From Data to Policy : Strengthening Essential Climate Variable Monitoring with Deep Learning Algorithms and Data Quality Standards

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***Abstract*—Essential Climate Variables (ECVs) are critical for understanding and monitoring climate systems, providing important data to assess climate change and supporting policy formulation. This review emphasizes the importance of ensuring data quality, traceability, and consistency to derive reliable features from ECV datasets, addressing challenges such as temporal and spatial coverage gaps, calibration discrepancies, and harmonization across diverse sources. Furthermore, we highlight both the transformative potential and limits of advanced analytics, including artificial intelligence (AI), in enhancing the monitoring and prediction of ECVs using three case studies: (i) climate modeling and prediction of temperatures for planning scenario with machine learning, (ii) the Earth's surface processes, and (iii) monitoring the Earth radiation budget. This article also explores how ECVs are integrated into global frameworks like the Global Climate Observing System (GCOS) and the WMO Integrated Global Observing System (WIGOS), which establish standardized protocols for reliable and interoperable data. By synthesizing advances in technology, data quality practices, and global collaboration efforts, this review underscores the importance of interdisciplinary approaches to bridge the gap between scientific knowledge and actionable climate policies.**

I. INTRODUCTION

CLIMATE change is one of the most significant challenges facing our society, which requires precise monitoring, assessment, and modeling of the Earth's climate systems [1], [2]. Essential Climate Variables (ECVs) are an important component that serves as the cornerstone for understanding climate variability. Defined and promoted by the Global Climate Observing System (GCOS), ECVs encompass a diverse range of physical, chemical, and biological parameters that capture dynamic interactions within the climate system [3].

ECVs are standardized climate indicators that enable systematic monitoring of Earth system changes and support climate policy development [4]. According to GCOS, ECVs are classified into three domains: atmospheric, oceanic, and terrestrial. Monitoring of the atmospheric domain relies on variables such as tropospheric and atmospheric temperature, precipitation, greenhouse gas concentrations, and Earth radiation budget, among others, though it is not limited to these variables alone. Oceanic ECVs include sea surface temperature, sea level rise, and ocean acidity, while some terrestrial ECVs include soil moisture, land cover, land surface temperature, albedo, and glacier mass balance [3]. GCOS developed the ECV framework that now guides international climate monitoring efforts and policy development. This conceptual model has inspired similar initiatives in other domains, such as Essential Ocean Variables (BLUE-PLANET), Essential Biodiversity Variables (GEO-BON) and Essential Water Variables (GEOGLOWS), demonstrating the versatility and societal value of essential variables [5]. These frameworks also emphasize the need for essential variables to serve as indicators to track progress toward the Sustainable Development Goals (SDGs) [4], [6]. Essential Variables (EVs) defined by NASA are fundamental monitoring indicators for the SDGs. While GCOS focuses on climate using the ECVs, the GEO has launched the GEO-EV (Group of Earth Observations - Essential Variables) initiative extending the EVs framework by promoting interdisciplinary collaboration [7], [8], [5].

By ensuring the development of consistent and traceable datasets, GCOS enables reliable prediction of climate dynamics and supports the formulation of adaptive strategies to mitigate climate-related risks. A key objective of GCOS is to provide high-quality ECV datasets to scientific communities, government agencies, and the public together with a robust error estimate (uncertainties) [2]. To achieve this objective, assessing data quality is essential for the accurate interpretation and application of Earth observation data, particularly in creating long-term Climate Data Records (CDRs). Realistic uncertainty quantification is a cornerstone of traceability and robustness in EO-derived products. For instance, [9] emphasized the need to systematically attach uncertainty estimates to CDRs, arguing that transparent and rigorous error characterization underpins both scientific integrity and effective policy use. Similarly, [10] differentiated between "known unknowns" and "unknown unknowns" in satellite remote sensing, offering a framework to address challenges in uncertainty estimation. In [11], the authors advocated for the application of metrological standards to historical satellite datasets, ensuring reproducibility, comparability, and alignment with global best practices in measurement science. [12] examined uncertainties in ECVs

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derived from deep learning (DL) methods, highlighting emerging risks such as hidden biases and stressing the need for rigorous validation frameworks. More recently, [13] explores some sources of uncertainty that arise when validating ECVs against independent measurements. Together, these studies highlight that uncertainty quantification and systematic data quality assessment are not optional add-ons but essential components for making ECV datasets reliable, actionable, and fit for both scientific analysis and evidence-based policy.

The novelty of this review lies in bridging three dimensions of ECVs: data quality assessment, advanced analytics, and policy relevance. While earlier studies have examined some of these challenges, they have not done explicitly within the ECV framework [14], [15]. This work highlights the importance of systematically integrating data quality monitoring and uncertainty quantification in the generation and use of ECVs, which help maintain traceability and robustness across various observational platforms. Based on these findings, we propose specific actions for policymakers to ensure the use of reliable ECVs. Three case studies illustrate how to combine stringent ECV quality control with advanced analytical methods, including AI approaches that are difficult to trace [16], while ensuring policy relevance and societal benefits: (i) the assessment of drought risk, (ii) the monitoring of Urban Heat Islands (UHI), and (iii) the characterization of the Earth Radiation Budget (ERB). Overall, this study emphasizes how methodological rigor, analytical innovation, and policy relevance combine to enhance the scientific utility and societal impact of ECVs by linking high-quality datasets with quantified uncertainties to evidence-based policy formulation and adaptive decision-making [17], [8], [18]. Our contribution advances the application of physics-informed DL methods to ECV monitoring, not only to fill data gaps and enable near–real-time prediction but also to expose hidden biases that require rigorous validation.

