions.

Additionally, the hygroscopic growth of subpollen particles (SPP) as CCN is crucial for understanding their impact on cloud formation and atmospheric processes [11]. These particles can significantly alter microphysical characteristics, affecting cloud development and precipitation likelihood.

2.3 Atmospheric Profiling and Calibration

Atmospheric profiling is essential in meteorological research, offering detailed vertical profiles of parameters like temperature, humidity, and aerosol concentration, critical for understanding weather patterns and validating satellite observations. Ground-based sky imagers (GSIs) have emerged as cost-effective alternatives to satellite measurements, providing valuable data for Earth observations [12]. However, continuous measurement of aerosol and cloud vertical structures remains challenging, particularly for long-term climate change studies and satellite validation.

Remote sensing technologies, particularly LIDAR (Light Detection and Ranging), play a crucial role in atmospheric profiling by delivering high-resolution vertical profiles. These systems can operate effectively in challenging conditions, such as fog and low clouds, utilizing polarization techniques to enhance performance. Recent studies indicate that LIDAR can accurately measure atmospheric parameters, including cloud phase and aerosol classification, essential for understanding aerosol-cloud interactions. This capability is vital for improving weather forecasts and climate models, enabling precise observations of cloud development and atmospheric influences [13, 14, 4, 15]. Nonetheless, LIDAR performance can be impeded under low visibility conditions, complicating accurate atmospheric profile retrieval. Advanced calibration techniques are employed to enhance the reliability of remote sensing data.

Calibration is crucial in remote sensing, enhancing measurement precision and accuracy vital for image analysis and interpretation. This process ensures that data from remote sensing technologies, such as satellite imagery, can be reliably used for various applications, including environmental monitoring. By maintaining measurement integrity, calibration supports the integration of advanced techniques from Natural Language Processing and knowledge distillation, improving computational efficiency and model performance in remote sensing tasks [16, 17]. The Extended Three-Signal Calibration Approach (ETSC) for three-signal polarization LIDAR systems adjusts for elliptically polarized light and cross talk among detection channels, improving atmospheric constituent characterization. Integrating Raman LIDARs with other monitoring devices enhances data accuracy by providing complementary measurements that correct systematic errors.

The detection of Cherenkov light from extensive air showers offers a novel method for analyzing atmospheric distribution and properties of clouds and aerosols [18], exemplifying the integration of multiple sensing modalities for comprehensive atmospheric profiling.

Reliable calibration targets are essential for precise electromagnetic property measurements, particularly beyond 20 GHz, crucial for advanced remote sensing applications. Enhancing accuracy and reliability in remote sensing data relies on sophisticated calibration techniques and robust atmospheric profiling methods that account for systematic errors, significantly improving our understanding of atmospheric processes, including aerosol-cloud interactions, and reducing uncertainties in climate predictions [17, 15, 19]. These advancements support satellite observation validation and climate change studies.

2.4 Importance in Meteorological Research

Mixed-phase clouds are vital in meteorological research due to their intricate interactions with atmospheric processes and significant influence on global climate systems. The simultaneous presence of supercooled liquid droplets and ice crystals introduces substantial uncertainties in climate models, particularly in accurately representing cloud phase and supercooled liquid water distribution, which are critical for predicting climate dynamics [7]. The degree of glaciation in mixed-phase clouds remains a major uncertainty in climate prediction, highlighting the need for improved cloud phase identification.

Remote sensing technologies, such as polarized Micro Pulse Lidar (MPL) systems, are essential for profiling atmospheric conditions and analyzing cloud properties. However, calibrating these systems, especially for weakly depolarizing layers, is a significant challenge that must be addressed to ensure data reliability [20]. Accurate identification of cloud regions in remote sensing images is complicated by similar reflection characteristics between clouds and surfaces like snow and ice, underscoring the need for precise data interpretation [21].

Retrieving accurate aerosol optical depth (AOD) values from satellite remote sensing and reconciling them with ground-based measurements is crucial for improving aerosol characterization, a key component of meteorological research [22]. The climate effects of aerosols, both directly and through cloud interactions, remain uncertain, necessitating comprehensive four-dimensional observations of aerosols and clouds [13].

Understanding cloud microphysics, including spatial variability of drop size distribution (DSD), is vital for accurate precipitation remote sensing, a fundamental aspect of meteorological research [23]. The study of secondary ice formation, particularly around -15 °C, reveals that existing models may underestimate secondary ice production in mixed-phase clouds [24]. Furthermore, inadequate measurements of water vapor density, ash mass distribution, and particle sizes in volcanic eruption clouds hinder accurate modeling and forecasting of ash dispersion, emphasizing the need for enhanced observational capabilities [25].

The performance and data quality of remote sensing instruments, such as Cherenkov telescopes, are significantly influenced by atmospheric conditions, necessitating robust calibration techniques to account for variations in atmospheric transmission affecting data reconstruction [26]. Additionally, the seeder–feeder process is critical for improving weather forecasts and climate models, influencing precipitation patterns and cloud dynamics [27]. Continuous advancements in remote sensing technologies and calibration methods are essential for enhancing our understanding of mixed-phase clouds and their meteorological impact, contributing to more accurate climate modeling and improved predictive capabilities regarding weather and climate phenomena.

The integration of advanced methodologies, such as MT-HCCAR, leveraging multi-task learning to enhance cloud property retrieval accuracy across different satellite sensors, exemplifies progress in remote sensing technology [3]. These technological advancements are crucial for refining our understanding of cloud processes and their implications for climate prediction and atmospheric science.

In recent studies of atmospheric sciences, the understanding of mixed-phase clouds has become increasingly critical due to their significant impact on climate modeling and weather prediction.

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Figure 2 illustrates the hierarchical structure of mixed-phase clouds, focusing on their characteristics, impact on climate modeling, recent research advancements, and microphysics. This figure categorizes key atmospheric conditions, modeling challenges, influential factors, and observational techniques, emphasizing the complex interactions and feedback mechanisms involved. By analyzing these elements, researchers can better comprehend the intricate dynamics of cloud formation and its implications for climate systems.

