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PERSPECTIVE

Perspective on measurements and modeling of Earth's climate

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Abstract

This paper celebrates the achievements in the modeling of the Earth's atmosphere, ocean, and land that led to the discovery of anthropogenic climate change and, ultimately, to the awarding of the 2021 Nobel Prize in Physics to Syukuro Manabe and Klaus Hasselmann. The paper will succinctly recap its history, from the first pioneering years of Tyndall and Arrhenius, to the introduction of computers, to the latest breakthroughs and refinements. It will connect the work of modelists, who strive to create 'digital twins' of our planet in order to simulate its hydro-dynamical, chemical, and physical evolution through computerized models, and the observations needed to initialize the models themselves and validate them through comparisons and reanalysis, bridging the delicate gap between theory and measurements. Finally, we will present an overview of the future direction of this field of research, trying to highlight the challenges but also the opportunities and the importance of understanding the evolution of the Earth, especially for thermal-related quantities.

1. Introduction

Climate monitoring has grown increasingly important in the twenty-first century due to the crucial consequences of climate change on the onset of extreme events—floods [1], heat waves [2], hailstorms [3], and droughts [4]—and, ultimately, on human activities [5].

While public awareness of this phenomenon is relatively recent [6], scientists have been measuring the physical parameters of the planet for more than 200 years, and have become aware of a systematical modification of them—with temperature as a key variable—for more than 100 years; consensus on the anthropogenic nature of such modifications has steadily grown among specialists for the last 50 years [7]. Climate change deniers have been active since the 1980s, in large campaigns driven by oil and coal companies in order to protect economic interests [8]; however, the recent growth of social media has greatly enhanced the base and pervasiveness of deniers [9]. In this context, the Nobel Peace Prize being awarded in 2007 to Al Gore and the Intergovernmental Panel on Climate Change (IPCC) was seen as the first formal worldwide recognition of climate change science [10]. However, only in 2021, for the first time since its inception, the Physics Prize was given specifically for studies related to climate change: recipients Syukuro Manabe and Klaus Hasselmann were awarded 'for the physical modeling of Earth's climate, quantifying variability and reliably predicting global warming'.[3]

Climatology, as well as weather prediction, is one of the research fields in which observations and theory are inextricably intertwined: to explain the reasons that led to the awarding of the Nobel Prize in Physics to Manabe and Hasselman, the importance of both of these aspects needs to be recognized [11–13]. For this reason, the present work will recap both the achievements in the modelization of the climate, and the milestones in the monitoring and measurement of the Earth's essential climate variables, which constitute at the same time parameters of the simulations and the verification basis of their predictive power.

[3] Nobel Prize press release: www.nobelprize.org/prizes/physics/2021/press-release/.

2. Early measurements

Since the pioneering works of the 1800s by Fourier and Eunice Foote, which laid out the first theoretical grounds of the greenhouse effect induced by gases like water vapor and carbon dioxide, and the first measurements by Tyndall [14] and Arrhenius [15], the notion of a possible modification of the chemical composition of the Earth's atmosphere, and its relation to the temperature of the planet—let alone their possible anthropogenic origin—have been largely ignored.

Only in 1938 the first coherent attempt at measuring climate was performed. Guy Callendar collected and analyzed historical data and measurements of atmospheric temperature and carbon dioxide from around the world and revealed that, between 1880 and 1935, the mean air temperature rose 0.3 °C while the content of CO_2 in the atmosphere grew by 6% [16]. Using these data, he was able to correct Arrhenius' formulas and concluded that changes in CO_2 levels were responsible for about half of the temperature increase during the period under scrutiny. Both works were criticized for being too simplistic and not representative of the true state of the atmosphere.

The views of both Arrhenius and Callendar on the increase of CO_2 in the atmosphere were, however, positive: they considered that a warmer world would benefit agriculture, people would live under better circumstances, and 'the return of deadly glaciers should be delayed indefinitely'.

It was only after World War II that views on the subject started to change. In 1953, Plass presented his work on the dangers of CO_2 pollution to the audience of the American Geophysical Union: 'The large increase in industrial activity during the present century is discharging so much carbon dioxide into the atmosphere that the average temperature is rising at the rate of 1.5° [Fahrenheit] per century' [17]. For the first time, scientists were warning the community and the general public about the risks of fossil fuel pollution for the climate.

At the end of the 1950s, Keeling *et al* published a work that documented 4 years of CO_2 measurements from several stations in the US and Antarctica, and found that concentrations were steadily rising, while exhibiting diurnal and seasonal cycles [18]. By the mid-70s, the 'Keeling curve' was widely known and regarded as one of the most important achievements in climate monitoring [19].

3. Earth system models

A key method for studying the Earth's climate and, consequently, its modifications, is through the use of earth system models (ESMs). These are complex, computer-based simulations that represent the physical, chemical, and biological processes of the Earth, including the atmosphere, ocean, land, and ice. ESMs integrate interactions between these components, such as the carbon cycle, to understand how they affect each other and the global climate [20].[4]

Before the electronic computer era, the ideas and concepts that would be later used for the construction of ESM were laid out by a few pioneers at the beginning of the century: Abbe [22] published his work after 30 years as an operational forecaster, and in his paper showed the theoretical synthesis of its expertise by listing the necessary equations of state, thermodynamics, and motion that govern the evolution of the atmosphere. Bjerknes [23] took a more computational approach. Both, however, emphasized the importance of data, especially from the upper atmosphere, which were not available at that time [24]. A few years later, Richardson [25] attempted a direct solution of the equations of motion for the first ever numerical weather prediction, calculating them by hand over the course of several weeks. Despite the resounding failure (he predicted a completely implausible pressure change of 145 hPa in 6 h), it was the first real attempt at using the laws of physics to predict the weather [26], although several advances in the comprehension of the physics of the atmospheric flow and in the observational coverage of the free atmosphere (which provided reliable initial conditions) were yet to be achieved [21].

By 1950, the availability of the first mainframe computers enabled the production of numerical prediction models that simulated the evolution of the atmosphere—under important simplifications. The first groundbreaking use of computer resources was carried out by Charney *et al* [27], whose 24 h prediction was calculated by the Electronic Numerical Integrator and Computer in 24 h. In subsequent years, progress was made on the integration of radiative transfer [28], the use of three-dimensional models [29], and the implementation of unresolved physics by means of parametrizations [30].

The first dynamical simulation of the climate was performed by Phillips [31], who successfully computed the general circulation of the atmosphere over the course of a few weeks, after which truncation

[4] For a comprehensive and exhaustive history of ESM, refer to [21].