II. Monitoring Carefully Essential Climate Variables: a data quality approach

The significance of ECVs lies in their ability to bridge gaps in understanding climate across spatial and temporal scales. By applying statistical techniques, such as trend analysis and continuous estimation of their associated uncertainties, monitoring ECVs can reveal long-term changes in Earth's climate, contributing to a deeper understanding of phenomena such as regional sea level rise, glacial melting, and shifts in hydrological cycles [19].

One of the main challenges in monitoring ECVs is ensuring that input datasets are both high quality and consistent. The GCOS and the Committee on Earth Observation Satellites (CEOS) have emphasized that all ECV related products should provide documented uncertainty budgets and traceability chains, in line with metrological best practices [2], [9]. These include identifying error sources (instrumental, sampling, and retrieval-related), propagating them through processing chains, and expressing them as confidence intervals suitable for climate trend analysis. Anchoring ECV monitoring in these frameworks allows practitioners to assess not only the

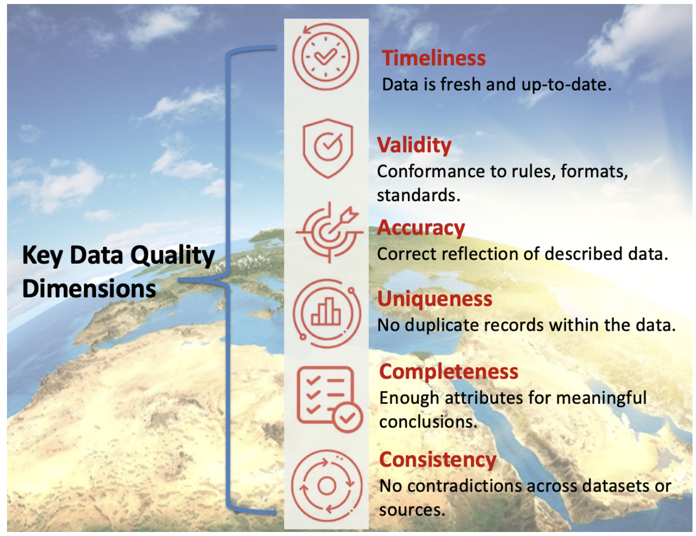

Fig. 1: Key dimensions used to assess the quality of datasets: timeliness, validity, accuracy, uniqueness, completeness, and consistency, as they relate conceptually to uncertainty propagation and traceability in climate EO.

magnitude of climate signals but also their robustness relative to known uncertainties. Fig. 1 summarizes the key dimensions used to assess dataset quality, as outlined in [20]. These include: Timeliness, referring to how current or up to date the data are; Validity, or the degree to which data conform to established formats, standards, and regulations; Accuracy, reflecting how precisely the data capture the intended measurements or phenomena (closely related to specificity); Uniqueness, which prevents duplication that could increase uncertainty in ECV assessments; Completeness, a measure of how well a dataset supports meaningful analysis or conclusions; and Consistency, which addresses internal contradictions or artifacts that may undermine the integrity of ECV monitoring. When framed within the metrological principle of traceability, each of these dimensions directly contributes to the reliability of uncertainty assessments. For example, incomplete or inconsistent datasets compromise the propagation of uncertainties through time series, while validated, harmonized datasets enhance traceability across observing systems. Thus, data quality dimensions provide a complementary framework to the metrological treatment of uncertainty in ECVs, as recommended by the GUM (Guide to the Expression of Uncertainty in Measurement) and GCOS guidelines [21], [22].

Data quality issues can arise from a variety of factors, including discrepancies in measurement techniques, gaps in observational coverage, and biases introduced by sensor drift or calibration errors [2], [13]. These problems are particularly pronounced in remote or extreme environments, such as the polar regions, where data collection is logistically challenging [23]. To mitigate these risks, practitioners are advised to adopt established protocols for calibration, validation, and uncertainty estimation. For instance, the Fiducial Reference Measurements (FRM) approach developed by the European Space Agency (ESA) emphasizes traceable reference data, comprehensive uncertainty budgets, and rigorous inter-comparison exercises [9]. Similarly, harmonizing satellite-derived data with in situ measurements, underpinned by consistent error models, has proven effective in improving the reliability of sea-level rise and temperature records [24]. Several challenges and strategies are critical to improving data quality monitoring. For example:

- Inconsistent Data Quality across Regions and Timescales: Climate data often exhibit inconsistencies in quality across regions and timescales. Variations in data accuracy can arise due to differences in the availability of observation infrastructure, instrument calibration, and regional environmental conditions [2]. Practitioners need to explicitly quantify the regional representativeness of their datasets and propagate related uncertainties into climate model forcing and assessments.
- Integration of New Measurements with Existing Datasets: As new measurement technologies and instruments are developed, they must be carefully integrated with existing datasets. This integration requires robust protocols for labeling and certifying the data to assess their quality [5]. Adopting traceability documentation — e.g., calibration lineage, algorithm maturity levels, and uncertainty budgets — is a minimum requirement for dataset acceptance.
- Spatial Coverage, Particularly in Remote Regions: One of the ongoing challenges in monitoring ECVs is the limited spatial coverage in remote and difficult to reach areas, such as the polar regions [23]. These areas are critical for understanding global climate dynamics, including sea-level rise and polar amplification. Establishing FRM reference stations in these locations, with documented traceability to SI units where possible, ensures that sparse but critical measurements retain high value for global analyses.
- Adoption of Standard Protocols for Calibration and Validation: To ensure the consistency and comparability of ECVs across different measurement platforms, the adoption of standardized protocols for calibration and validation is essential [17]. Following ISO 19157 [25] and GCOS guidelines [22], practitioners should adopt uncertainty quantification frameworks that include both systematic and random components, ensuring comparability across instruments and agencies.
- Harmonization of Datasets Across Diverse Sources: ECVs are derived from a wide range of observational platforms, including satellites, ground-based stations, and climate models. Harmonization explicitly include traceability chains that link back to FRMs and standard references, so that the uncertainties from diverse sources are consistently expressed.

Beyond the challenges listed above, a critical but often overlooked source of uncertainty lies within the measurement devices themselves. Remote sensing instruments, for instance, undergo on-board signal processing that can filter out low-amplitude signals before they reach ground stations. Retrieval algorithms embed assumptions about atmospheric state, surface properties, and viewing geometry that are rarely fully documented in final products. This creates layers of "hidden uncertainty" that propagate through the entire processing chain. When AI models are trained on such data, they inherit these biases—and may amplify them if systematic errors correlate with features the model learns to exploit. For operational ECV products, end-to-end uncertainty budgets should trace errors from raw sensor counts through all processing steps, following the FRM principles advocated by ESA and aligned with GUM standards [9], [11].

To maintain the accuracy, transparency, and dependability of climate science, the ECV data's traceability and consistency are essential. The International Organization for Standardization (ISO) has established a suite of standards widely adopted by EO data providers that offer robust frameworks for addressing data quality. Standards such as ISO 19113 and ISO 19115 define quality principles and geographic metadata, respectively, while ISO 19138 focuses on quality measures. These are now transitioning to ISO 19157, which consolidates and supersedes previous standards, providing a comprehensive approach to data quality [25], [26]. The metadata records in the current Global Earth Observation System of Systems (GEOSS) are based on the ISO 19115 data model and its XML encoding companion, ISO 19139. Certified data resources can display the tagline *Certified complying with GEO data management principles*, further enhancing their credibility and utility for research, policy making, and social applications.

Following this framework, we suggest specific legislative and operational actions to strengthen the traceability and uncertainty management of climate datasets. These include: (1) a Data Quality Passport for each dataset (listing calibration dates, uncertainty budgets, and error margins), with non-certified datasets excluded from official reports; (2) installation of FRM reference stations in key observational gaps (Arctic, mountain regions, vulnerable coastlines) under long-term maintenance contracts; (3) adoption of a Climate Data Liability Act, penalizing providers of uncertified or misleading datasets; (4) development of a European Climate Data Quality Standard [27] certifying measurement instruments and publishing a public database of performance ratings; (5) mandatory use of certified datasets in financial-sector climate risk assessments; and (6) open APIs for real-time dashboards monitoring data quality metrics. These measures operationalize traceability and uncertainty management, providing practitioners with clear guidance and policymakers with dependable, evidence-based datasets.

III. Monitoring ECVs with Advanced Analytics

Advanced analytics, including ML and DL, are increasingly used to process heterogeneous Earth observation datasets [28]. This section presents three representative examples demonstrating their application to ECV monitoring.

A. Use Case I: Temperature Monitoring for Multi-Sectoral Climate Applications

Background: Temperature serves as a fundamental ECV driving multiple Earth system processes across scales, from local microclimates to global circulation patterns as described in the last Global Climate Highlights 2024 report published by the Copernicus Climate Change Service (C3S) [29]. Local-scale air temperature data serve multiple critical functions, e.g., enabling effective urban heat mitigation strategies for vulnerable populations [30], [31] or supporting agricultural management through monitoring of crop development rates, pest dynamics, and water requirements [32], [33]. This multi-sectoral importance extends to biodiversity conservation, which depends on understanding thermal habitats and species migration patterns [34], and risk finance sectors that require precise temperature data for parametric insurance products, catastrophe bonds, and climate risk assessments [31], [35].