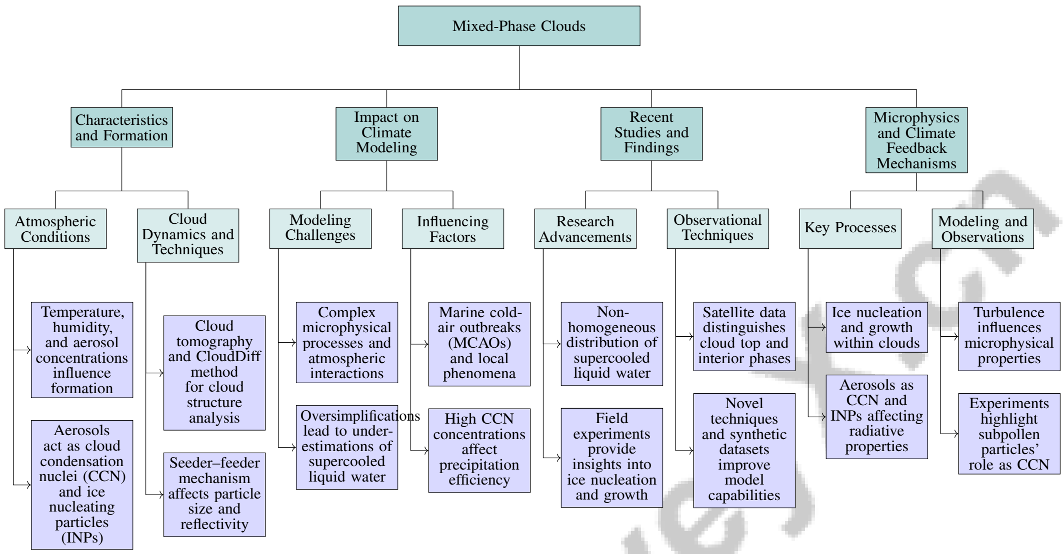

Figure 2: This figure illustrates the hierarchical structure of mixed-phase clouds, focusing on their characteristics, impact on climate modeling, recent research advancements, and microphysics. The diagram categorizes key atmospheric conditions, modeling challenges, influential factors, and observational techniques, emphasizing the complex interactions and feedback mechanisms involved.

3 Mixed-Phase Clouds

3.1 Characteristics and Formation

Mixed-phase clouds, featuring both supercooled liquid droplets and ice crystals, form under specific atmospheric conditions including temperature, humidity, and aerosol concentrations. Aerosols serve as cloud condensation nuclei (CCN) and ice nucleating particles (INPs), significantly influencing cloud microphysics and precipitation dynamics [15, 5]. These factors impact cloud top temperature (CTT) and liquid water path (LWP), which are vital for understanding ice production [28]. In orographic clouds, both warm and cold, CCN and INPs modulate supercooled water content and precipitation efficiency. Techniques like cloud tomography are essential for examining cloud structure and improving property retrieval [29]. The CloudDiff method enhances understanding of cloud dynamics during high-impact weather events by addressing retrieval uncertainties [30].

The seeder–feeder mechanism affects mixed-phase clouds by increasing particle size and reflectivity [27]. Cloud particle micro-porosity also influences optical properties [31]. Persistent low-level mixed-phase clouds can be analyzed by evaluating their profiles and surface coupling [9]. Multiwavelength-polarization lidar aids in categorizing aerosols and clouds, clarifying mixed-phase cloud evolution [13]. Radiative transfer models simulate light interactions with planetary atmospheres, enhancing understanding of mixed-phase cloud radiative impacts [32]. Despite these advancements, differentiating primary and secondary ice formation remains challenging [24].

3.2 Impact on Climate Modeling

Mixed-phase clouds present significant challenges in climate modeling due to their complex microphysical processes and atmospheric interactions. Assuming a homogeneous mixture of ice and liquid particles leads to underestimations of supercooled liquid water and biases in climate sensitivity [33].

These oversimplifications hinder accurate climate predictions by failing to capture the spatial and temporal variability of mixed-phase clouds.

During marine cold-air outbreaks (MCAOs), factors influencing ice formation significantly affect cloud dynamics and climate feedback mechanisms [1]. Radar reflectivity simulation uncertainties, arising from hydrometeor-related model parameters, complicate cloud and precipitation measurements, impacting climate model reliability [34]. Current methods inadequately address local boundary layer dynamics and surface interactions, particularly in complex environments like Arctic fjords, creating substantial knowledge gaps about mixed-phase cloud behavior. Local and large-scale phenomena, such as katabatic winds and regional wind direction, influence cloud characteristics and persistence [7, 9, 5, 6]. Kilometer-scale variability in drop size distribution (DSD) further complicates climate modeling and precipitation estimation.

The seeder–feeder process enhances precipitation efficiency by transferring moisture and ice crystals between cloud layers, presenting measurement challenges. Monitoring multiple cloud layers with high temporal and vertical resolution is necessary to analyze these interactions [11, 23, 27, 28]. High CCN concentrations can enhance snow precipitation in orographic clouds by altering microphysics and local circulation patterns, emphasizing the need for improved aerosol-cloud interaction parameterization in models. Limitations in cloud classification methods, particularly in determining small cloud particle phases, impede understanding of mixed-phase cloud dynamics. Misclassification due to polarimetric lidar biases can lead to significant errors, affecting cloud property comprehension and surface energy budget evaluations [2, 4, 24]. Inadequate radar sampling of weather echoes further complicates accurate cloud process representation in climate models.

Addressing these challenges requires sophisticated modeling and remote sensing technologies to capture the complex interactions within mixed-phase clouds and their climate implications. The innovative MT-HCCAR approach, with a hierarchical classification network, exemplifies progress in enhancing cloud property retrieval [3].

As illustrated in Figure 3, the hierarchical structure of challenges and advancements in climate modeling related to mixed-phase clouds encompasses key areas such as cloud microphysics, local dynamics, and innovative approaches like MT-HCCAR, thereby providing a visual context that complements the discussion of these intricate processes.