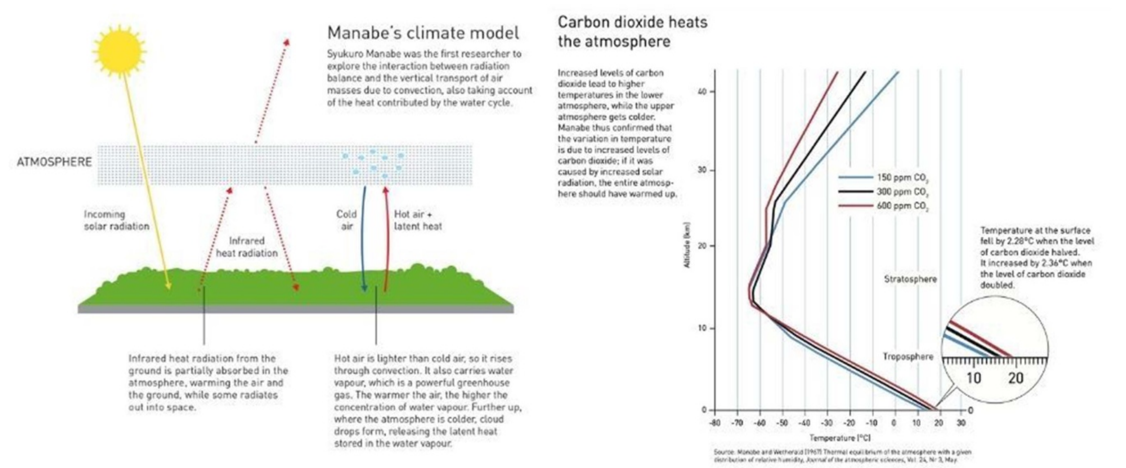

Figure 1. The Manabe climate model and the response of the atmospheric temperature profile to a doubling and halving of the atmospheric CO_2 concentration in the Manabe and Wetherald (1967) model. Reproduced with permission from [47]. © Johan Jarnestad/The Royal Swedish Academy of Sciences.

effects disrupted the physical plausibility of the predictions. However, the first climate model *per se* is said to be the one produced by Manabe and Bryan [32], which coupled the oceanic model developed by Bryan and Cox [33] to the model already developed at the Geophysical Fluid Dynamics Laboratory (GFDL) of the US National Oceanic and Atmospheric Administration (NOAA) by Smagorinsky and Manabe [34, 35].

3.1. Manabe

Syukuro Manabe's team at GFDL was the first to realize an ESM expressly dedicated to climate simulation: during the 1960s and 1970s, they achieved an impressive series of firsts, such as the already cited first parametrization of radiation [30, 36], the first land surface model [37], the first convective cumulus adjustment [38], and the first coupling between land and ocean [32], sea ice [39], and realistic topography [40]. Those first models included the atmosphere, modeled with different numbers of layers, only up to the troposphere: the stratosphere was included for the first time, again, by Manabe's team at the GFDL [41, 42].

In a highly celebrated paper issued in 1967 [43]—voted by the IPCC in 2015 as the most influential work on climate change [44], and explicitly cited by the Nobel Prize committee in 2021 together with its predecessor [36]—Manabe and collaborators successfully predicted the impact of a modification of CO_2 concentration in the atmosphere in terms of the temperature: they predicted that a doubling in carbon dioxide in the atmosphere would lead to a global temperature increase of 2.36 °C, remarkably close to the value calculated by IPCC in 2021 [45]. This work also underlined the importance of water-vapor feedback for climate change, which was instrumental for their subsequent work [46], widely regarded as the first true simulation of global warming with a true climate model, and again cited by the Nobel Prize committee (figure 1).

This model was capable of successfully predicting many changes that were actually observed in the real atmosphere, such as warming of the troposphere with Arctic amplification, a cooling stratosphere, increased water vapor in the air, and a subsequent increase in precipitation frequency and intensity. More refined models were subsequently studied by Manabe's team [48, 49].

3.2. Hasselmann

While the landmark studies by Manabe focused on the dynamics of the atmosphere–ocean–land system (basically, a digitized version of the Earth), and the response of this system to hypothetical variations in the composition of the atmosphere without distinguishing their origin (natural or human-made), the work of Hasselmann, former director of the Max Planck Institute for Meteorology in Hamburg, was the first in which the possibility to distinguish between different possible causes of climate change [50, 51] was explored.

In the first work considered by the Nobel Committee [52], Hasselmann was able to discriminate weather and climate by treating the ocean–atmosphere system as particles immersed in a source of Brownian motion: the fast variability of the atmospheric conditions (the 'weather') is then integrated by