ECV-related Challenges: Temperature monitoring faces scale-dependent challenges spanning orders of magnitude in spatial and temporal resolution. Agricultural applications require field-scale (e.g., 10-100 m) temperature gradients to optimize irrigation scheduling and predict harvest timing, yet conventional weather stations provide point measurements every 10-50 km [36]. Food security assessments depend on understanding temperature stress during critical crop development phases, as temperature extremes can reduce yields by 10-25% for major staple crops, but current monitoring networks cannot capture the fine-scale thermal heterogeneity within agricultural landscapes [37]. UHI monitoring demands less than sub-kilometer resolution (preferably a few meters) to identify vulnerable neighborhoods and assess cooling interventions. Nocturnal temperature differences of 2-3°C are documented between urban cores and surrounding areas in cities like Thessaloniki [38], Hong Kong [39], and multiple U.S. metropolitan areas [40], yet existing station networks are often sparse to support targeted heat mitigation strategies [41], [42]. Biodiversity monitoring demands understanding of microhabitat thermal refugia and elevation-dependent warming rates, particularly in mountainous regions where species range shifts occur. Risk finance applications require statistically robust temperature records with quantified uncertainties for pricing weather derivatives and validating climate models used in catastrophe risk modeling [43]. Data gaps and outliers persist across all sectors, with particular deficiencies in developing regions where agricultural vulnerability, urban heat exposure, and biodiversity hotspots coincide, creating compounding risks for food security, human health, and ecosystem stability.

Current Monitoring State: Existing temperature monitoring combines ground-based networks, satellite observations, and reanalysis products with sector-specific limitations [44], [45]. Weather stations provide localized data but miss field-scale variability critical for urban heat island or agriculture. Satellite land surface temperature products offer global coverage but require atmospheric corrections and suffer from clouds for interpretation [46]. Biodiversity applications rely on interpolated climate surfaces that smooth out topographic complexity essential for species habitat modeling. Risk finance sectors depend primarily on reanalysis products like ERA5 [47], which provide consistent global coverage but may not capture extreme events accurately at local scales where insurance payouts occur. Regarding UHI analysis, a powerful alternative to measurements is numerical modeling, which provides continuous high-resolution wind fields and temperature estimates. FITNAH-3D [48], [49] is one model that enables simulation down to 5 m resolution, capturing fine-scale microclimatic variations driven by urban morphology, green space, and terrain. FITNAH-3D is better suited for regional modeling and scenario analysis than microscale models like ENVI-met [50] or MUKLIMO-3 [51]. It facilitates the evaluation of present and anticipated urban climates under different IPCC RCP scenarios [52], offering a foundation for intervention planning. Structure height from LiDAR-derived DSMs, land use classification, and homogenized terrain data are all inputs to the model. High correlations (0.97–0.99) and mean absolute errors of 1.6 °C were found when validation was done against German Weather Service measurements in Baden-Württemberg [53]. However, uncertainties persist because of external data limitations and internal model simplifications [54], [55].

AI Monitoring Opportunities: Machine learning (ML) approaches enable integration of disparate data sources to create sector-specific temperature products addressing scale mismatches. For agriculture, neural networks can downscale satellite thermal infrared data using topography, soil properties, and vegetation indices to generate daily temperature fields at field scales [56], [57], [58]. Biodiversity applications benefit from ensemble modeling approaches that combine species occurrence data with fine-scale climate predictors to map thermal microhabitats and project range shifts under climate change scenarios [59], [60]. Risk finance sectors apply deep learning to correct climate model biases, enhancing temperature extreme predictions for catastrophe modeling and parametric insurance products [61], [62]. High-resolution urban temperature fields have been created by combining AI techniques with measurement networks and numerical modeling. A feedforward neural network in Mannheim, Germany, generated real-time temperature maps with a 5 m resolution by combining 95 station measurements and FITNAH-3D outputs [63]. The principle of the innovative method is presented in Fig. 2, and the interpolated temperature in Fig. 3. The network was trained using historical data from June to August 2023, which included several simulation scenarios that reflected the current wind conditions.

Quality Assessment and Traceability: Multi-sectoral applications require rigorous uncertainty quantification and validation protocols adapted to specific use cases. Agricultural applications validate against crop development stage observations and yield records [32], [64], [65], while biodiversity models undergo validation against independent species occurrence databases and phenological observations [60]. Risk finance applications require validation against historical loss records and stress-testing under extreme climate scenarios [43]. Traceability frameworks document data lineage from raw satellite observations through processing algorithms to final products, enabling users to assess fitness-for-purpose [44]. Standardized metadata schemes ensure interoperability across sectors while maintaining sector-specific quality indicators relevant to end-user applications [66], [67]. These quality assessment principles are exemplified in UHI monitoring applications, where AI-enhanced temperature products have measurable performance metrics.

Guidelines for Historical Data Integration: A persistent challenge in AI-enhanced ECV monitoring is the integration of historical observations (often sparse, poorly standardized, and collected under different climatological conditions) with modern high-quality data. Training models on mixed-era datasets risks either biasing predictions toward current climate states or degrading overall performance. Several strategies can mitigate these risks. First, physics-informed constraints can be embedded directly into loss functions, enforcing energy conservation, hydrological balance, or thermodynamic consistency across all variables [68]. This ensures that individual predictions remain physically coherent as a whole. Second, climate-invariant transformations [69] rescale input variables so that their statistical distributions remain stable across different climate periods, improving generalization from historical to current conditions. Third, given that climate change is accelerating beyond historical precedent, monitoring the rate of change rather than absolute values can flag when observations depart from the training distribution. Finally, scenario-conditional training, e.g., incorporating CMIP6 projections alongside historical data, would expose models to plausible future states, reducing the problem of systematic out-of-distribution extrapolation. These approaches complement traditional uncertainty quantification (e.g., Bayesian methods) by addressing the structural challenge of non-stationarity in climate data. The Mannheim neural network system illustrates successful integration of multi-source data with rigorous validation protocols. The model's ability to capture fine-scale urban temperature variability was demonstrated by its 97% hit rate within 1°C across 20 million unseen data points. Following the GCOS climate monitoring principles [22], the resulting maps show cooler areas associated with green infrastructure and hotspots linked to sealed surfaces (Fig. 3). This information supports urban planning, public health interventions, and targeted heat mitigation strategies, demonstrating how sector-specific quality requirements translate into actionable products for policymakers and urban managers. Although measurement networks are susceptible to uncertainties such as outliers, data gaps, and station sparsity [54], [55], climate modeling introduces a different set of uncertainties that can be categorized into:

1) **Model-related uncertainties ("internal uncertainties")**: Models are simplified representations of reality. FITNAH-3D, for example, uses a turbulence simulation method (Reynolds-Averaged Navier-Stokes, RANS) that does not explicitly resolve small-scale turbulence, unlike Large Eddy Simulation (LES).
2) **Input data-related uncertainties ("external uncertainties")**: These include:
   - Data processing errors.
   - Outdated data affecting accuracy.
   - Variations in data quality and resolution.
   - Simplified representation of urban structures.

The method is partially based on numerical modeling and, thus, associated with uncertainties that must be acknowledged transparently.

Policy Applications: Temperature data products support evidence-based policy across multiple domains beyond urban planning [70]. Agricultural policies can benefit from early warning systems for crop stress, optimized planting date recommendations, and assessments of climate change adaptation measures. Biodiversity conservation policies utilize thermal habitat mapping for the design of protected areas, corridor planning, and species reintroduction programs [71]. Risk finance applications enable the development of climate-resilient financial instruments, including index-based crop insurance, catastrophe bonds for extreme temperature events, and climate risk disclosure frameworks required by financial regulators [72], [73]. Integration across sectors supports comprehensive climate adaptation strategies, such as nature-based solutions (tree planting) that simultaneously address urban heat, agricultural productivity, and biodiversity conservation while providing measurable co-benefits for risk reduction and climate finance mechanisms [74], [75].

B. Use Case II: Monitoring Earth's Surface Processes with Satellite Geodesy

Background: Recent advances in satellite geodesy provides essential measurements for monitoring multiple ECVs related to Earth's surface processes. InSAR and GNSS measure surface deformation with millimeter-to-centimeter accuracy, revealing land subsidence, crustal motion, and hydrological loading effects [76], [77]. ICESat/ICESat-2 and CryoSat altimetry captures elevation dynamics over ice sheets and glaciers [78]. SWOT mission provides new possibilities for monitoring surface water levels (SWLs) of rivers, lakes and reservoirs, as well as river discharge (Q) with unprecedented spatial and temporal resolution [79]. Both SWL and Q are considered as ECVs, which can get benefits from RS-based techniques. Distinct from these geometry-based methods, GRACE and GRACE-FO (Gravity Recovery and Climate Experiment – Follow-On) sense time-variable variations in the Earth's gravity field, enabling detection of mass redistribution across the hydrosphere, cryosphere, and solid Earth [80]. Their unique advantage lies in providing integrated estimates of terrestrial water storage (TWS) changes at regional to global scales, including both surface and subsurface components, which are beyond the reach of other satellite techniques. Consequently, GRACE/GRACE-FO data have become indispensable for monitoring large-scale water balance variations driven by climate and human activities, providing critical insights for understanding climate change impacts, informing water resource management, and supporting risk assessments across agricultural, biodiversity, and disaster finance sectors [81], [82], [83]. In what follows, we focus on TWS and the relevant AI opportunities.

ECV-related Challenges: Despite the wide applications of GRACE/GRACE-FO, several factors hinder its operational use for monitoring the ECV of TWS. Data latency is a major limitation, as GRACE/FO products typically require one to three months for extensive processing and validation, significantly limiting their utility for real-time monitoring of water availability and hydrological droughts, and constraining their support for downstream applications [84]. Data gaps arise from instrument anomalies and the mission gap, leading to temporal discontinuities [85]. Besides, the short

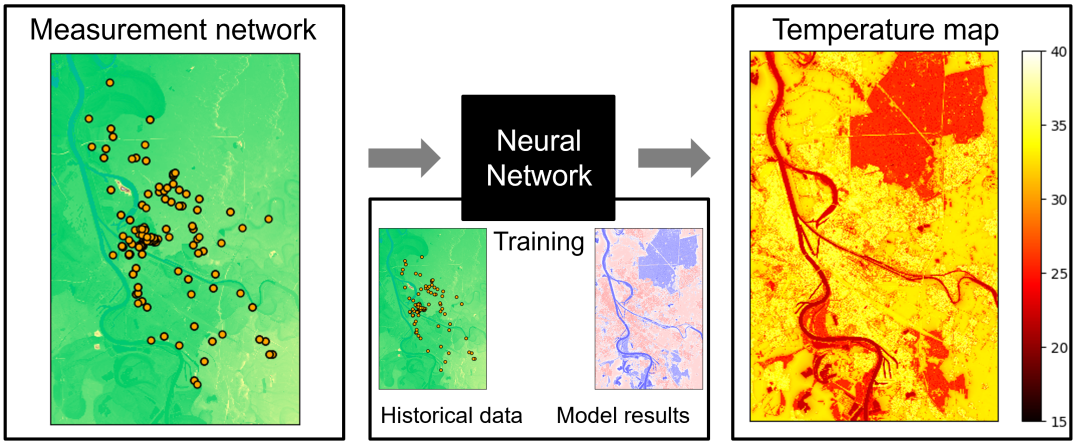

Fig. 2: Flowchart explaining the methodology used to combine measurement network data with numerical modeling results using a neural network for temperature interpolation

