

Remote Sensing and Atmospheric Modelling: Data, Processes, Integration and Future Directions

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Abstract

Atmospheric modelling plays a central role in weather forecasting, climate projection, and air quality assessment; however, the availability, accuracy, and representativeness of atmospheric observations fundamentally constrain its reliability. Over the past two decades, rapid advances in remote sensing (RS) have transformed atmospheric observation by providing spatially continuous, multiscale measurements of key atmospheric variables, including aerosols, trace gases, clouds, precipitation, and atmospheric thermodynamic profiles. This review synthesises recent progress in integrating RS observations with atmospheric modelling frameworks, with a specific focus on observation–model synergy rather than sensors or models in isolation. We examine the physical foundations of atmospheric models, major RS platforms and retrieval principles, and the role of data assimilation in coupling observations with the model dynamics. Beyond assimilation, this review highlights approaches for model initialisation, forcing, evaluation, bias correction, and downscaling using satellite-derived products. Key applications in weather prediction, air quality modelling, climate monitoring, and regional-to-urban studies are discussed, illustrating the practical value of integrated observation–model systems in these fields. Emerging machine learning (ML) and hybrid physical–data-driven approaches were assessed for their potential to enhance computational efficiency and represent unresolved processes, alongside their limitations in interpretability and uncertainty quantification. Finally, this review identifies persistent challenges, including retrieval uncertainty, scale mismatch, model structural bias, and data continuity. It outlines future research directions involving next-generation observing systems, multi-sensor data fusion, coupled Earth system modelling, and atmospheric digital twins. Together, these developments point toward more adaptive, observation-driven atmospheric modelling frameworks capable of supporting robust scientific understanding and decision-making in changing climates.

Keywords: Remote sensing; atmospheric models; data assimilation; air quality; climate; machine learning

INTRODUCTION

The atmosphere is a highly dynamic system that regulates weather, climate, and air quality through complex interactions among physical, chemical, and radiative processes. Understanding and predicting these processes is central to addressing pressing societal challenges, including extreme weather events, climate variability and change, and deteriorating air quality issues.

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Atmospheric models have long served as the primary tools for simulating these processes; however, their reliability depends critically on the availability of accurate, spatially continuous, and temporally consistent observations (Alizadeh, 2022; Tian et al., 2023) [1,2]. In this context, the rapid advancement of remote sensing (RS) technologies has fundamentally reshaped the observation, analysis, and modelling of the atmosphere (Tian et al., 2023) [2].

Atmospheric modelling underpins modern weather forecasting, climate projection, and air quality assessment. Numerical weather prediction models provide short- to medium-range forecasts that are essential for disaster preparedness and resource management (Bi et al., 2023; Mohapatra, 2024) [3, 4]. Climate models are indispensable for understanding long-term trends, feedback mechanisms, and future climate scenarios under different emissions pathways (Meinshausen et al., 2024; Wang et al., 2024a) [5, 6, 7]. Chemical transport and air quality models support regulatory decision-making by simulating pollutant transport, transformation and exposure. Across these applications, models offer a physically consistent framework for integrating observations, testing hypotheses and exploring scenarios that cannot be directly observed (Gettelman et al., 2022; Thyer et al., 2024) [8, 9].

RS has become a cornerstone of atmospheric observation, providing near-global coverage of key atmospheric variables, including aerosols, trace gases, clouds, precipitation, temperature, and humidity. Satellite- and airborne-based observations enable the systematic monitoring of atmospheric states and processes at scales inaccessible to ground-based networks (Gómez García et al., 2025) [10]. These observations are essential for diagnosing atmospheric variability and constraining, initialising, and evaluating atmospheric models.

Despite their high accuracy, traditional in-situ measurements are spatially sparse, unevenly distributed, and often limited to specific regions or vertical strata. Many parts of the world, particularly over oceans, in complex terrain, and in developing regions, remain poorly instrumented. These limitations limit atmospheric models' ability to represent spatial heterogeneity and large-scale transport processes, leading to uncertainties in forecasts and simulations (Alizadeh, 2022; Giovannini et al., 2020) [1, 11].

The last two decades have witnessed an explosion of atmospheric datasets derived from satellite missions, unmanned aerial vehicles (UAVs), and global reanalysis systems (GRSs) (Affek and Szymański, 2024; Gaffey and Bhardwaj, 2020; Naderi et al., 2026) [12, 13, 14]. High-resolution satellite observations, targeted UAV measurements, and physically consistent reanalysis products now provide multi-decadal gridded representations of atmospheric states (Naderi et al., 2026) [14]. Together, these datasets offer unprecedented opportunities to bridge observational gaps, improve model realism, and enable multiscale atmospheric analysis.

The primary objective of this review is to synthesize recent advances in the integration of RS observations with atmospheric modelling frameworks. Rather than cataloguing sensors or models in isolation, this review focuses on how observational data and models interact to improve understanding, prediction, and decision-making across weather, climate, and air quality applications. This review emphasises the synergy between observations and models, including data assimilation, model evaluation, bias correction, and hybrid physical–data-driven approaches. By examining how RS products are translated into model-relevant information, this review highlights pathways to reduce uncertainty, enhance predictive skills, and improve process representation.