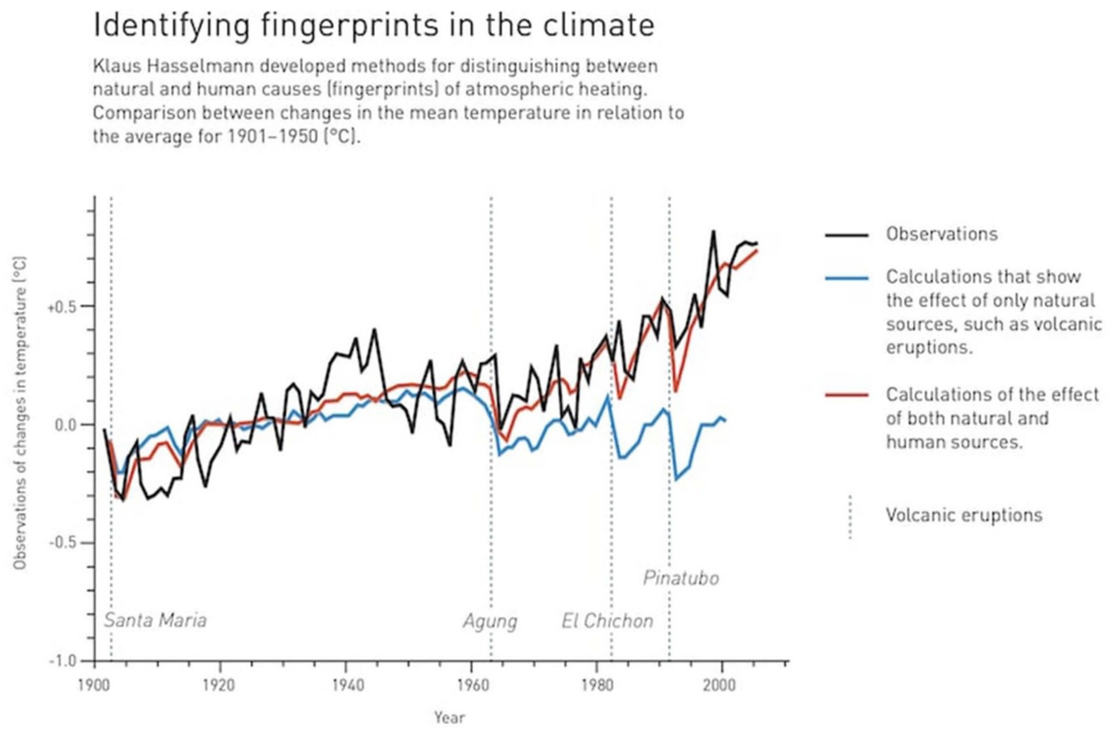

Figure 2. 'By applying Klaus Hasselmann's fingerprinting approach, climate scientists compare projected changes in atmospheric temperature driven by volcanic eruptions and other natural factors (blue) with projections that incorporate both natural variability and human influences (red). The close match between the latter and observed data (black) provides evidence of human contribution to climate change.' Reproduced with permission from [47]. © Johan Jarnestad/The Royal Swedish Academy of Sciences.

the slowest component (the 'climate') in a deterministic way, such that non-averaged 'weather' components are retained and show in the 'climate' as low-frequency modes whose probabilities are described by a Fokker–Planck equation. The climate was rendered predictable, without the need to invoke external factors (such as solar activity or changes in the Earth's orbit) or internal feedback mechanisms (e.g. increasing or decreasing albedo), but only by integrating the forcing produced by natural weather variability. This gave the possibility to produce very long timescale simulations (of the order of millennia) of natural climate variability, to be compared with the ones containing other kinds of climate-altering sources [53].

The second and third of Hasselmann's works cited by the Nobel Committee are related to the possibility of identifying human-caused warming signals. Coupled with the 'null-hypothesis' of natural climate variability (without external forcing) described in the previous paper, which can be well described by the so-called 'red noise'[5], Hasselmann laid out a theoretical framework for recognizing the signals generated by external forcing. At the end of the 1970s, when the first of these two works came out [54], computing power was still insufficient to produce a large ensemble of natural climate simulations, with adequate low-frequency statistics, to compare to externally forced ones. By the 1990s, computer technology had reached a point where such computationally demanding tasks could be achieved, and Hasselmann was able to revise and extend his work to time-dependent multivariate climate signals in the third work [55], in which a so-called 'optimal fingerprint' for the detection of forced signals of climate change was established in a simple and elegant form (figure 2).

These studies emphasize that models and observations offer substantial insight into the properties of both signals and noise. For instance, variations in solar irradiance, volcanic aerosols, and greenhouse gas concentrations generate signals with distinct patterns (amplitudes and frequencies) [56, 57]. These characteristic 'fingerprints' can be used to differentiate genuine climate signals from background climate noise.

A schematic of the progression of the advancements described in this section is shown in figure 3.

[5] 'Red' as the variations are localized in the long-wavelength part of the spectrum, as opposed to 'white' noise, which exhibits a flat distribution of wavelengths.

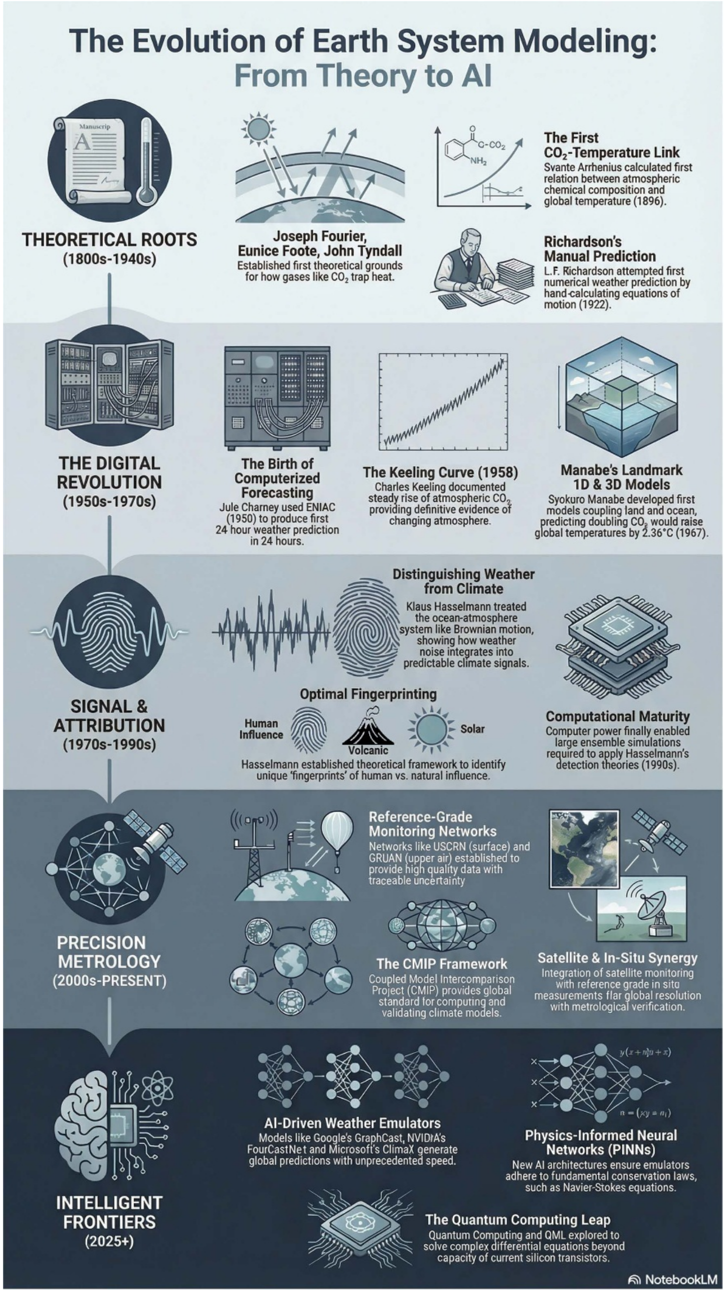

Figure 3. An infographic representing conceptual and technological advances in earth system modeling and climate predictions, as described in the paper.

3.3. Recent developments

As shown in section 3, the development of climate models has been very competitive in the past years, with several laboratories and institutions involved in the process. Comparisons among models have therefore been a fundamental part of the research activities [58, 59], and have fueled improvements and new directions [60, 61].

While these comparisons, in the beginning, were performed in an uncoordinated way, the World Climate Research Programme (WCRP)[6] of the WMO was established in 1980 in order to achieve 'a better understanding of the climate system and the causes of climate variability and change'. In 1995, the WCRP started a collaborative framework for systematic comparison among climate models, called the Coupled Model Intercomparison Project (CMIP)[7].