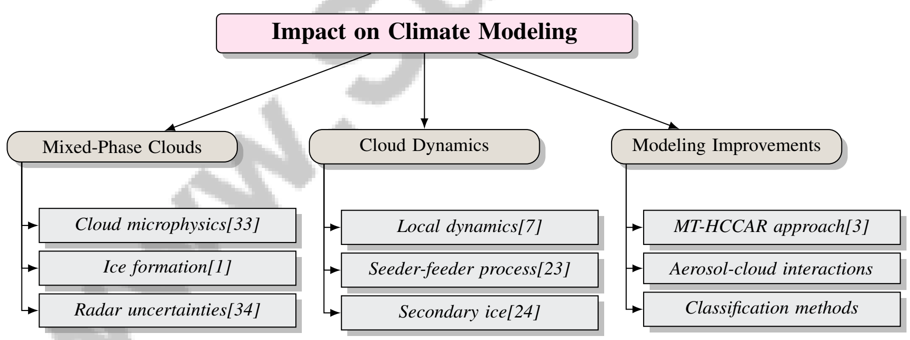

Figure 3: This figure illustrates the hierarchical structure of challenges and advancements in climate modeling related to mixed-phase clouds, cloud dynamics, and modeling improvements. Key areas include cloud microphysics, local dynamics, and innovative approaches like MT-HCCAR.

3.3 Recent Studies and Findings

Recent research has advanced understanding of mixed-phase cloud behavior and atmospheric impacts. The non-homogeneous distribution of supercooled liquid water challenges traditional climate model assumptions, emphasizing the need for novel approaches [7]. This finding is crucial for refining cloud microphysics in climate models, affecting predictions of cloud radiative properties and feedback mechanisms.

Variability in cloud feedback estimates, particularly shortwave feedback, contributes to significant inter-model spread, highlighting the necessity for improved parameterization [35]. Addressing these discrepancies is vital for enhancing climate projection reliability. Experiments using synthetic datasets for cloud type and optical thickness prediction show promise for real satellite applications, improving classification and retrieval accuracy [36]. However, geographical biases in cirrus cloud studies limit capturing diverse climatic characteristics [37], underscoring the need for comprehensive observational campaigns. Field experiments at Jungfraujoch have provided insights into mixed-phase cloud microphysics, enhancing understanding of ice nucleation and growth processes [24].

Ongoing research and technological advancements are essential for understanding mixed-phase cloud behavior and atmospheric influence. These clouds, characterized by ice and supercooled liquid water coexistence, significantly affect climate projections due to interactions with anthropogenic aerosols. Research shows mixed-phase clouds are prevalent in regions like the Arctic, where conditions such as cloud top cooling and strong updrafts influence formation. Advances in observational techniques, such as satellite data distinguishing cloud top and interior phases, reveal mixed-phase clouds are often more liquid at the top, impacting climate models underestimating future warming. Understanding these dynamics is crucial for improving climate models and accurately predicting mixed-phase cloud impacts on climate systems [7, 5, 6, 24]. Novel observational techniques and synthetic datasets show promise for overcoming limitations and enhancing climate model capabilities.

3.4 Microphysics and Climate Feedback Mechanisms

Cloud microphysics and climate feedback mechanisms are crucial for understanding mixed-phase clouds' implications on climate systems. Cloud microphysics, involving particle behavior and properties, significantly influence radiative processes and climate feedback loops [33]. The coexistence of liquid droplets and ice crystals leads to unique feedback mechanisms challenging current climate models.

Advancements have elucidated key microphysical processes within mixed-phase clouds, such as ice nucleation and growth, critical for accurately modeling cloud dynamics and climatic impacts [6]. Aerosols acting as CCN and INPs complicate interactions, affecting cloud radiative properties and precipitation efficiency. The vertical distribution of microphysical properties, organized by cloud phase, plays a crucial role in determining radiative impacts [38]. Supercooled liquid water and ice crystals affect cloud albedo and longwave radiation balance, influencing climate feedback mechanisms. Theoretical frameworks underscore the need for accurate cloud microphysics representation in models to enhance predictive capabilities.

Turbulence within clouds significantly influences microphysical properties, particularly in mixed-phase conditions. It alters particle distribution and interactions, affecting cloud dynamics and climate feedback [10]. This complexity requires sophisticated modeling to capture cloud microphysics' dynamic nature. Experiments on hygroscopic growth of subpollen particles (SPP) highlight their role as CCN, especially at high humidity levels, impacting cloud microphysics and climate feedback mechanisms [11]. These findings enhance understanding of aerosol-cloud microphysics interactions, essential for improving climate models.

Studying cloud microphysics and climate feedback mechanisms is vital for advancing mixed-phase clouds' understanding and climatic implications. Ongoing research is crucial for improving predictions and mitigating climate change effects, focusing on clouds as a significant uncertainty source in climate models. Recent observational advancements, such as satellite differentiation of cloud-top and interior phases, reveal mixed-phase clouds are more liquid at tops globally. Incorporating this understanding into global models, like NorESM2, suggests up to 1°C increase in 21st-century warming. Refining cloud process representation, particularly for mixed-phase clouds, is essential, as modeling discrepancies can lead to substantial climate sensitivity and warming estimate variations. Continued innovation in observational methods and theoretical frameworks is vital for narrowing climate model projection ranges and addressing climate change impacts [7, 35].

4 Remote Sensing Technologies

4.1 Advancements in Remote Sensing

Recent advancements in remote sensing technologies have substantially improved our ability to observe atmospheric conditions, particularly mixed-phase clouds. By tracking air mass trajectories and collocating them with satellite data, researchers gain comprehensive insights into cloud dynamics and their climatic implications [1]. The integration of multi-grained angle representation techniques enhances angle prediction accuracy, merging coarse-grained angle classification with fine-grained angle regression to reduce computational complexity while improving precision [39]. This advancement refines atmospheric parameter retrieval and data interpretation.

A two-likelihood hierarchical model using Markov random field approximation effectively captures discrepancies across spatial information sources, bolstering atmospheric analyses' robustness and supporting climate modeling [19]. The MT-HCCAR model, an end-to-end deep learning framework, exemplifies progress in cloud property retrieval through multi-task learning [3]. This approach optimizes retrieval processes, enhancing the accuracy and efficiency of satellite data analysis.