Fundamentals of Atmospheric Modelling

Atmospheric models provide a quantitative framework for representing the evolution of atmospheric states and processes across a wide range of spatial and temporal scales. They translate physical laws into numerical formulations that can be solved computationally, enabling simulations, predictions, and scenario analyses for weather, climate, and air quality applications (Li et al., 2023; Silva and Lambers, 2021) [15, 16]. Figure 1 presents a schematic representation of the core components of atmospheric models, illustrating the coupling between the dynamical processes, radiative transfer, cloud microphysics, atmospheric chemistry, and surface interactions. The equations of motion govern large-scale circulation and frontal systems, whereas radiative processes control energy exchange through shortwave and longwave fluxes. Cloud microphysics and chemistry regulate precipitation formation and pollutant transformation, and surface interactions link the atmosphere with the land, ocean, and cryosphere, collectively determining atmospheric evolution across scales.

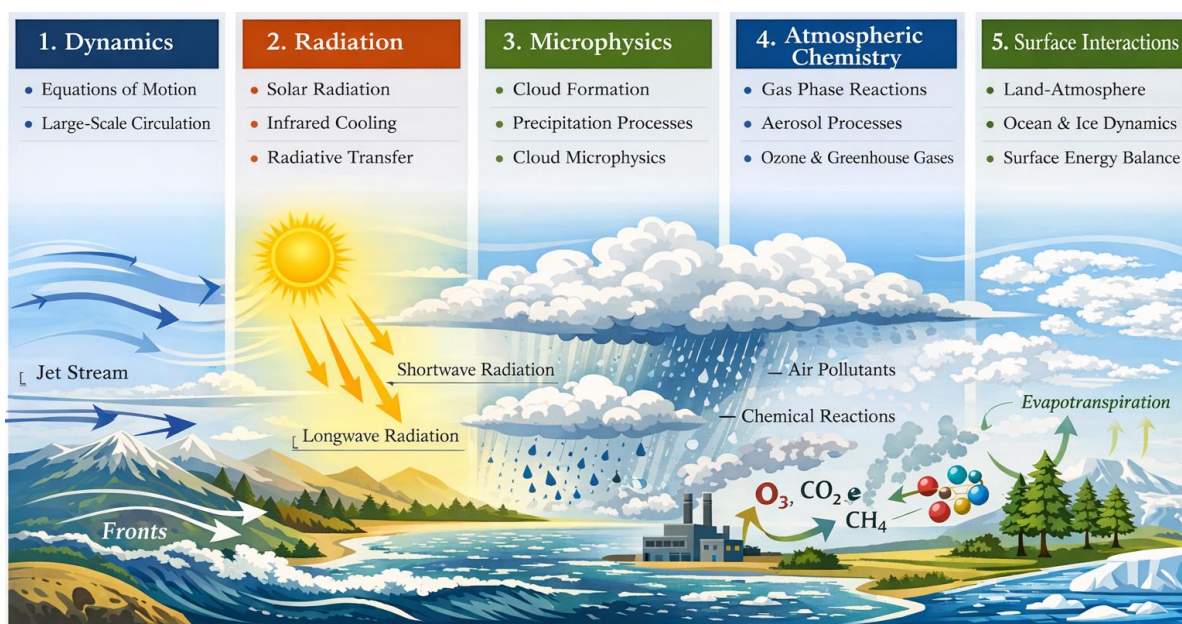


Figure 1. Core components of atmospheric models and their coupled physical and chemical processes

Governing Equations and Physical Basis

At the core of atmospheric models are the fundamental conservation laws of physics. These include the conservation of mass (continuity equation), momentum (Navier–Stokes equations), energy (thermodynamic energy equation), and, where relevant, chemical species mass balance (Achatz et al., 2022; Sreeraj et al., 2024) [17, 18]. Together with the equation of state and parameterisations of radiative transfer, turbulence, cloud microphysics, and surface exchanges, these equations describe the coupled dynamics in the atmosphere. Because many atmospheric processes operate at scales smaller than the model grid, they cannot be explicitly resolved and must be parameterised, which introduces uncertainty (Alizadeh, 2022; Christensen and Zanna, 2022; Lean et al., 2024) [1, 19, 20].

Model Types and Spatial–Temporal Scales

Atmospheric models have been developed for different purposes and scales. Global Circulation Models (GCMs) simulate large-scale atmospheric circulation and climate dynamics over decades to centuries, typically at coarse spatial resolutions. Regional Climate Models (RCMs) dynamically downscale global simulations to better represent mesoscale processes and regional climate variability. Numerical Weather Prediction (NWP) models focus on short- to medium-range forecasts, emphasising accurate initialisation and rapid control of error growth.

Chemical Transport Models (CTMs) simulate the emission, transport, chemical transformation, and removal of atmospheric constituents and play a central role in air quality assessment. The choice of model type is inherently linked to the scientific question, spatial extent, and temporal horizon of interest of the study (Alizadeh, 2022; Balaji, 2022; Kochkov et al., 2024) [1, 21, 22].

Discretization and Numerical Implementation

Atmospheric models discretise the continuous atmosphere in space and time using structured or unstructured grids and finite-difference, finite-volume, or spectral methods to solve the governing equations (Zhang et al., 2023) [23]. Vertical coordinates can be defined using pressure, height, or terrain-following systems, each with implications for representing boundary layer and topographic processes (Mesinger, 2023; Yang et al., 2023) [24]. Time-stepping schemes must balance the numerical stability, computational efficiency, and physical fidelity. Errors arising from discretisation, numerical diffusion, and time integration can accumulate and interact with physical parameterisations, influencing model performance (Shen et al., 2023) [25].