[6] www.wcrp-climate.org/about-wcrp/wcrp-overview.
[7] https://wcrp-cmip.org/.

The CMIP [62] has been organized in several phases (e.g. [63, 64]), each with new and improved climate model experiment protocols, standards, and data distribution mechanisms. CMIP6 [65] is the most recent phase open for general use, while CMIP7 is in an early development phase. CMIP coordinates climate model experiments globally, enabling comparison, diagnosis, and the multi-model ensembles that underpin IPCC assessments [66, 67].

4. Measurements and their uncertainty

In a recent plenary lecture at the TEMPMEKO-ISHM 2025 symposium, climatologist Peter Thorne stated that 'for a long time now, the problems with atmospheric simulation models have been the measurement data they are fed. Give me any dataset, and I will prove you it is wrong in some way'.

The problem of atmospheric—and, more in general, meteorological and climatological—measurement data quality has been recognized by the WMO and BIPM as crucial since the mutual recognition agreement between the two organizations in 2010 [68, 69]. However, even before that, there was a wide consensus that one of the major concerns with detecting climate change lies in the 'quality' of data, in terms of representativeness [70], time series changepoints [71, 72], outliers [73], missing data [74], and ultimately their uncertainty [75]. There have been examples of climatic data integrating evaluation of uncertainties, for example from satellites [76], land observations [77] (see section 4.1), and radiosondes [78] (see section 4.2), but the translation of these efforts into uncertainty-aware models is difficult and not largely practiced [79, 80].

The evaluation of measurement uncertainties itself, for many environmental quantities, is no trivial task: a complete and comprehensive uncertainty budget for the air temperature, among all other essential climate variables (ECVs), is still lacking [81], despite some attempts [82–84]. Recently, thanks in particular to metrology projects (e.g. MeteoMet[8] [85, 86]) progress has been made in this field, especially on the contribution of associated quantities of influence (AQIs), such as rain [87], surface albedo [88, 89], and physical obstacles [90, 91], but more work is necessary to understand and quantify the effect of other AQIs, like wind, radiation, etc. Regarding solar radiation, there is more complication due to the fact that air thermometers must be shielded [92], and each different kind of shield (aspirated, naturally ventilated, helical, planar, Stevenson, etc.) performs differently for different sensors and in different conditions. This has sparked countless comparisons [93–98] and theoretical works on the internal airflow and thermodynamics [99–102] and aging [103]. Sensors themselves can have different characteristics and respond differently to air temperature variations [104–106]. Finally, there exists no formal metrological definition of air temperature as a measurand yet, for which the Consultative Committee on Thermometry of BIPM has created a Task Group[9] currently working on a white paper [107].

The introduction of satellite monitoring marked a generational leap in the capacity of acquiring information on Earth's ECV, the most obvious advantage being the possibility of measuring atmospheric, oceanic, and land physical quantities without the need for *in situ* equipment [108, 109], and with greater spatial resolution [110]. A key limitation of satellite-derived data is the limited ability to rigorously quantify biases and uncertainties, with the result of model-observation discrepancies [111], as well as satellite-to-satellite inconsistencies [112, 113]. This has sparked some investigations on the reliability of satellite measurements [114, 115]. After accounting for known biases and short-term temperature variations (e.g. El Niño), *in situ* and satellite observations generally agree [116, 117], but the measurement uncertainty evaluation remains generally absent, with a few exceptions [118, 119]. Recently, projects like FIDUCEO[10] have been developed expressly to tackle the issue of data quality and uncertainty in satellite measurements [120–123].

In the field of *in situ* observations, this heightened awareness about data quality has led to the recognition of the need for a more systematic and comprehensive approach to climate observations [124] and, consequently, the establishment of several global networks of reference-grade measurement stations, created in close cooperation with the metrological community—which helped drafting the measurement protocols, evaluating the uncertainties, selecting instruments, and designing *ad hoc* calibration systems—with the aim of being the highest-quality providers for climatological measurements under the WMO's tiered networks approach [125].

[8] www.meteomet.org.
[9] www.bipm.org/en/committees/cc/cct/wg/cct-tg-env-airt.
[10] www.fiduceo.eu.

4.1. United States Climate Reference Network

The first such network was actually realized prior to these WMO requirements, and was designed and implemented not as a WMO coordinated effort but by the US alone. The United States Climate Reference Network (USCRN)[11] [126, 127] was commissioned in 2004 and reached its complete dotation of 114 stations throughout the contiguous United States in 2008 [128], with 25 more stations in Alaska and two in Hawaii. USCRN stations are equipped with three redundant shielded temperature sensors, and with sensors of surface temperature, precipitation, soil moisture and temperature, solar radiation, wind speed and direction, and relative humidity [129, 130].

One of the most distinctive features of USCRN stations is the fact that they are all identical: this reduces the complexity of data products and greatly simplifies the evaluation of an uncertainty budget. On the other hand, this extreme standardization could cause problems in the case of instrument phase-out by the manufacturers or, conversely, hinder further technological development of the methods of measurement.

All the measurements performed within the USCRN have been thoroughly characterized in a metrological way [131] and distributed through the Copernicus Climate Data Store[12], while the ECMWF portal provides the product user guide and specifications [132], where all contributions of uncertainty for temperature measurements have been detailed.

4.2. GCOS Reference Upper Air Network

The GCOS Reference Upper Air Network (GRUAN)[13] [133], envisaged by the WMO in 2007 and implemented one year later [134], was designed as a network of 30–40 stations worldwide, with the task of performing measurements of atmospheric ECVs from the surface to the stratosphere (10–30 hPa, corresponding to altitudes of 32–25 km [135]). These measurements are mainly performed by means of radiosondes attached to helium balloons, launched at regular intervals and for extended periods of time, which measure the temperature, solar radiation, wind speed, pressure, humidity, and other variables of interest (e.g. ozone, aerosols, etc.).

Contrary to USCRN, GRUAN chose not to allow only one instrument type; the network employs different instruments by different manufacturers, and is open to all the instruments that meet certain quality requirements in terms of performances and uncertainty [136–138]. Moreover, homogenization procedures are employed [139, 140] in order to make the comparison among different radiosonde model measurements possible. GRUAN put forward an extensive program of these evaluations [140], such as comparisons between models at phase-out times, in the form of dual soundings [141, 142] or laboratory comparisons [143].

The datasets provided by GRUAN measurements have proven invaluable in calibrating data from satellites [144] and other instruments [145], in assessing climate trends [146–148], and even improving historical time series [149].