Technological advancements in Lidar systems, particularly compact systems capable of real-time measurements without complex polarization-switching devices, have been noteworthy [40]. These innovations enhance remote sensing capabilities, providing high-resolution, real-time atmospheric profiles critical for understanding cloud microphysical processes and climatic impacts.

To illustrate these advancements, Figure 4 categorizes key developments in remote sensing into three main areas: cloud dynamics, technological innovations, and modeling and analysis. Each category highlights significant contributions from recent studies, showcasing improvements in understanding cloud behavior, technological progress in sensing equipment, and novel modeling techniques.

Innovations in deep learning techniques and sophisticated algorithms are pivotal for improving our understanding of atmospheric conditions. Fully Convolutional Neural Networks facilitate precise cloud detection in satellite imagery, while Knowledge Distillation streamlines model efficiency [21, 16]. Techniques like TECROMAC enable the recovery of cloud-contaminated satellite images, and advancements in polarimetric lidar systems enhance cloud phase determination, addressing biases in surface energy budget evaluations [41, 4]. Collectively, these innovations transform remote sensing, offering deeper insights into cloud behavior and atmospheric processes [17].

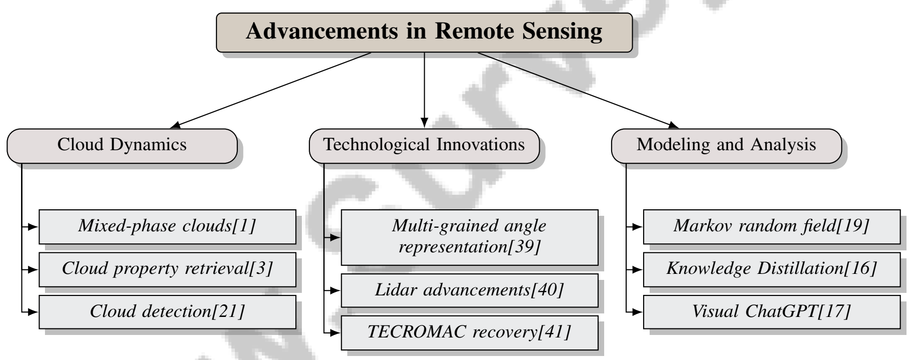

Figure 4: This figure illustrates the key advancements in remote sensing, categorized into cloud dynamics, technological innovations, and modeling and analysis. Each category highlights significant contributions from recent studies, showcasing improvements in understanding cloud behavior, technological progress in sensing equipment, and novel modeling techniques.

4.2 Advancements in Polarized Lidar Technology

Advancements in polarized lidar technology have significantly enhanced atmospheric condition studies, especially within mixed-phase clouds. Utilizing the polarization state of emitted lidar signals mitigates atmospheric interference, improving detection capabilities in low visibility conditions [14]. Scanning polarization lidar systems now measure crystalline particle orientation at two wavelengths, advancing ice cloud behavior understanding [42].

Enhancements in polarimetric lidar measurements through non-orthogonal polarization retrievals and advanced signal processing techniques improve cloud phase classification [4]. A comprehensive calibration method combining rigorous techniques with a rotating half-wave plate ensures high accuracy in polarimetric imaging [43].

The development of compact lidar systems using a polarization modulator, modulated by a 159-MHz RF signal, signifies a technological leap, providing real-time measurements without complex devices [40]. These advancements are crucial for understanding atmospheric processes and cloud dynamics, enabling accurate cloud phase measurements and addressing uncertainties in aerosol-cloud interactions [14, 15].

4.3 Millimeter-Wave Cloud Radar Innovations

Millimeter-wave cloud radar (MMCR) technology innovations have significantly improved cloud microphysical property observation, particularly in mixed-phase environments. Ground-based Ka-band MMCR systems, combined with microwave radiometer data, provide comprehensive insights into cloud vertical structure and dynamics [27]. Methods employing millimeter-wave frequencies matched to ash particle sizes enhance sensitivity to fine ash, crucial for assessing volcanic ash impacts [25].

Large-scale datasets integrating mmWave radar signals with synchronized RGB(D) images enable comprehensive cloud radar technology assessments, facilitating advancements in data interpretation [44]. Structured simulation frameworks incorporating sensitivity analyses of multiple hydrometeor parameters refine radar reflectivity simulation accuracy, enhancing cloud microphysics understanding and climate model reliability [34].

These MMCR advancements enhance comprehension of cloud dynamics and atmospheric processes, enabling accurate cloud microphysical property measurements and facilitating the observation of seeder-feeder interactions and volcanic ash monitoring [44, 25, 45, 27].

4.4 Remote Sensing and Cloud Detection

Remote sensing technologies have advanced cloud detection and analysis capabilities, with lidar technology playing a pivotal role. Polarized lidar, utilizing multiple planes of linear polarization and advanced detection schemes, has improved cloud phase classification accuracy under challenging conditions [40]. Concurrent detection of copolarization and cross-polarization components in systems like CAPCL simplifies measurement processes.

Integrating models like the Atmospheric Transmission Model (ATM) has refined cloud detection by accounting for atmospheric effects, leading to more accurate cloud removal and data interpretation. Frameworks like SEnSeI facilitate seamless integration of data from diverse multispectral sensors, enhancing remote sensing technologies' versatility [17, 16, 46].

Hybrid approaches combining thresholding techniques for snow identification with deep-learning algorithms for cloud detection have further enhanced accuracy. Calibration of polarimetric performance across various camera models has advanced polarized light detection and analysis, improving atmospheric observation precision [43, 47, 15].

The MGAR method has shown improvements in accuracy and speed for arbitrary-oriented object detection, supporting remote sensing technologies' advancement [39]. The dataset including 3D skeleton and mesh annotations, mmWave radar point clouds, and synchronized RGB(D) images enhances cloud property retrieval robustness [44].

These advancements in remote sensing technologies, including lidar innovations and sophisticated data integration frameworks, have significantly improved cloud detection and analysis. Ongoing advancements in global climate models and geospatial cyberinfrastructure deepen our understanding of atmospheric processes, facilitating precise climate sensitivity and rainfall detection predictions [8, 48].