Initialization, Boundary Conditions and Forcing

Atmospheric models require accurate initial conditions and boundary forces to produce reliable simulations. The initial conditions define the atmospheric state at the start of a simulation, whereas the boundary conditions specify exchanges with the surface, oceans, and upper atmosphere (Anav et al., 2024; Zhao et al., 2022) [26, 27]. External forcing, such as greenhouse gas concentrations, aerosols, land-use change, and solar variability, is significant in climate modelling. Errors in the initial or boundary conditions can rapidly amplify, particularly in weather and air quality simulations, underscoring the importance of observational constraints (Shen et al., 2023; Zhao et al., 2022) [25, 27].

Sources of Uncertainty in Atmospheric Models

Uncertainty in atmospheric modelling arises from multiple sources, including imperfect initial conditions, incomplete or biased parameterisations, limited spatial resolution, and structural assumptions embedded in model design (Kahn et al., 2023; Peatier et al., 2024) [28, 29]. Additional uncertainty is introduced by input data such as emission inventories and surface properties, as well as by the internal variability of the atmospheric system. Understanding how these uncertainties propagate through model simulations is essential for interpreting the model outputs and effectively integrating observational data (Kahn et al., 2023; Mourot et al., 2025; Peatier et al., 2024) [28, 29, 30]. Atmospheric models balance physical realism and computational feasibility. Their effectiveness depends not only on advances in numerical methods and process representation but also on how well they are constrained and evaluated using observational data. This dependence provides the foundation for integrating RS data into atmospheric modelling frameworks, which is discussed in the following sections.

RS of the Atmosphere

RS provides an observational backbone for modern atmospheric science by enabling systematic, repeated, and spatially continuous measurements of atmospheric states and processes (Rahman et al., 2023; Tian et al., 2023) [31, 2]. Unlike point-based in-situ observations, RS captures the horizontal and vertical structure of the atmosphere over regional to global scales, making it indispensable for atmospheric modelling, monitoring, and diagnosis.

Observation Platforms and Measurement Principles

Atmospheric RS observations are acquired from various platforms, including satellites, aircraft, and ground-based systems. Satellite platforms dominate large-scale atmospheric observations and are broadly classified into polar-orbiting and geostationary systems. Polar-orbiting satellites provide near-global coverage with high spatial resolution, whereas geostationary satellites offer high temporal resolution over fixed regions, enabling continuous monitoring of rapidly evolving atmospheric phenomena. In recent years, unmanned aerial vehicles (UAVs) have emerged as a complementary platform, bridging the scale gap between in situ measurements and satellite observations by providing targeted, high-resolution data in the lower atmosphere (Xing et al., 2025; Zhang and Zhu, 2023) [32, 33].

RS measurements rely on the interaction between electromagnetic radiation and atmospheric constituents. Passive sensors detect naturally emitted or reflected radiation, whereas active sensors emit their own signals and measure the backscattered response. The choice of measurement technique determines the sensitivity to specific atmospheric variables and vertical layers.

Passive RS of Atmospheric Variables

Passive RS instruments, such as radiometers and spectrometers, retrieve atmospheric information by measuring radiation across the visible, infrared, and microwave wavelengths. These observations are widely used to infer aerosol optical depth, trace gas column concentrations, cloud properties, surface temperature, atmospheric temperature, and humidity profiles. Passive sensors provide broad spatial coverage but often have limited vertical resolution and reduced sensitivity near the surface, particularly in cloudy conditions. Consequently, the retrieved products typically represent column-integrated or layer-averaged quantities rather than direct point measurements (Kotthaus et al., 2022; Liu, 2022) [34, 35].

Active RS: Radar and LiDAR

Active RS systems, including radar and LiDAR, offer enhanced capabilities for resolving the vertical structure of the atmosphere. Radar systems are particularly effective for observing precipitation, cloud dynamics, and hydrometeor properties, whereas LiDAR systems provide detailed profiles of aerosols, clouds, and, in some cases, trace gases (Bluestein et al., 2022; Liu, 2022) [36, 35]. These systems play a crucial role in understanding boundary-layer processes, cloud–aerosol interactions, and vertical transport mechanisms, which are often poorly represented in atmospheric models.

Retrieval Algorithms and Uncertainties

RS instruments do not directly measure atmospheric variables; instead, geophysical parameters are inferred using retrieval algorithms that invert radiative transfer models. These retrievals depend on the assumptions regarding atmospheric composition, surface properties, and cloud conditions. Consequently, uncertainties arise from instrument noise, retrieval assumptions, and limited sensitivity to specific atmospheric layers (Bluestein et al., 2022; Peatier et al., 2024) [36, 29]. Vertical averaging kernels and weighting functions further complicate the interpretation of retrieved products, particularly when integrated with model outputs that operate on discrete vertical grids.

Advantages and Limitations for Atmospheric Modelling

RS observations offer unparalleled spatial and temporal coverage, making them essential for constraining atmospheric models, evaluating simulations, and detecting large-scale patterns and trends in the data. However, their indirect nature, vertical representativeness limitations, and susceptibility to cloud contamination pose challenges for the direct integration of models. Therefore, the effective use of RS data requires careful consideration of the retrieval characteristics, uncertainty structures, and scale mismatches between the observations and model grids.