4.3. GSRN

The GCOS Surface Reference Network[14] [150] ‘represents the surface equivalent of the GRUAN’, as its founding document states. Envisaged by the WMO for more than a decade, it is a worldwide network of near-surface measurement stations—now in its pilot phase with 17 sites (in 11 countries) out of the expected 180–200 total. Its rationale, background, metrological principles, and practical considerations regarding the implementation and maintenance of a stable and metrologically well-characterized global land surface climate fiducial reference measurement network have already been laid out [151], and practical implementations of such advanced stations are already available [152]. It will expand the experience of USCRN to the whole world, with a philosophy closely borrowed from the GRUAN—no standardized equipment, carefully evaluated uncertainty budgets, strict maintenance routines—and will be used to craft the first high-quality near-surface time series of the most important ECVs, expressly devoted to climatological studies.

4.4. AERONET

A key player in aerosol observation and monitoring is the Aerosol Robotic Network (AERONET) program. Established by NASA and the Laboratoire d’Optique Atmosphérique (LOA), a joint research

11 www.ncei.noaa.gov/access/crn/.

12 https://cds.climate.copernicus.eu/datasets/insitu-observations-near-surface-temperature-us-climate-reference-network?tab = overview.

13 www.gruan.org/.

14 https://gsrn.pub/.

department of the CNRS, and the University of Lille, AERONET is a consortium of ground-based, remote-sensing, aerosol networks involving many national agencies, institutes, universities, researchers, and business partners [153]. The network aims to provide a continuous, long-term, publicly accessible database of aerosol optical, microphysical, and radiative properties. These data are used for aerosol research and characterization, to validate satellite retrievals, and to harmonize with other databases. Their data have most recently been used to study long-term trends in aerosol properties [154], as well as to perform a classification of global aerosol types [155]. Aerosol studies are crucial for understanding climate change due to the feedback processes they can trigger and their differing impacts on the climate system [156–158].

AERONET demands instrument calibration and standardization of processing and distribution, to always provide high-quality data.

4.5. Atmospheric radiation measurement program

The atmospheric radiation measurement (ARM) program was established by the US Department of Energy in 1989, with the objective of investigating the crucial role of clouds and the transfer of radiation in the atmosphere [159].

The ARM program's key activity is acquiring detailed observations of clouds, solar, and thermal infrared radiative fluxes at the Earth's surface, and all the atmospheric quantities affecting these fluxes, to evaluate and improve climate models. The atmospheric observables are performed using active sensors, such as radar and LIDAR, and the deployment of passive sensors for the measurement of their radiative properties necessitates [160]. ARM is responsible for the collection, processing, quality-checking, storage, and distribution of continuous atmospheric measurements. These measurements are gathered 24 hours a day in a variety of meteorological regimes, providing researchers with atmospheric observations and data to advance basic science knowledge to better understand the Earth's atmosphere [161, 162].

Currently, ARM data are collected from three fixed atmospheric observatories located in the Southern Great Plains, the North Slope of Alaska, and the Eastern North Atlantic. In addition to these stationary sites, ARM operates three mobile facilities that researchers can utilize for proposed field campaigns [163], and the ARM aerial facility offers valuable airborne measurements [164–168]. In 2025, there were over 18 000 data products available for the users.

4.6. Ocean Observatories Initiative

The Ocean Observatories Initiative (OOI) is a scientific ocean observation network comprising more than 900 instruments of 36 different types, which collectively measure over 200 ocean parameters [169]. The ultimate objective of the OOI is to provide real- to near-real-time oceanographic data in order to answer many pressing scientific questions [170], such as ocean–atmosphere exchange, turbulent mixing and biophysical interactions, and coastal ocean dynamics and ecosystems.

The observation network is made up of five arrays that continuously collect ocean data. The Regional Cabled Array consists of submarine fiber-optic cables that power sub-arrays of seafloor instruments located on the Juan de Fuca plate in the north-east Pacific Ocean. The Coastal Endurance Array and the Coastal Pioneer Mid-Atlantic Bight Array contain moored arrays and autonomous vehicles positioned off the coasts of Washington and Oregon, and North Carolina, respectively. The Global Irminger Sea Array and the Global Station Papa Array also consist of moored arrays and autonomous vehicles, located off the coast of Greenland and in the Gulf of Alaska, correspondingly [171].

A wide range of studies have benefited from the observation network, with its applications including monitoring ocean health, acoustically locating autonomous vehicles, and even creating a digital twin of the ocean [172–174]. Most recently, it played a crucial role in studying marine heat waves [175].

5. Measurement uncertainty in models

To operate climate models, accurate representations of the current state of the atmosphere are needed. The data assimilation (DA) process defines the 'optimal' initial condition for the numerical forecast, makes the best estimation of the initial condition, and quantifies the uncertainty of the estimate. Several assimilation techniques have been developed in the fields of meteorology and oceanography [176, 177]. In a nutshell, DA combines a model (on a grid) with its own errors and uncertainty, and observations with their own errors and uncertainty to provide an output, the 'analysis', with statistically smaller errors, that can be used to forecast the future state of the atmosphere (e.g. the next hour, day, or season). However, the measurement of the state of the atmosphere is subject to an uncertainty, which can arise from gaps in historical records, measurement errors due to equipment, inconsistencies between different data sources, or limited spatial coverage in remote regions [178]. Each of these issues introduces uncertainty into the modeling process. Since errors exist in both models and observations, a variety of techniques can be employed to minimize the average discrepancy between the analysis and the 'truth'. Uncertainty is modeled through a probabilistic framework, converting the analysis into an optimization problem [179].

To further reduce uncertainty in the DA process, an ensemble of models can be used. For instance, the ECMWF employs 51 lower-resolution assimilation systems known as ensemble DAs (EDAs) [180]. Here, observations and models are perturbed to account for the chaotic nature of the atmosphere and associated prediction uncertainty. The EDA provides a sample of the analysis uncertainties and a starting point from which an ensemble of forecasts can be initialized. These ensembles provide a probabilistic forecast, offering an estimate of the predictability of a given weather situation.

A similar challenge arises when combining models with observations to produce climate reanalyses, which are numerical descriptions of recent climates. Also in that case, a significant amount of work is being conducted on the integration of DA related to the ocean, sea ice, land and hydrology, atmospheric composition, and air quality [181–183]. An example is CERA-SAT, a coupled reanalysis with the full observing system available in the modern satellite age, produced by ECMWF [184, 185]. Another initiative to develop a comprehensive DA system is the joint effort for DA integration (JEDI), which is the result of a collaborative development between the NOA and the Joint Center for Satellite DA [186, 187]. JEDI aims to unify DA practices across Earth system components, including the atmosphere, ocean, land, and atmospheric composition.