5 Cloud Microphysics

5.1 Optical and Physical Properties of Cloud Particles

Understanding cloud microphysics hinges on the optical and physical properties of cloud particles, which significantly influence atmospheric radiation interactions. Particle size, shape, and refractive index are crucial as they determine light scattering and absorption, affecting clouds' radiative properties and climatic impact. The size distribution, encompassing droplets and ice crystals, dictates optical thickness and albedo, essential for climate modeling [33]. Variations in ice crystal morphology, driven by environmental conditions such as temperature and humidity, impact scattering phase functions and asymmetry parameters, complicating radiative transfer calculations [6]. Complex ice crystal shapes, like dendrites and columns, challenge theoretical models due to deviations from idealized geometries.

The refractive index, shaped by cloud particles' chemical composition, plays a pivotal role in optical behavior. Aerosols or impurities can alter refractive indices, affecting absorption and scattering, especially in mixed-phase clouds with coexisting liquid droplets and ice crystals [11]. Advancements in remote sensing, including polarized lidar and millimeter-wave cloud radar, have enhanced measurements of cloud particles' optical and physical properties. These technologies provide high-resolution data on particle size distribution, phase state, and optical depth, facilitating accurate cloud property retrieval and deeper microphysical understanding [40]. Multi-wavelength and polarization measurements aid in distinguishing liquid from ice phases, enhancing phase classification and reducing climate model uncertainties.

Comprehensive examination of cloud particles' optical and physical properties is vital for understanding their significant atmospheric impacts. Remote sensing advancements allow precise cloud phase determination and characterization, crucial for evaluating surface energy budgets and interpreting radiative effects of varied cloud compositions, including microporous and non-spherical particles in terrestrial and extraterrestrial atmospheres [31, 18, 4]. Continued research is essential for refining climate models and enhancing predictive capabilities regarding clouds' climatic effects.

5.2 Cloud Microphysics and Ice Formation

Ice formation in clouds is a pivotal aspect of cloud microphysics, influencing atmospheric dynamics and precipitation. Ice nucleating particles (INPs) and cloud condensation nuclei (CCN) are critical in transitioning supercooled droplets to ice crystals, affecting cloud phase, precipitation efficiency, and radiative properties [49]. Ice formation involves complex microphysical processes, including homogeneous and heterogeneous nucleation. Homogeneous nucleation occurs at low temperatures and high supersaturation, while heterogeneous nucleation is facilitated by INPs, lowering the energy barrier for ice formation. The efficiency of these processes is influenced by the chemical and physical properties of aerosols, impacting cloud microphysics and precipitation dynamics [11].

Advancements in remote sensing have improved real-time data capture on cloud particle concentrations and sizes, providing insights into cloud seeding effects on microphysical properties. These technologies enable evaluations of cloud seeding impacts, revealing changes in particle size distribution and concentration crucial for understanding ice formation dynamics and precipitation processes [49]. The role of subpollen particles (SPP) as CCN is increasingly recognized for their impact on cloud microphysics and climate change. SPP's hygroscopic growth under high humidity enhances their CCN activity, influencing cloud formation and properties, highlighting their importance in atmospheric studies [11].

Studying cloud microphysics and ice formation is essential for understanding atmospheric processes, including secondary ice formation mechanisms, which can increase ice crystal concentrations in mixed-phase clouds at around -15 °C. This understanding is crucial for refining climate models, particularly in accounting for ice number concentration variations influenced by aerosol loadings across hemispheres and seasons. Integrating these insights can enhance climate simulation accuracy and improve predictions of mixed-phase clouds' impacts on global and regional radiation budgets [5, 24]. Continued research and technological advancements are vital for enhancing predictive capabilities regarding cloud behavior and its climatic effects.

5.3 Influence of Aerosols and Subpollen Particles

Aerosols and subpollen particles (SPP) are significant in cloud microphysics, acting as cloud condensation nuclei (CCN) and ice nucleating particles (INP), influencing cloud formation, phase, and precipitation. Aerosols modify cloud microphysical properties by altering droplet and ice crystal size distribution and concentration, crucial for understanding cloud optical properties, radiative forcing, and precipitation dynamics [6]. Depending on their chemical and physical characteristics, aerosols can enhance or inhibit cloud formation. Some aerosols promote smaller, more numerous droplets, increasing cloud albedo and cooling the Earth's surface. Conversely, aerosols facilitating ice nucleation can result in larger ice crystals, enhancing precipitation efficiency and altering cloud dynamics [5].

SPP, smaller fragments from pollen grains, are recognized for their CCN role, particularly under high humidity. Their hygroscopic growth enhances CCN activity, influencing cloud microphysical properties, cloud lifetime, and precipitation patterns [11]. This interaction underscores the importance of including SPP in atmospheric studies and their implications for air quality and climate change.

Research on aerosols and SPP impacts on cloud microphysics is critical, as these particles influence the Earth's radiative balance by modifying cloud optical properties and precipitation processes. Advanced remote sensing and modeling approaches are essential for quantifying aerosols and SPP effects on cloud dynamics, improving climate models, and enhancing atmospheric process understanding. Continued research is vital for developing strategies to mitigate aerosols' complex climate and weather impacts, especially regarding their roles as CCN and INP in mixed-phase clouds. Understanding these interactions is crucial, as anthropogenic aerosols significantly influence cloud microphysics, radiative forcing, and climate feedback mechanisms, particularly in regions like the Arctic, where mixed-phase clouds are prevalent. Enhanced aerosol effect knowledge is necessary for improving global climate models and accurately predicting changes in cloud behavior and their subsequent effects on the Earth's radiation budget [11, 5, 6, 13].

6 Applications and Case Studies

6.1 Modeling and Simulation Techniques

Modeling and simulation are pivotal in understanding mixed-phase clouds, offering insights into their dynamics and climatic effects. Incorporating observational constraints enhances model precision, as demonstrated by the Temporal Scaling Function (TSF), which refines simulations of time-dependent optical properties [50]. Dual-wavelength polarization lidar facilitates precise characterization of cloud microphysical properties by measuring low particle depolarization ratios, crucial for accurate cloud phase classification [47]. Machine learning, such as neural network-based multivariate regression on aerosol optical depth data, further enhances model accuracy by addressing aerosol biases [22].