Data Assimilation and Observation–Model Coupling

Data assimilation is the primary mechanism through which RS observations are integrated into atmospheric models. By optimally combining observations with model dynamics, data assimilation frameworks aim to produce physically consistent estimates of the atmospheric state that are superior to either observations or model simulations alone. This observation–model coupling is central to improving forecast accuracy, reducing uncertainty, and ensuring dynamic coherence across scales.

Conceptual Basis of Data Assimilation

At its core, data assimilation treats atmospheric modelling as an estimation problem in which model predictions (the background or prior) are updated using observations to generate an improved state estimate. This process accounts for uncertainties in both the model and observations, typically through statistical error covariance structures. Assimilation exploits the physical constraints embedded in models while leveraging the spatial and temporal information contained in RS data, thereby extending the influence of observations beyond their immediate measurement locations (Nair et al., 2022; Wang et al., 2024b) [37, 38].

Variational and Ensemble-Based Techniques

Several assimilation approaches are commonly employed in atmospheric sciences. Variational methods, such as three-dimensional (3D-Var) and four-dimensional variational assimilation (4D-Var), minimise a cost function that measures the mismatch between model states and observations over space and time. These methods are widely used in numerical weather prediction and reanalysis systems because they enforce dynamic consistency (Maulik et al., 2022; Patel et al., 2025) [39, 40].

Ensemble-based approaches, including the Ensemble Kalman Filter (EnKF), use a collection of model realisations to represent flow-dependent error statistics. Ensemble methods are particularly well suited to high-resolution, nonlinear systems, such as air quality and convective-scale models, where error characteristics evolve rapidly (Silva et al., 2023) [15].

Assimilation of Satellite Radiances Versus Retrieved Products

RS data can be assimilated as raw radiances or retrieved geophysical products. Radiance assimilation preserves the original information content of the observations and avoids additional uncertainties introduced during retrieval; however, it requires accurate forward radiative transfer models and careful bias correction. In contrast, the assimilation of retrieved products, such as aerosol optical depth or trace gas columns, is computationally more straightforward and intuitive but may propagate retrieval assumptions and smoothing effects into the model (Raoult et al., 2025) [41]. The choice between these approaches depends on data availability, model capabilities, and application objectives.

Reanalysis Datasets as Integrated Observation–Model Products

Atmospheric reanalysis datasets represent a comprehensive application of data assimilation, combining multi-source observations with a fixed modeling system to generate long-term, spatially consistent records of atmospheric states. Reanalysis products are widely used for climate diagnostics, trend analysis, and model evaluation (Jadhav et al., 2025) [42]. However, changes in observing systems over time and model biases can introduce artificial discontinuities, which must be considered when interpreting long-term variability.

Impact on Forecast Skill and Uncertainty Reduction

The integration of RS observations through data assimilation has demonstrably improved forecasting accuracy in weather prediction, enhanced the representation of atmospheric composition in air quality models, and increased confidence in climate reanalyses. Assimilation helps constrain poorly observed regions, correct for model drift, and reduce initial condition uncertainty. Nevertheless, challenges remain in representing observation errors, handling scale mismatches, and assimilating variables with indirect or nonlinear relationships to model state variables (Jadhav et al., 2025; Lean et al., 2024) [42, 19].

INTEGRATION OF RS WITH ATMOSPHERIC MODELS

Beyond formal data assimilation, RS observations are integrated with atmospheric models in several ways to improve model realism, interpretability, and applicability. These integrations span model initialisation and forcing, performance evaluation, bias correction, and scale bridging, collectively strengthening the link between observed atmospheric behaviour and simulated processes (Kotthaus et al., 2022) [34].

The conceptual framework showing the major pathways through which RS observations are integrated with atmospheric models (Figure 2). Satellite-derived variables are used for model initialisation and external forcing, land–atmosphere and aerosol–radiation coupling, model evaluation and validation, and bias correction and downscaling. The figure highlights how observational constraints improve model realism, reduce systematic errors, and enhance predictive skills across weather, climate, and air quality applications.

Model Initialization and External Forcing

RS data play a critical role in defining the initial conditions and external forcing for atmospheric models. Satellite-derived temperature, humidity, wind fields, soil moisture, sea surface temperature, aerosols, and trace gases are routinely used to initialise weather and air quality models. In climate simulations, long-term satellite records inform estimates of radiative forcing, land-use and land-cover changes, and aerosol–cloud interactions. Accurate initialisation is particularly important for short-term forecasts, where minor errors can rapidly amplify, whereas consistent forcing is essential for capturing long-term climate responses (Achatz, 2022; Kotthaus et al., 2022) [16, 34], .

Land-Atmosphere and Aerosol–Radiation Coupling

The integration of RS products into land–atmosphere and aerosol–radiation coupling schemes has improved the representation of the surface energy balance, boundary layer dynamics, and feedback mechanisms.