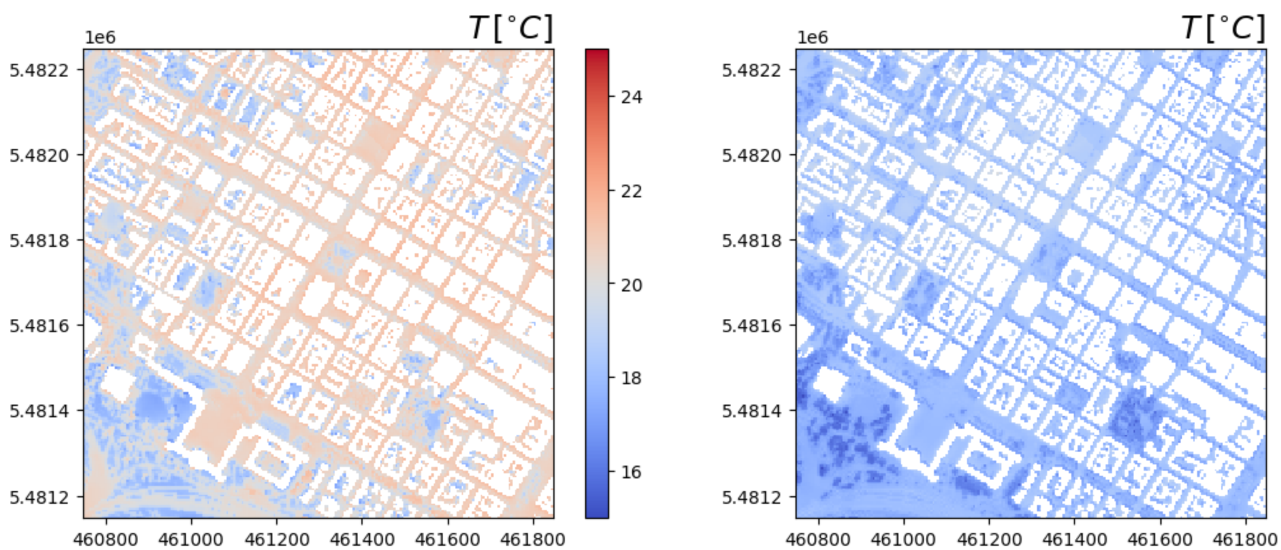

Fig. 3: Interpolated temperature at a height of 2 m generated by the neural network for Mannheim, Germany (03.10.23 at 3 a.m. and 3 p.m.). Coordinates are in ETRS89/UTM zone 32N (EPSG:25832), with X representing easting and Y representing northing in meters.

observation period (2002-present) constrains the assessment of long-term hydrological trends and climate variability [86]. Coarse spatial-temporal resolution (∼300 km spatial, monthly temporal) further limits the ability to resolve localized and rapid hydrological changes [87], [88]. In addition, resolving TWS from complex satellite measurements is rather complex and calls for sophisticated Signal separation frameworks [89], [90], [91]

Current Monitoring State: Current TWS monitoring relies primarily on the GRACE/GRACE-FO missions, which observe mass variations associated with surface and subsurface water storage. Due to their coarse spatial resolution, these data are best suited for large-scale hydrological applications [92]. Since 2002, GRACE/GRACE-FO observations have revealed global "hotspots" of water depletion driven by climate variability and human activities [81], [83]. They are extensively used to evaluate storage deficits and surpluses during droughts and floods, supporting improved understanding and management of extreme events. To isolate specific storage components such as groundwater, GRACE/GRACE-FO data are often integrated with land surface models, reanalysis products, and complementary remote sensing or in situ observations (e.g., GNSS, InSAR, ICESat, and hydrological monitoring networks), revealing major groundwater depletion zones in, for instance, California's Central Valley, the High Plains Aquifer, northern India, and the North China Plain [77], [93], [94], [95], [96], [97]. Assimilating GRACE data into hydrological models seems necessary for estimating water storage especially in the groundwater component of the water cycle [98], [99], [100]. Nonetheless, coarse resolution, data latency, mission gaps, and a relatively short record still limit the operational use of GRACE/GRACE-FO-based TWS products for regional water management and near-real-time applications.