Disdrometer networks reveal small-scale spatial variability in drop size distribution, aiding model validation and precipitation simulation [23]. Super-resolution likelihood estimation (SLE) methods, using stereo images, improve spatial resolution and cloud height estimation, enriching model inputs [51]. Technologies like the Water Vapor and Ash Measurement System (WAMS) and LAMSkyCam contribute valuable data for model enhancement, with WAMS enabling real-time volcanic ash monitoring and LAMSkyCam providing high-frequency cloud imagery [25, 12].

A novel simulation framework achieves radar reflectivity prediction accuracy, with errors within 20

6.2 Cloud Seeding and Microphysical Interactions

Cloud seeding aims to enhance precipitation by introducing artificial ice nucleating particles (INPs), influencing microphysical processes. This technique alters the balance of cloud condensation nuclei (CCN) and INPs, affecting cloud formation and precipitation dynamics. Studies show effective precipitation enhancement through seeding, significantly impacting cloud microphysical properties [49]. Seeding agents like silver iodide modify cloud properties by increasing ice crystal concentrations and altering droplet size distributions, enhancing primary and secondary ice formation in mixed-phase clouds [11, 49, 5, 27, 24].

Cloud seeding effectiveness depends on existing microphysical properties, atmospheric conditions, and seeding agent types. Future research should focus on improving mixed-phase cloud representation in climate models through enhanced observations and modeling of aerosol-cloud interactions [6]. Understanding aerosols as CCN and INPs is crucial for predicting cloud seeding outcomes and broader atmospheric implications.

Cloud seeding's success relies on understanding microphysical interactions and employing advanced modeling techniques for accurate predictions. Continued research and technological advancements, particularly in cloud computing and machine learning, are vital for refining cloud seeding practices and addressing environmental impacts. Geospatial cyberinfrastructures like A2CI enhance atmospheric data analysis and visualization, improving cloud feedback models and climate prediction accuracy. Innovative approaches, such as synthetic datasets for cloud optical thickness estimation and advanced algorithms for cloud removal in satellite imagery, optimize remote sensing applications and support sustainable cloud seeding strategies [41, 36, 48, 17].

6.3 Data Analysis and Visualization

Integrating diverse data sources with advanced analysis and visualization frameworks is crucial for enhancing atmospheric understanding and improving climate models. The A2CI framework exemplifies this by providing a user-friendly environment for comprehensive data analysis and visualization [48]. Publicly accessible datasets, such as CloudSat and CALIPSO, form a robust foundation for atmospheric research, aiding in cloud detection and analysis [5].

Advancements in image-based retrieval methods, like ITLM, have improved cloud detection and analysis, outperforming traditional pixel-based models [52]. Performance metrics, including the Jaccard index, precision, recall, and overall accuracy, evaluate cloud detection algorithms, providing quantitative measures of reliability [21].

Integrating diverse datasets, such as MODIS, ERA5 reanalysis data, and CMIP6 model output, supports comprehensive observational frameworks for atmospheric research [33]. These datasets facilitate complex atmospheric interaction analysis, advancing climate models with high-quality data for input and validation.

Developing advanced frameworks for data analysis and visualization, supported by diverse datasets and robust evaluation metrics, is essential for advancing atmospheric research. These frameworks enhance the analysis of cloud dynamics and refine climate model accuracy, addressing uncertainties related to cloud feedback mechanisms, particularly in mixed-phase and low-level clouds. By integrating high-resolution satellite data and innovative computational techniques, these frameworks improve cloud process representation in global climate models and contribute to reliable future climate scenario projections [7, 48, 33, 53].

7 Challenges and Future Directions

7.1 Technological and Methodological Challenges

The study of mixed-phase clouds (MPCs) and their atmospheric interactions faces significant technological and methodological challenges, hindering advancements in remote sensing and climate modeling. A major issue is the lack of observational data on the hygroscopic properties of subpollen particles (SPP) at various relative humidities, which limits understanding of their role in cloud formation and atmospheric chemistry [11]. This gap complicates accurate modeling of cloud microphysical processes, as the roles of aerosols as cloud condensation nuclei (CCN) and ice nucleating particles (INP) are not well comprehended [6].

Remote sensing technologies are constrained by the complexity and cost of Lidar systems, which often require multiple detectors or polarization-switching devices for high-resolution atmospheric profiling [40]. These technological limitations restrict advanced Lidar deployment, affecting the collection of detailed atmospheric data essential for MPC studies.

Methodological challenges include integrating complex atmospheric conditions into remote sensing models. The MT-HCCAR method, for example, may falter in real-world applications due to simulated datasets' inability to capture atmospheric complexities [3]. Additionally, the periodicity of angle representations in remote sensing data can introduce ambiguities, complicating predictions for models reliant on angle regression [39]. These issues are exacerbated by a shortage of datasets for 3D body reconstruction from mmWave signals and inadequate performance evaluations under adverse conditions [44].

In cloud microphysics, the dearth of detailed observational data on ice nucleation processes in real atmospheric conditions presents a significant challenge [5]. Simplifications in radar signal models, such as neglecting receiver noise and ground clutter, introduce substantial uncertainties in cloud feedback predictions and climate sensitivity estimates [33].

Addressing these challenges is crucial for advancing our understanding of MPCs and their climatic impacts. Continued innovation in remote sensing technologies and refined data analysis methodologies are essential. Improved integration of anthropogenic aerosols' effects on MPCs and a deeper understanding of the microphysical processes governing their formation and dynamics are vital for future climate research. These advancements are particularly relevant given that aerosols can act as both CCN and INP, influencing cloud dynamics and radiative forcing, especially in the Arctic and orographic terrains where stratiform MPCs are prevalent. Recent studies highlight the need for improved models that accommodate these interactions, significantly affecting the estimated effective aerosol radiative forcing, currently around 1.2 W m2 for MPCs, with variations reflecting the complexity of these processes [11, 6].