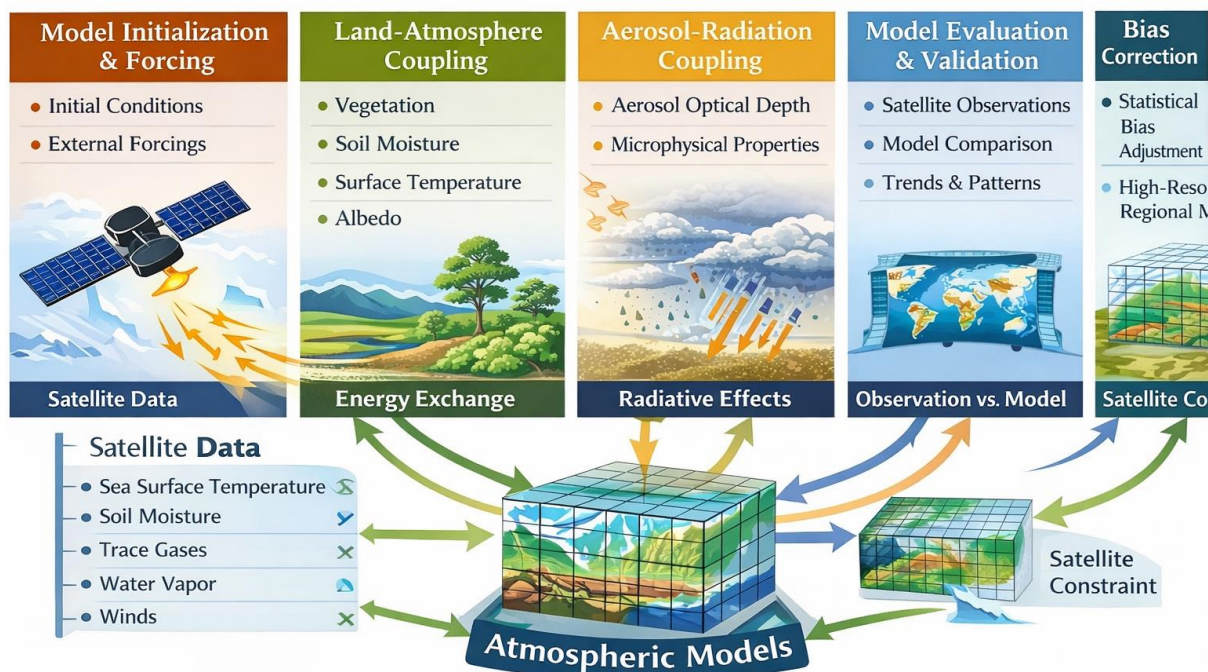


Figure 2. Key pathways for integrating RS observations with atmospheric models.

Satellite observations of vegetation, albedo, surface temperature, and soil moisture enhance the characterisation of surface heterogeneity. Simultaneously, aerosol optical and microphysical properties constrain the radiative effects in both weather and climate models. These couplings are crucial for simulating extreme heat, droughts, and aerosol-driven responses (Raoult et al., 2025) [41].

Model Evaluation and Validation Using RS

RS datasets are widely used to evaluate atmospheric model performance across spatial and temporal scales. Satellite observations enable systematic comparisons of the modelled and observed fields, supporting the validation of circulation patterns, cloud distributions, aerosol loading, and trace gas concentrations. However, differences in spatial resolution, vertical sensitivity, and temporal sampling introduce additional challenges. Therefore, practical model evaluation requires careful consideration of observation operators, averaging kernels, and representativeness errors to ensure meaningful comparisons (Raoult et al., 2025; Shen et al., 2023) [41, 25].

Bias Correction and Downscaling Approaches

Systematic biases in atmospheric models can limit their predictive utility, particularly at the regional and local scales. RS data provide an independent reference for diagnosing and correcting these biases. Statistical bias correction techniques leverage satellite observations to adjust model outputs, whereas dynamical downscaling uses high-resolution regional models constrained by satellite-derived boundary conditions. Hybrid approaches that combine physical modelling with observation-based corrections have been increasingly used to improve near-surface weather and air quality estimates in recent years (Achatz, 2022; Anav et al., 2024)[16, 26].

Scale Mismatch and Information Transfer

A persistent challenge in integrating RS with atmospheric models is the mismatch between spatial and temporal scales. Satellite observations represent area-averaged quantities over pixels or columns, whereas models operate on discrete grid cells and time intervals. Bridging this gap requires the use of observation operators, spatial aggregation or disaggregation techniques, and multiscale modelling frameworks (Achatz, 2022; Anav et al., 2024; Raoult et al., 2025) [16, 26, 41]. Addressing scale mismatch is essential for maximizing the information content of RS data and ensuring physically consistent model–observation integration.

APPLICATIONS OF INTEGRATED RS AND ATMOSPHERIC MODELLING

The integration of RS observations with atmospheric models has enabled a wide range of scientific and operational applications worldwide. By combining the spatial completeness of satellite data with the physical consistency of models, these approaches support an improved understanding, prediction, and management of atmospheric processes across multiple domains.

Weather Forecasting and Extreme Events

RS–model integration is central to modern weather prediction. Satellite observations provide critical information for initializing numerical weather prediction models, particularly over oceans, complex terrain, and data-sparse regions. High-frequency geostationary observations enhance the short-term forecasting and nowcasting of rapidly evolving phenomena, such as convective storms, cyclones, heatwaves, fog, and dust storms. Satellite data assimilation improves the representation of moisture fields, cloud dynamics, and upper-level circulation, leading to more accurate forecasts of extreme events and their associated hazards (Christensen et al., 2022; Gámez García et al., 2025) [18, 9].