AI Opportunities: ML models offer multiple strategies to address key limitations of GRACE/GRACE-FO TWS observations. It can reduce data latency by learning the empirical relationships between TWS and hydrometeorological predictors, enabling near-real-time estimation during the latency period [84], [101]. Similarly, ML approaches can fill the data gaps within the GRACE/GRACE-FO missions and extend TWS records to the pre-GRACE era using historical predictor data. Traditional ML methods, such as decomposition techniques [89], [102], random forest and the fully connected network, learn these relationships in a grid-wise manner [86], [103], [104], while the convolutional neural network (CNN) treats TWS and predictor fields as images to perform image-to-image regression [105], [106], [107], fully leveraging the CNN's strong ability to exploit spatial dependencies within images [108], [109], thereby enhancing predictive performance. Predictive uncertainties of CNNs can be quantified by employing Bayesian strategies, such as Stein variational gradient descent [110] and Monte Carlo dropout [111], as shown in [84], [105], [106]. ML approaches can also mitigate the coarse spatial-temporal resolution of GRACE/GRACE-FO TWS data [87], [112]. For instance, [112] developed a self-supervised data-assimilation CNN to spatially downscale TWS fields, recovering local details by leveraging high-resolution hydrological model outputs, meteorological data, and topographic information. An illustration of the CNN-based spatial downscaling framework is shown in Fig. 4.

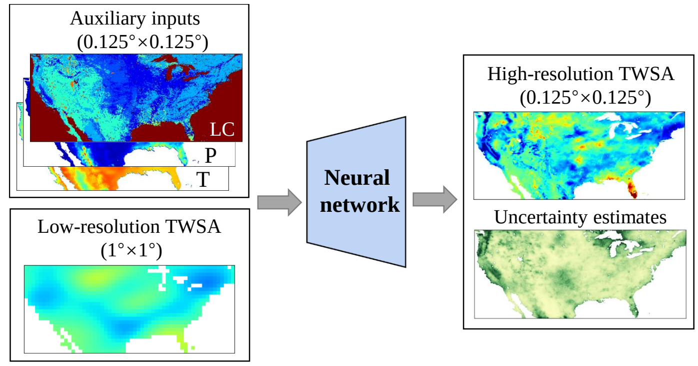

Fig. 4: Illustration of a deep learning model for downscaling the GRACE/GRACE-FO-derived terrestrial water storage anomaly (TWSA) field. Inputs include the low-resolution TWSA field and high-resolution auxiliary inputs like temperature (T), precipitation (P), and land cover (LC) type. The downscaled uncertainties are quantified.

Quality Assessment and Traceability: Uncertainty quantification represents a critical component of AI-enhanced TWS products. Bayesian optimization frameworks provide confidence bounds essential for risk analysis and policy applications [110]. Validation protocols compare AI-reconstructed fields against independent hydrological observations and assess mass conservation at basin scales. Traceability frameworks document the integration of satellite observations, auxiliary data sources, and processing algorithms, enabling users to understand data provenance and assess fitness-for-purpose across different applications.

Policy Applications: Enhanced TWS monitoring plays a key role in supporting evidence-based policy development in diverse sectors. By providing accurate, timely, and spatially resolved data, TWS observations enable decision-makers to design policies based on scientific evidence rather than assumptions. For example, *Water resource management* is one of the most direct beneficiaries. Improved drought early warning systems, informed by TWS anomalies, allow authorities to anticipate water scarcity and implement mitigation strategies before crises escalate. Similarly, groundwater depletion assessments based on TWS trends help protect aquifers, ensuring sustainable extraction and long-term water security. In the US, the National Integrated Drought Information System (NIDIS) is a multi-agency partnership that coordinates drought monitoring, forecasting, planning, and information at national, tribal, state, and local levels, which uses a GRACE(-FO)-fed system for motioning droughts across the country [113]. For *agricultural policy*, high-resolution TWS data can support irrigation scheduling optimization, reducing water waste while maintaining crop health. It also improves crop yield forecasting by integrating soil moisture dynamics with climate models, allowing farmers and policy makers to plan food security under variable conditions [114]. Potentially in the future, *the risk finance sectors* can leverage TWS-derived insights for innovative financial instruments. Parametric insurance products, which rely on objective environmental triggers, will be more accurate when informed by TWS data. TWS can support *climate adaptation planning* and *resilience strategies* by providing input for Water security assessments and identifying vulnerable regions. These insights are critical for national adaptation plans and international climate commitments [115]. Finally, the integration of AI-enhanced satellite geodesy with GCOS data quality frameworks ensures that all policy-relevant information maintains scientific rigor. This alignment guaranties that datasets meet stringent accuracy standards while complying with operational timeliness requirements—an essential balance for real-world decision-making processes.

C. Use Cases III : Monitoring the ERB and the future application of AI

Background: The Earth Radiation Budget (ERB), defined by the GCOS as an ECV, represents the balance between incoming solar radiation and outgoing thermal energies. On the incoming side, the Total Solar Irradiance (TSI), the spectrally integrated energy at a distance of 1 AU from the Sun, is measured at the Top Of the Earth's Atmosphere (TOA). TSI measurements started in 1978 using numerous space instruments [116], [117]. For more than 30 years, the challenge was that the calibration uncertainty of the TSI radiometers with respect to the official international standards for measurement was large ($> 0.35\%$) compared the solar cycle variability (0.1%) and expected Earth Energy Imbalance (EEI) (approx. 0.04% of the TSI), making it a) difficult to concatenate the measurements from different satellites and b) impossible to estimate the EEI. These problems were solved with improved laboratory facilities for the pre-launch calibration of TSI radiometers [118]. The IAU 2015 resolution [119] recommends