Coupled DA activities present several challenges. These include the requirement for multidisciplinary approaches, the need for easily exchangeable data, and the identification of the optimal degrees of coupling required, which is not a trivial task [188]. In order to achieve effective DA (coupled or not), it is essential to obtain high-quality observations across the various components of the Earth system.

As this paragraph shows, the quality of measurements can greatly influence the quality of a climate model output, and therefore the quality of climate projections.

6. The future, the opportunities, and the challenges

6.1. Artificial intelligence and machine learning

In October 2025, a WMO congress resolution officially endorsed and promoted the use of artificial intelligence (AI) and machine learning (ML) in weather forecasting and early warning systems [189]under the initiative 'Early Warnings for All' launched by Secretary General Guterres in 2022 [190].

This resolution substantially sanctions a trend that is already in place: the presentation in 2023 of Google's AI-driven weather forecaster GraphCast [191] was seen as a huge leap forward and a perfect scope of application for AI/ML models. Meteorological agencies and private companies around the world are already developing and training their models (e.g. the UK Met Office's FastNet [192] and ECMWF's AIFS [193]) and assessing their performances [194] by comparing them with classical NWP models [195]. While developers generally show extreme confidence in their model's prediction powers [196], others are more cautious, pointing out their underperformance in some areas [197], for some variables [198], or for extreme event predictions [199].

Despite being a relatively new field, AI-driven weather forecasts can already compete with traditional models. However, the road is tougher for climate predictions [200, 201], mainly due to the limited availability of independent training data, two orders of magnitude smaller than for weather forecasts [202]; however, for intermediate timescales, such as sub-seasonal to seasonal (S2S), ML is already competitive [203]. Other current implementations of AI/ML models for the climate deal with the quantification of extreme events [204], impact mitigation [205–207], and greenhouse gas reduction strategies [208]. Much less advanced seems to be the use of AI/ML for the quantification and propagation of observational and model uncertainties [209]. From a metrologist's point of view, this is one of the most important weaknesses of AI/ML approaches: most works lack uncertainty evaluation or confidence intervals [210, 211], and basically all of them neglect measurement uncertainty in the training datasets. As a matter of fact, uncertainty-aware methods are very rarely addressed, not only in AI/ML for climate sciences [212, 213], but in general [214–216]. Nonetheless, uncertainty quantification for large ensembles can be greatly benefited by AI/ML [217–219].

It has been demonstrated that deep learning-based emulators can reduce uncertainty in near-surface air temperature projections by up to 54% compared to traditional state-of-the-art ensemble methods [220]. Traditional ESMs often encounter the 'curse of dimensionality' [221, 222] when propagating errors through high-fidelity simulations. AI addresses this by functioning as a stochastic emulator, mapping input parameters to probability distributions of climatic outcomes.

Other systems are equipped for faster computation of traditional ESMs, like Pangu-Weather [223] or Aurora [224], by using 3D neural networks and Swin transformers. Such approaches can be very relevant to the parametrization focus of many model developers.

Current AI/ML implementations are often aimed at the simulation of an 'equilibrium climate', i.e. without anthropogenic forcing [161]—the baseline sought by Hasselmann in his studies. Comparatively fewer works use AI/ML to predict climate change, and they often focus on regional rather than global scales [225], or simulate climatological index variations (be they produced by anthropogenic forcing or not) considering an unlikely sudden stop of greenhouse gases released into the atmosphere [226]. AI/ML methods are also criticized for ontological reasons: are models merely following pattern recognition, or can they autonomously derive the physics behind them (or, alternatively, be fed physics and proceed autonomously from there [227, 228])? Specifically, in recent times, physics-informed neural networks (PINNs) [229, 230] have emerged as a robust architecture to ensure that ML-driven emulators adhere to fundamental conservation laws, such as the Navier–Stokes equations for atmospheric flow.

FourCastNet[15]—an acronym of the Fourier Forecasting Network—is a global data-driven weather forecasting model able to generate short- to medium-range global predictions at a resolution of 0.25° (which corresponds to a 30×30 km grid area near the equator [231]). According to the authors, FourCastNet has been trained on data from 1979 to 2015, therefore under a climate changing scenario, but may not predict weather reliably under the extreme climate change expected in the decades to come. Future versions will take this into account, also trying to incorporate PINNs, also for S2S timescales [232].

ClimaX[16], on the other hand, has the objective to extend its prediction beyond S2S timescales into climate projections [233]; for example, by downscaling, i.e. creating locally accurate climate information from global climate projections by linking those to observed local conditions [234]. Among others, ClimaX can use physics-informed simulations like CMIP6 as pretraining material, so while the ML framework is not physics-informed *per se*, it is sufficiently flexible to take into account this information and generate predictions based on actual atmospheric and terrestrial physics [235].

The current landscape of climate observation is undergoing a transformative shift from classical variational and ensemble-based DA to hybrid and end-to-end neural architectures. Historically, DA has relied on the optimization of a cost function to minimize the distance between a background state and sparse observations, typically governed by the 4D-Var framework. Currently, the operational status is defined by the successful deployment of AI-augmented hybrid systems, such as the already mentioned AIFS, which leverages classical initial conditions while outperforming physics-based models in forecast accuracy by up to 20% for variables like surface temperature [236]. These systems utilize neural networks as learned observation operators and to estimate the previously elusive model-error covariance term, allowing for a more accurate representation of non-Gaussian error statistics and sub-grid-scale processes that traditional parameterizations fail to capture [237].

The perspective for the foreseeable future focuses on the realization of fully differentiable, end-to-end ESM [238]. Emerging frameworks like NeuralGCM and Aardvark Weather demonstrate a move toward 'differentiable physics', where the entire pipeline—from raw satellite radiance to multidecadal climate state estimation—is trained as a single optimized graph [239]. This approach circumvents the computational bottleneck of traditional DA by utilizing Latent Space Assimilation, where observations are mapped into a compressed manifold that preserves critical non-linear spatio-temporal dependencies [240]. Furthermore, the integration of generative AI (e.g. GenCast) into the assimilation cycle offers a novel pathway for uncertainty quantification, providing high-fidelity ensemble spreads that are physically consistent and computationally efficient, thus enabling more robust 'storyline' assessments of extreme climate events in a warming world [241].