Air Quality and Atmospheric Chemistry

In air quality applications, RS data are used to constrain emissions, track pollutant transport and evaluate chemical transport models. Satellite-derived aerosol optical depth and trace gas columns provide valuable insights into the spatial patterns of pollution, particularly in regions with limited ground monitoring. Inverse modelling frameworks leverage these observations to refine the emission inventories and assess the source contributions. Integrated modelling approaches support exposure assessment, regulatory planning, and the evaluation of mitigation strategies under varying meteorological conditions (Giovannini et al., 2020; Naderi et al., 2026) [10, 13].

Climate Monitoring and Climate Change Assessment

Long-term satellite records combined with climate models and reanalysis datasets play crucial roles in monitoring atmospheric composition, radiative forcing, and climate variability. Integrated approaches enable the detection of trends in aerosols, greenhouse gases, clouds, and water vapour, as well as the attribution of observed changes to natural variability or anthropogenic drivers. Climate models constrained and evaluated using RS observations improve confidence in the projections of future climate states and extremes (Peatier et al., 2024; Shen et al., 2023) [25, 29].

Regional and Urban-Scale Applications

At regional and urban scales, the integration of RS and atmospheric modelling supports the analysis of localised phenomena such as urban heat islands, boundary-layer pollution buildup, and land–atmosphere feedback. High-resolution satellite products, coupled with mesoscale and urban-scale models, allow the assessment of intra-urban variability in temperature, air quality, and ventilation. These applications are increasingly important for climate adaptation, public health, and urban planning (Gámez García et al., 2025; Giovannini et al., 2020) [9, 10].

Disaster Risk Reduction and Environmental Management

Integrated atmospheric modelling and RS frameworks contribute to disaster risk reduction by supporting early warning systems for floods, wildfires, air pollution, and severe storms. They also inform environmental management by enabling scenario analyses of land-use change, emission control policies, and climate adaptation measures.

The ability to simulate alternative futures under different forcing conditions enhances decision-making at the local, regional, and global levels (Achatz et al., 2022; Kotthaus et al., 2022) [16, 34]. The major application domains in which the integration of RS observations with atmospheric modelling has significantly enhanced predictive capability, process understanding, and decision support are listed in Table 1.

Table 1. Applications of RS-atmospheric model integration

Application Domain	Key Atmospheric Processes	RS Inputs	Atmospheric Models Used	Primary Outcomes
Weather Forecasting & Nowcasting	Convection, moisture transport, cloud dynamics, large-scale circulation	Satellite radiances, cloud properties, water vapor, winds	Numerical Weather Prediction (NWP) models	Improved forecast accuracy, better initialization, enhanced extreme-event prediction
Extreme Events	Cyclones, heatwaves, dust storms, heavy precipitation	Geostationary imagery, precipitation radar, aerosol optical depth	NWP and regional mesoscale models	Early warning, impact-based forecasting, disaster preparedness
Air Quality & Atmospheric Chemistry	Emission, transport, chemical transformation, deposition	Aerosol optical depth, NO ₂ , SO ₂ , CO, O ₃ columns	Chemical Transport Models (CTMs)	Emission estimation, pollution mapping, exposure assessment
Climate Monitoring & Trend Analysis	Radiative forcing, circulation variability, composition change	Long-term aerosol and trace gas records, cloud climatology	Global Climate Models (GCMs), Reanalysis systems	Detection of trends, attribution studies, climate variability assessment
Climate Change Projections	Feedback mechanisms, aerosol–cloud–radiation interactions	Aerosols, greenhouse gases, surface properties	Coupled Earth System Models	Improved forcing representation, constrained projections
Regional Climate Studies	Monsoon dynamics, land–atmosphere feedback	Land surface temperature, soil moisture, vegetation indices	Regional Climate Models (RCMs)	Downscaled climate information, regional impact assessment
Urban-Scale Applications	Urban heat island, boundary-layer pollution	High-resolution thermal imagery, NO ₂ , PM proxies	Urban-scale and mesoscale models	Urban climate diagnostics, heat and air quality mitigation planning
Disaster Risk Reduction	Flood-triggering rainfall, wildfire smoke transport	Precipitation, fire radiative power, aerosols	Coupled atmosphere–hydrology models	Early warning systems, risk mitigation
Environmental Management & Policy	Scenario-based emissions and land-use change	Multi-sensor atmospheric datasets	Integrated assessment models	Policy evaluation, regulatory support

Machine Learning and Hybrid Modelling Approaches

Recent advances in machine learning (ML) have introduced new paradigms for integrating RS data with atmospheric modelling. Rather than replacing physical-based models, ML techniques are increasingly used to complement them, leading to hybrid frameworks that combine data-driven flexibility with physical interpretability. These approaches aim to address long-standing challenges in computational costs, subgrid-scale processes, and nonlinear system behaviour (Maulik et al., 2022; Raoult et al., 2025) [39, 41].

Figure 3 shows an overview of the ML and hybrid physical–data-driven approaches for integrating RS data with atmospheric models. ML is applied to satellite retrievals, data assimilation and emulation, and the representation of unresolved processes within hybrid modelling frameworks. The concept of atmospheric digital twins is illustrated as an emerging paradigm that combines real-time observations, ML, and numerical models, alongside a summary of the key strengths and limitations of data-driven approaches.