7.2 Calibration and Data Quality Challenges

Benchmark	Size	Domain	Task Format	Metric
GPS-PWV[54]	1,000,000	Meteorology	Pwv Measurement Comparison	Correlation Coefficient, RMS Error
COT-Dataset[36]	200,000	Cloud Detection	Cloud Optical Thickness Estimation	Mean Absolute Error
mmBody[44]	200,000	3D Body Reconstruction	3D Mesh Reconstruction	Mean Joint Error, Mean Vertex Error

Table 1: Table showcasing representative benchmarks pertinent to various domains, including meteorology, cloud detection, and 3D body reconstruction. Each benchmark is characterized by its size, specific domain, task format, and the metrics used for performance evaluation. This comprehensive overview aids in understanding the scope and scale of datasets utilized in remote sensing and related fields.

Calibration and data quality are critical challenges in the effective application of remote sensing technologies for atmospheric research. Accurate calibration of polarized lidar systems is essential for reliable data retrieval, yet current methodologies face substantial limitations. Factors such as elliptically polarized laser light, angular misalignment of the receiver unit, and cross talk among receiver channels complicate precise depolarization measurement, crucial for accurate cloud phase classification [15]. These issues introduce uncertainties in lidar data, undermining the reliability of atmospheric profiling and cloud property retrieval.

The status of polarized lidar systems indicates ongoing challenges in achieving data accuracy due to calibration issues. Enhanced methodologies are necessary to process polarized lidar signals effectively, addressing limitations that affect atmospheric observations' precision [20]. These challenges highlight the need for advanced calibration techniques to mitigate systematic errors and improve lidar measurement fidelity.

Integrating diverse data sources, as seen in the A2CI framework, raises potential data quality concerns and reliance on external datasets, which can impact the overall reliability of analyses [48]. Ensuring consistency and accuracy across various platforms and sensors is crucial for maintaining the integrity of atmospheric research and supporting robust climate model development. Table 1 provides a detailed overview of representative benchmarks used in remote sensing and related domains, highlighting the diversity in dataset size, domain application, task format, and evaluation metrics.

Addressing calibration and data quality challenges is essential for enhancing remote sensing technologies' accuracy and reliability. This is particularly relevant as advancements in machine learning and knowledge distillation techniques improve model efficiency and performance, alongside innovative approaches like Visual ChatGPT and synthetic datasets for cloud optical thickness estimation, which offer new avenues for image analysis and interpretation [16, 41, 19, 36, 17]. Continued advancements in calibration techniques and data processing methodologies are vital for improving atmospheric observations' quality and supporting accurate representations of cloud microphysics in climate models.

7.3 Uncertainties in Measurement and Retrieval Techniques

Uncertainties in measurement and retrieval techniques present significant challenges in remote sensing, particularly in analyzing atmospheric processes and cloud microphysics. A primary source of uncertainty is distinguishing signal from noise, affecting atmospheric observations' accuracy. The model proposed by [19] exemplifies this challenge, as its lack of identifiability complicates the effective separation of true atmospheric signals from background noise, leading to substantial errors in retrieving cloud properties and atmospheric parameters.

Retrieving cloud microphysical properties, such as particle size distribution and phase state, is particularly vulnerable to uncertainties due to complex interactions between aerosols and cloud particles. Aerosols, acting as CCN and INP, introduce significant variability in cloud dynamics, complicating the quantification of their effects. Research indicates that CCN and INP interactions dramatically influence precipitation processes in warm and cold mixed-phase orographic clouds, with distinct mechanisms governing snow production in each case. For instance, high CCN concentrations can suppress precipitation in warm mixed-phase clouds but may enhance snow precipitation under certain conditions by promoting shallow cloud formation that facilitates moisture transport. Furthermore, INP's role varies across cloud types, impacting the balance between riming and deposition, thus influencing ice crystal formation and cloud properties. This complexity underscores the need for improved parameterizations of aerosol-dependent ice number concentrations in climate models to enhance mixed-phase cloud behavior simulations, especially in regions with varying aerosol loads [5, 24, 28]. Such variability complicates remote sensing data interpretation and cloud process modeling, leading to discrepancies in climate predictions.

Moreover, calibrating remote sensing instruments, including lidar and radar systems, is crucial for minimizing uncertainties. Challenges in achieving precise calibration, particularly under fluctuating atmospheric conditions, can introduce systematic biases that compromise data quality. These biases may arise from factors like measurement discrepancies linked to varying solar and sensor angles, surface reflectivity, and lidar systems' dynamic range limitations, which can misclassify cloud phases and affect aerosol-cloud interaction evaluations. Thus, addressing calibration challenges is essential for improving atmospheric observations' accuracy and enhancing climate models' reliability [22, 15, 8, 4, 19]. These biases are further exacerbated by the complexities of atmospheric phenomena that current measurement techniques inadequately capture.

Tackling these uncertainties requires developing advanced retrieval algorithms and calibration methods that effectively account for atmospheric processes' variability and complexity. Integrating diverse data sources, supported by advanced statistical models and machine learning techniques, is vital for enhancing remote sensing measurements' precision and improving climate models' reliability. This integration involves addressing systematic errors in proxies and leveraging high-dimensional remote sensing data alongside numerical model outputs to bridge traditional observation gaps. By employing innovative approaches, such as hierarchical models and synthetic datasets, researchers can better separate signal from noise, optimize cloud detection, and ultimately refine predictive capabilities in atmospheric research. Additionally, advancements in knowledge distillation and natural language processing are anticipated to facilitate more efficient data processing and analysis in remote sensing applications, paving the way for significant improvements in climate modeling accuracy and operational effectiveness [19, 16, 36, 48, 17]. Continued research in this domain is crucial for enhancing our understanding of cloud microphysics and their broader implications for atmospheric science.

7.4 Future Directions and Technological Advancements

Future research in atmospheric science and remote sensing technologies aims to deepen our understanding of mixed-phase clouds and their climatic implications. A primary focus is improving observational data related to ice nucleation in mixed-phase clouds, essential for refining aerosol simulations in climate models and enhancing predictions of cloud behavior and climate impacts [1]. Expanding datasets to encompass a broader range of atmospheric conditions will bolster the robustness of classification algorithms and elucidate cloud phase transitions [2].