6.2. Quantum computing

Classical computers are approaching an unavoidable computing speed limit as the miniaturization of their components goes further: current transistor production processes at 5 nm imply a distance between electrodes in the transistors of only 20 atoms, and the more the miniaturization goes on (with future 3 nm production processes), the more unstable the transistor will become because electrons will spontaneously migrate among electrodes due to the quantum tunneling effect [242]. Other problems, like the

[15] https://build.nvidia.com/nvidia/fourcastnet.
[16] https://microsoft.github.io/ClimaX/.

increased complexity of parallelization [243–245]—which the key to the development of current classical supercomputers—to heat dissipation [246, 247], to energy demands [248, 249], are on the verge of hindering the improvement of supercomputers' efficiency and power.

At the beginning of the 1980s, long before these limits on classical computing were even feared, quantum computing (QC)—and computers—were theorized to improve efficiency and speed on certain specific problems, starting with the famous quantum Turing machine by Benioff [250] and the first quantum algorithm on cryptography [251].

While the practical realization of quantum computers is only in its infancy [252], claims of 'quantum supremacy' [253, 254] (the point where a quantum computer solves a problem that no classical computer can in a feasible amount of time) have already been issued [255], only to be disproved shortly after [256]—and the re-titling from 'Computational supremacy in quantum simulation' of the print [257] to 'Beyond-classical computation in quantum simulation' of the published paper [258] seems resoundingly significant.

Right from the beginning, climate applications seemed like perfect candidates for QC. There are already many review papers [259, 260] that highlight the potential—and the challenges—that QC can bring to the field. For instance, the superior capability of QC to solve ordinary and partial differential equations can be employed to simulate efficiently dynamical conservation laws and chemical processes [261–263] currently used in ESM. It can be used for more efficient parametrization [264] and lead to the improved tuning of climate models [265].

Recently, there have been attempts to use AI/ML and QC together to fully unleash their combined capabilities [266]. Quantum machine learning (QML) is already a flourishing field of research and provides quantum equivalents of well-known classical algorithms: quantum principal component analysis [267], quantum support vector machines [268], quantum basic linear algebra subroutines [269], and many others. The integration of QML kernels into DA cycles is expected to revolutionize the way we handle the 'curse of dimensionality' in multi-source satellite data fusion, providing a more robust framework for uncertainty quantification in decadal climate projections.

However, several problems must be addressed before QC can effectively be used for climate applications; in particular, the emergence of short coherence times in noisy intermediate-scale quantum (NISQ) devices, the need for an efficient coupling to classical high-performance computers, the large amount of data needed for typical climate applications, and the limited capacity for read-out [270].

While fault-tolerant quantum computers remain a long-term goal, the current realistic pathway involves hybrid QC [271]. In late 2025, the European Space Agency initiated the integration of silicon spin-qubit systems (e.g. the Bell-1 system) into its high-performance computing infrastructure. These hybrid systems utilize QML kernels for synthetic aperture radar (SAR) data processing—accelerating the computationally intensive inversion of SAR data—and combinatorial optimization—optimizing mission planning and constellation duty cycles to maximize the temporal resolution of climate-critical observations [272].

Recent benchmarks by the DLR QC Initiative [273] demonstrate that quantum neural networks can parameterize unresolved sub-grid processes, such as cloud microphysics and convection, with a performance that matches or exceeds classical counterparts while utilizing fewer free parameters.

The long-term perspective for the late 2020s and beyond focuses on moving past the limitations of NISQ devices to achieve a measurable 'quantum advantage' in fluid dynamics and global optimization. While current hybrid models often face 'noise-induced' performance deterioration [274], the roadmap suggests that as qubit coherence times improve, quantum algorithms for solving partial differential equations will enable climate models to resolve kilometer-scale atmospheric turbulence that is currently computationally prohibitive.

6.3. Uncertainty estimation in models

Climate models require DA to run; essentially, this involves comparing observations and previous estimates of the 'true' state of the atmosphere to improve our estimates on a model grid (see section 5). This process requires an understanding of uncertainties in both the observed data and prior estimates [275].

Even in the absence of any measurement or instrumental uncertainty, previous estimates of the model variables may differ substantially from the observed values. Hence, the observation uncertainty R is the sum of two parts: the representation uncertainty F and the measurement uncertainty E, which is dependent on the instrument ($R = E + F$). Since F depends on the state of the geophysical system, correlations between R and F can arise. However, for computational efficiency, and because the uncertainty statistics of observations are typically unknown, covariance matrices are usually assumed to be diagonal. To reduce the effect of these neglected correlations, observations are thinned, and uncertainty variances are inflated [276, 277]. In general, to optimize the use of observations, a good specification of their uncertainty is important both in DA and forecast verification [278–280].

Uncertainties in observation cannot be calculated directly. They can be estimated using different methods, each with its own pros and cons. The most used methods are the metrological approach, the triple collocation, and residual-based methods. The metrological approach consists of building a traceable uncertainty budget using uncertainty propagation [281, 282]. While this approach allows for a complete uncertainty estimation, it is very time-consuming and complex. In triple collocation, the uncertainty is estimated by comparing three different independent data sources. This method can characterize systematic biases and random uncertainty and identify specific sources of error [283]. However, acquiring independent data sources is not always easy.

The method based on residuals uses the by-products of the assimilation scheme: they are simple to use but may require isotropic, homogeneous, and ergodic assumptions. Among the most used residual-based methods, we can recall the Hollingsworth–Lönnberg method [284], which does not require prior specification of uncertainty, but assumes that the observation errors are uncorrelated. The Hollingsworth–Lönnberg method separates contributions from background and observation errors, assuming that the background ones are spatially correlated and the observation ones are not.

The method by Desroziers *et al* [285] assumes that background and observation errors are mutually uncorrelated and describes them with autocorrelations. The diagnostic has provided estimates that are qualitatively similar to those estimated using metrological approaches [286–288]. Additional methods use an ensemble of models, statistical adaptation, and stochastic modeling.

An emerging methodology for the reduction of uncertainty in future climate projections that integrate models and measurements is the emergent constraint (EC) [289]. This approach involves the combination of an ensemble of climate simulations with contemporary measurements, with the objective of identifying a relationship between a feature of the future climate and an observable variable in today's climate. The combination of this relationship with observations has the potential to reduce the uncertainty surrounding future climate change [290–292].

The objective of research in EC is to identify observable parameters of the present climate that are demonstrably associated with pivotal elements of future climate, as predicted by climate models that are currently in use. The first emergent relationship is associated with the snow albedo feedback mechanism [293], while another example combines contemporary observations of atmospheric CO_2 concentration and tropical temperature [294]. Later on, their study led to emergent constraints on climate-carbon cycle feedbacks in CMIP5 [295]. An EC connected to the present-day spatial distribution of permafrost was also identified [296].

The EC method can be used to reduce the ensemble spread, provided the links rely on physical argumentation and demonstrate that this is not a statistical artifact. However, EC relationships are often misunderstood, and even unconfirmed ones are combined with observations and assumed to have constraining power. It will require a significant endeavor from theorists, modelers, and observational scientists to ensure that the ECs produced are valid [297].