ML for RS retrievals

ML has been widely adopted to enhance atmospheric retrievals from RS data. Neural networks, random forests, and deep learning architectures are used to map satellite radiances to geophysical variables, including aerosol optical depth, surface temperature, and trace gas concentrations. ML-based retrievals can exploit non-linear relationships and multi-sensor information, often improving accuracy and computational efficiency compared to traditional inversion methods. However, their performance depends strongly on the representativeness of training datasets and the availability of reliable reference observations (Maulik et al., 2022; Shen et al., 2023) [39, 25].

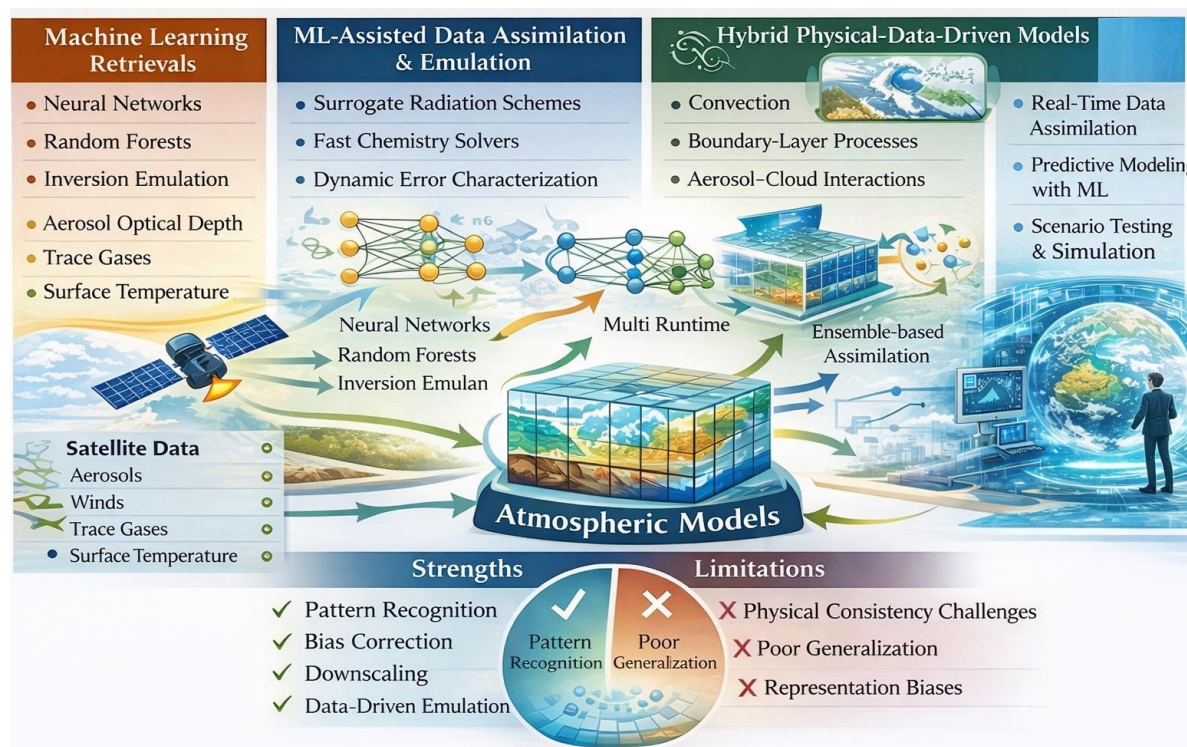


Figure 3. ML and hybrid approaches for coupling RS data with atmospheric models

ML-Assisted Data Assimilation and Emulation

In atmospheric modelling, ML techniques are increasingly applied to emulate complex physical processes or serve as surrogate models within data assimilation systems. Emulators can approximate computationally expensive components, such as radiation schemes or chemistry solvers, enabling faster ensemble simulations and real-time applications. ML-assisted assimilation frameworks also help characterise model and observation error structures, improving the efficiency of ensemble-based methods. Ensuring physical consistency and stability remains a key challenge in these applications (Raoult et al., 2025; Xing et al., 2025) [41, 32].

Hybrid Physical-Data-Driven Models

Hybrid modelling frameworks explicitly integrate physical constraints with data-driven components. In such systems, ML models may represent unresolved or poorly parameterised processes, while physical equations govern the core atmospheric dynamics. Examples include ML-based parameterisations of convection, boundary-layer turbulence, or aerosol-cloud interactions informed by RS observations. These hybrid approaches seek to improve model fidelity while retaining interpretability and generalizability (Maulik et al., 2022; Raoult et al., 2025; Xing et al., 2025) [39, 41, 32].

Strengths And Limitations of ML-Based Approaches

ML offers notable advantages, including the ability to handle large, heterogeneous datasets and capture complex nonlinear relationships. It is particularly effective for pattern recognition, downscaling, and bias correction using RS data. However, purely data-driven models often lack physical interpretability, struggle with extrapolation beyond training conditions, and may violate conservation laws. Hybrid approaches mitigate some of these limitations but require careful design, validation, and uncertainty quantification.

Toward Digital Twins of the Atmosphere

The convergence of RS, atmospheric modelling, and ML is enabling the development of high-fidelity, continuously updated digital twins of the atmosphere. These systems integrate real-time

observations, predictive models, and adaptive learning algorithms to support forecasting, scenario analysis, and decision-making. While still emerging, atmospheric digital twins represent a promising direction for operational meteorology, air quality management, and climate services (Li et al., 2023) [14].