The refinement of lidar technology presents another promising avenue, emphasizing improved calibration techniques and expanded measurements across diverse atmospheric conditions and cloud types [42]. This advancement will facilitate more accurate atmospheric profiling and cloud property retrieval, crucial for understanding mixed-phase cloud dynamics. Future research should prioritize further refining calibration techniques and exploring additional applications of calibrated detectors across various fields, including atmospheric science and biomedical imaging [43].

Incorporating more microphysical processes into stochastic models and examining their implications under various atmospheric conditions will enhance our understanding of cloud microphysics [10]. Additionally, optimizing the Water Vapor and Ash Measurement System (WAMS) for diverse eruption scenarios and validating its measurements against existing methods will refine ash dispersion models, improving our predictive capabilities in volcanic ash events [25].

Future research should also extend high-speed numerical simulation methods to include non-stationary effects, exploring their applicability to other fields such as optical communication and electromagnetic wave propagation. Furthermore, integrating spatial correlations in estimating abundances and transition probabilities will enhance spectral unmixing methods' performance, contributing to more accurate remote sensing data interpretation [55].

Developing robust frameworks like SEnSeI, capable of withstanding unfamiliar data and exploring applications to hyperspectral data, will advance our atmospheric research capabilities [46]. Furthermore, enhancing quantum annealing hardware and refining selection methods for training examples will improve quantum machine learning models' performance in atmospheric applications. Future research may focus on optimizing these models for greater efficiency and exploring additional applications in real-time object detection scenarios [39].

The future of atmospheric research will significantly benefit from integrating innovative methodologies and expanding observational capabilities, such as those provided by advanced geospatial cyberinfrastructure and novel satellite technologies. These advancements will enable scientists to better understand complex atmospheric processes, particularly mixed-phase clouds, a major source of uncertainty in climate projections. By enhancing the representation of cloud feedback mechanisms in global climate models (GCMs) and leveraging large-scale datasets for analysis, researchers can develop more accurate and reliable climate models, ultimately leading to clearer insights into climate sensitivity and more precise forecasts of future warming [7, 48].

7.5 Expanding Observational Networks and Data Coverage

Expanding observational networks and enhancing data coverage are essential for advancing our understanding of atmospheric processes and improving climate models. Future research should prioritize extending observational networks to encompass a wider range of geographical locations, particularly those underrepresented in current datasets. This expansion is crucial for capturing the full spectrum of cloud characteristics and behaviors across diverse climatic regions, thereby improving the robustness of climate models and predictions [37].

Advancements in lidar technology are pivotal for enhancing our understanding of atmospheric processes, as they facilitate high-resolution atmospheric profiling and improve cloud property retrieval accuracy. This enhancement is particularly significant, enabling precise identification of cloud phases, such as distinguishing between liquid and mixed-phase clouds, which is essential for evaluating surface energy budgets and understanding aerosol-cloud interactions. Enhanced polarimetric lidar systems, employing multiple planes of linear polarization and advanced detection methods, can correct biases in traditional measurements, yielding more reliable data on cloud dynamics and their radiative effects [4, 15]. Improvements in lidar systems, including compact and cost-effective designs, will facilitate deployment in remote and challenging environments, thereby increasing the spatial and temporal coverage of atmospheric observations. This technological advancement is vital for obtaining comprehensive data on cloud microphysics and dynamics, critical for understanding their impact on climate systems.

Moreover, the comprehensive investigation of cirrus clouds and their climate effects should be a focal point of future research. Cirrus clouds, due to their high altitude and extensive coverage, significantly influence the Earth's radiation balance and climate feedback mechanisms. Enhancing observational capabilities to monitor cirrus clouds' properties and distribution effectively is essential for gaining deeper insights into their climatic roles, as these clouds contribute considerable uncertainty to climate models. By utilizing advanced techniques, such as convolutional neural networks trained on extensive satellite data, researchers can improve the understanding of ice microphysical properties in cirrus clouds, refining climate projections and better assessing geoengineering strategies aimed at manipulating these clouds. Improved observational data will clarify the impacts of cloud-phase changes on cloud albedo and radiative feedback mechanisms, ultimately leading to more accurate climate models that consider the complexities of cloud behavior in a warming world [33, 53].

The expansion of observational networks and improvement of data coverage are imperative for advancing atmospheric research. These initiatives aim to deepen our understanding of cloud processes, particularly the complexities of mixed-phase clouds and their interactions with climate systems. By addressing the significant uncertainties surrounding cloud feedback mechanisms—especially the differing representations of supercooled liquid water and ice in climate models—these efforts will

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enhance climate predictions' accuracy. Improved simulations and observational constraints are expected to yield more reliable projections of future warming, ultimately contributing to better-informed climate policies and strategies [7, 53].

8 Conclusion

The exploration of mixed-phase clouds and the progression of remote sensing technologies underscore their essential contributions to atmospheric science. Mixed-phase clouds, characterized by the coexistence of supercooled liquid droplets and ice crystals, present substantial challenges for climate modeling due to complex microphysical interactions and the impact of aerosols. Technologies such as polarized lidar and millimeter-wave cloud radar have significantly enhanced the ability to profile atmospheric conditions and evaluate cloud properties, thereby improving the accuracy of cloud detection and phase classification.

Innovative approaches, including multi-task learning frameworks and advanced calibration techniques, are enhancing the precision of cloud property retrieval and atmospheric profiling. These advancements are crucial for refining climate models and enhancing predictive capabilities for weather and climate phenomena. Furthermore, sophisticated modeling and simulation methods, supported by extensive observational datasets, provide valuable insights into the dynamics of mixed-phase clouds and their broader climatic implications.

Future research should focus on expanding observational networks to cover a wider range of atmospheric conditions, particularly in underrepresented regions, to bolster the robustness of climate models. Additionally, examining the effects of non-i.i.d. signal entries and exploring more complex measurement scenarios will further deepen the understanding of remote sensing technologies and their performance limitations.

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