In summary, the EC approach has been proven to be a powerful, observationally informed method to reduce key uncertainties in future climate projections, thereby facilitating further insights on the climate system dynamic, especially regarding climate extremes, teleconnections, and tipping points [298].

6.4. Uncertainty estimation in observations

Observational uncertainties directly affect the evaluation and validation of climate models, because model credibility rests on comparisons with observational reference datasets whose errors and biases can be substantial and regionally varying [299]. Multiple studies show that observational uncertainties can rival or exceed model–data discrepancies in some variables and regions, underscoring the need to propagate observational errors through model evaluation and weighting schemes [300]. Consequently, neglecting observational uncertainty can mislead model validation and give a false sense of model skill or bias, especially for regional assessments where data gaps and inhomogeneities are pronounced.

Propagating observational uncertainties into model-scale assessments is essential for robust inference of climate change signals. Observational uncertainty can alter the estimated detection and attribution results, as well as the inferred emergence of forced trends against natural variability, by modifying both the reference state and the estimated signal-to-noise ratio across scales [300]. In near-term and regional analyses, the correlation of observational errors in space and time complicates straightforward error propagation, yet formal frameworks to carry these uncertainties through scale-dependent comparisons can yield more reliable confidence in model–observation fidelity. Empirical work demonstrates that propagating observational uncertainty to model scales tends to reduce overconfidence in seasonal to decadal forecasts and improves the realism of verification metrics, particularly when observational records are short or heterogeneous [301, 302].

Observational uncertainty also interacts with the internal variability and model structure to shape the overall uncertainty budget of climate projections. Observational data underpin both the calibration and evaluation of model ensembles; however, uncertainties in the observational reference datasets can propagate into ensemble weighting and calibration procedures, potentially biasing multi-model means and their uncertainty ranges [299, 303, 304]. Addressing this requires acknowledging observational uncertainties as integral components of the uncertainty framework, as well as leveraging multiple independent observational datasets to bracket the truth and to test sensitivity to reference choices. Moreover, studies using perturbed physics ensembles and constrained observational pathways illustrate that substantial portions of residual projection spread can arise from structural uncertainties and observational anchoring, not solely from parametric variability or scenario forcing [305, 306].

Moreover, advancing robust climate projections mandates explicit treatment of observational uncertainty in the design of data–model interfaces. Methodological advances to quantify and propagate observational errors into the evaluation of climate model performance and to formulate observationally informed constraints on model output are essential for improving near-term predictability and regional projections [299, 307]. In sum, observational uncertainty is not a peripheral nuisance but a core determinant of climate model validation, uncertainty quantification, and credible prediction, warranting explicit incorporation in all stages of climate modeling—from data curation and model calibration to evaluation and projection.

The revitalization of ground-truth measurements is increasingly driven by the synergy of Edge AI and quantum metrology, which address the historical limitations of remote *in situ* sensors in harsh or inaccessible environments. In terrestrial and sub-surface monitoring, AI now facilitates autonomous sensor calibration for massive, distributed networks (e.g. the Internet of Things for soil moisture or urban heat islands), where ML algorithms identify and correct for sensor drift caused by extreme weather without requiring manual intervention [308]. Furthermore, graph neural networks have revolutionized DA for irregular ground-based datasets, such as the Deep Argo float network, by learning the non-linear spatio-temporal correlations between ocean temperature, salinity, and pressure to provide high-fidelity state estimations even in data-sparse regions of the deep ocean [220, 237]. Concurrently, quantum technologies are providing 'drift-free' absolute references that redefine terrestrial uncertainty quantification. Ground-based cold atom gravimeters have transitioned from laboratory curiosities to field-deployable units, allowing for the measurement of minute changes in gravity linked to groundwater depletion and glacial mass loss with a precision that classical spring-based sensors cannot sustain over long durations [309]. By integrating these absolute quantum signals with AI-driven gap-filling models, researchers can now construct a digital twin of sub-surface hydrologic cycles that bridges the gap between local ground-truth and global satellite observations, significantly reducing the uncertainty budget in decadal climate projections.

From a modeling perspective, the explicit alignment of ground-based observations with ESM simulations benefits from corroborating air temperature measurements at both high temporal cadence and representative spatial coverage, and by treating temperature as a central linking observable in forward-operator workflows. Ground-based near-surface air temperature (T_{surf}) observations provide a direct diagnostic of boundary-layer processes, evapotranspirative fluxes, and surface energy balance that is parameterized within the land and atmospheric modules of ESMs, and they give critical constraints for DA and model calibration when used alongside cloud- and radiation-focused observables [310–312]. Integrating high-frequency T_{surf} data with instrument-simulator frameworks such as EMC^2 permits the generation of forward-modeled temperature variables that are comparable to model outputs under realistic sampling geometry and sensor response, thereby reducing sampling biases and enabling process-level evaluation rather than solely point-to-model comparisons [313, 314].

Temperature measurements at sub-daily scales help diagnose diurnal heating cycles, boundary layer evolution, and ground–air coupling strengths that drive land–atmosphere interactions in ESMs, and when used in conjunction with satellite-derived skin temperatures and radiative fluxes, support cross-validation of $T_{\text{skin}} - T_{\text{surf}}$ relationships and their parameterizations in energy and moisture exchange schemes [315–317]. Moreover, ground-based air temperature data aid the attribution of model biases to specific processes (e.g. cloud radiative heating, boundary-layer mixing, or snow/soil thermal properties) by providing a stable, high-resolution reference against which forward operators and observation-space diagnostics can be developed and tested, thereby guiding the design of regional dense networks in humid tropics, polar regions, and high-latitude continents where temperature–driven feedbacks are most informative for constraining ESM behavior [310, 311, 314, 318, 319].

In this integrated framework, the use of temperature-oriented observables is complemented by cross-validation with satellite temperature products to ensure consistency across ground- and space-based platforms, which in turn strengthens the diagnostic power of model assessments and supports targeted parameterization improvements (e.g. vegetation water use, soil depth, and cloud microphysics) across scales relevant to ESM sub-columns and single-column model evaluations [320, 321]. Collectively, these strands suggest that, for effective alignment with ESM simulations, ground-based observation strategies should prioritize high-frequency near-surface air temperature measurements, coupled with forward-operator-driven comparisons and multi-source temperature diagnostics that bridge ground-based and satellite observations, thereby enabling more reliable scaling of temperature-driven processes from the local to the global scale.

Data availability statement

No new data were created or analyzed in this study.

Author contributions

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