UNCERTAINTY, LIMITATIONS AND CHALLENGES

Despite significant advances in RS technologies and atmospheric modelling, substantial uncertainties and limitations remain in their integration. These challenges arise from both observational and modelling components and from the interfaces that connect them. Understanding and addressing these issues is essential for improving the reliability, interpretability, and operational value of integrated atmospheric modelling frameworks.

Uncertainty in RS Observations

RS products are affected by uncertainties related to instrument calibration, signal noise, viewing geometry, and retrieval assumptions. Many atmospheric variables are indirectly inferred through inversion of radiative transfer models, introducing sensitivity to a priori information and algorithmic choices. Cloud contamination, surface reflectance variability, and limited surface sensitivity further complicate retrievals, particularly of aerosols and trace gases (Lean et al., 2024) [19]. These uncertainties propagate into atmospheric models when satellite data are used for initialisation, assimilation, or evaluation.

Model Structural and Parameterization Uncertainty

Atmospheric models rely on parameterisations to represent sub-grid-scale processes such as convection, turbulence, and cloud microphysics. These parameterisations are often empirical and tuned for specific regimes, limiting their transferability across regions and scales. Structural differences among models, including numerical schemes and physical assumptions, lead to divergent simulations even under similar forcing conditions. Such model-form uncertainty remains a significant constraint in both weather and climate applications (Kahn et al., 2023) [28].

Data Gaps, Consistency and Long-Term Stability

Although satellite observations provide extensive coverage, data gaps persist due to orbital constraints, instrument failures, and cloud cover. Changes in sensor technology and retrieval algorithms over time can introduce artificial discontinuities in long-term datasets, complicating trend analysis and climate assessment (Achatz, 2022; Raoult et al., 2025) [16, 41]. Ensuring consistency and continuity across multiple observing systems is critical for reliable long-term atmospheric studies.

EMERGING TRENDS AND FUTURE RESEARCH DIRECTIONS

Rapid advances in observing systems, modelling strategies, and computational capabilities are reshaping the future of atmospheric science. Building on current observation–model integration frameworks, emerging trends aim to improve resolution, physical realism, uncertainty characterisation, and operational relevance of atmospheric modelling systems.

Next-Generation Observing Systems

Future satellite missions are increasingly focused on higher spatial, temporal, and spectral resolution, enabling improved characterisation of atmospheric composition, dynamics, and feedback. Hyperspectral sensors, advanced LiDAR systems, and multi-angle observations will enhance sensitivity to vertical structure and near-surface processes. At the same time, coordinated constellations of small satellites and the expanded use of UAVs are expected to provide flexible, targeted observations that complement traditional satellite platforms and ground-based networks.

Multi-Sensor Data Fusion and Integrated Products

A key research direction is the fusion of observations from multiple sensors and platforms to leverage complementary strengths and mitigate individual limitations. Integrating passive and active RS,

geostationary and polar-orbiting observations, and satellite and in situ measurements can yield more robust, physically consistent atmospheric products. Such fused datasets are particularly valuable for constraining atmospheric models and for improving the representation of coupled processes, such as aerosol–cloud–radiation interactions.

Digital Twins and Real-Time Atmospheric Intelligence

The concept of digital twins, dynamic, continuously updated virtual representations of the atmosphere, is gaining traction in both research and operational contexts. These systems integrate real-time observations, data assimilation, ML, and predictive models to support rapid forecasting, scenario testing, and decision-making. Atmospheric digital twins offer a pathway toward adaptive, user-oriented climate and weather services, though challenges related to data flow, model complexity, and uncertainty management remain.

CONCLUSIONS

This review examines the evolving integration of RS observations with atmospheric modelling frameworks, emphasising the importance of observation–model synergy for advancing atmospheric science. Atmospheric models remain indispensable tools for understanding and predicting weather, climate, and air quality. However, their performance and credibility are fundamentally constrained by the availability of observations, uncertainties, and limitations in scale representation. RS has transformed this landscape by providing spatially continuous, multi-scale observations of atmospheric states and processes that cannot be captured by in-situ networks alone.

The review highlights that the greatest scientific and operational gains arise not from advances in sensors or models independently, but from their effective coupling. Data assimilation frameworks, reanalysis systems, and observation-informed model evaluation have significantly improved forecast skill, reduced uncertainty, and enhanced process understanding. The integration of RS into model initialisation, forcing, bias correction, and validation has expanded the applicability of atmospheric models across diverse spatial and temporal scales.

Emerging ML and hybrid modelling approaches further extend this synergy by addressing computational limitations and improving the representation of unresolved processes. However, challenges related to physical consistency, uncertainty propagation, and transferability remain. Persistent issues such as retrieval uncertainty, model structural bias, scale mismatch, and data continuity continue to limit the full potential of integrated systems.

Looking ahead, next-generation observing systems, multi-sensor data fusion, coupled Earth system modelling, and atmospheric digital twins offer promising pathways for progress. Realising these opportunities will require sustained investment in observation continuity, open science infrastructure, and interdisciplinary collaboration. Ultimately, strengthening the integration between RS and atmospheric modelling is essential for delivering reliable, actionable information to support weather forecasting, climate resilience, air quality management, and informed environmental decision-making.

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