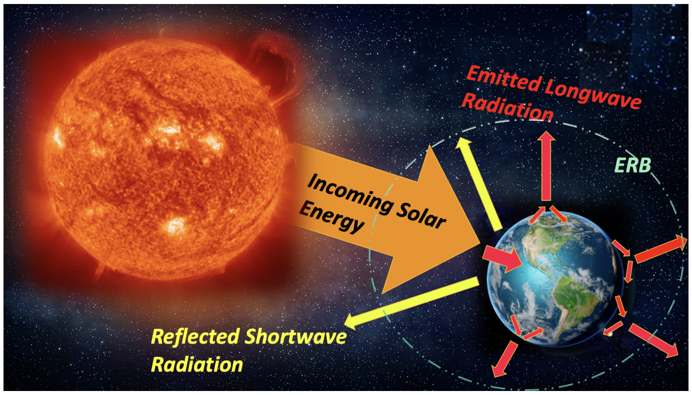

Fig. 5: Illustration of the Earth Radiation Budget with the different components (incoming solar energy, Outgoing Shortwave Radiation, Outgoing Longwave Radiation).

the nominal TSI value of 1361 W.m^{-2}. Now on the outgoing side, the radiations are split in two components: the Outgoing short-wave radiation (OSR), which is the portion of solar radiation reflected back into space by clouds, aerosols, and the Earth's surface; and the Outgoing long-wave radiation (OLR), which is the thermal energy emitted by the surface and atmosphere of the Earth. The sum of OSR and OLR forms the total incoming radiation (TOR), which is the spatially and spectrally integrated emission in the ToA. Fig. 5 is a schematic view of the ERB, illustrating the flow and partitioning of incoming solar radiation, OLR and OSR. If the incoming and outgoing energies are at equilibrium, the Earth's climate does not change, only a relative short-term internal variability is observed, but no long-term warming or cooling of the Earth's system is observed. However, this is not the case for the current climate. The increasing levels of greenhouse gases (GHGs) in the atmosphere allow less infrared radiation from the surface to be transmitted into space, leading to the so-called positive Earth Energy Imbalance (EEI). As a result, the global surface temperature increases. The ERB is assimilated as the EEI when climate scientists discuss the imbalance between the reflected and absorbed quantities of energy from the Earth system.

ECV-related Challenges: Although ERB is central to understanding climate forcing, it remains one of the most technically challenging ECVs to monitor. Some studies have estimated the ERB to be around $+0.5$ to $+1.0$ W.m^{-2} [120], [121], [122], [123], [124], largely consistent with the values given by 6th IPCC Report, WG1, [125]. Historically, calibration uncertainties of radiometers exceeded the magnitude of ERB, making it difficult to merge records across different satellite missions or to infer global trends with confidence. Even with recent advances in laboratory calibration [126], rigorous traceability remains necessary to meet the GCOS accuracy requirement of roughly 0.1–0.2 Wm^{-2}. The WMO has stressed that ERB products must be harmonized across missions and integrated into frameworks such as the WMO Integrated Global Observing System (WIGOS) to ensure interoperability and long-term continuity. Despite progress, absolute detection of EEI still requires combining satellite records with in situ ocean observations and model-based reconstructions [127], [128]. Limitations such as data gaps, instrumental noise, and difficulties in merging heterogeneous sources continue to constrain the construction of consistent long-term climate data records.

AI Monitoring Opportunities: Recent advances in AI offer new tools to address these challenges. ML algorithms have been applied to correct long-term degradation in radiometers such as VIRGO/PMO6 [129]. Deep learning has been applied to noise filtering in radiometer data, gap-filling [130], and direct estimation of OLR from high-resolution observations recorded by sensors such as MODIS and Himawari-8 [131], [132]. These approaches enhance continuity, exploit ancillary metadata, and can identify subtle signals that might otherwise be obscured. Looking forward, physics-informed networks and emerging foundation models may enable the assimilation of heterogeneous ERB datasets, opening the way for more robust and near-real-time estimates of EEI.

Quality Assessment and Traceability: For such innovations to be credible, however, they must be grounded in rigorous quality assurance. Standardized calibration of radiometers [118], [126], comprehensive metadata on instrument performance and retrieval algorithms, and systematic traceability to international metrological references remain essential [133]. AI can support anomaly detection and bias correction, but methods must be transparent and benchmarked against independent references. Probabilistic techniques, including Bayesian networks simulations [16], provide avenues for quantifying uncertainty, while integration into ISO-based data quality frameworks ensures interoperability across missions and observational systems.

Policy: ERB is identified as a key diagnostic for understanding climate variability and anticipating future changes [127], [128], [134], [135]. Its accurate estimation links directly to the Paris Agreement goal of limiting global warming, as it enables evaluation of whether mitigation measures translate into measurable physical changes in the climate system. ERB records feed into the IPCC assessments and the UNFCCC Global Stocktake [136], [137], providing governments with an independent benchmark to assess progress towards net-zero commitments. Looking ahead at the national and regional scale, accurate ERB products can support adaptation planning by informing projections of heat extremes, cryosphere melt, and water-cycle shifts that carry major socio-economic implications. As carbon dioxide removal and geoengineering proposals enter policy discussions, ERB-derived indicators could verify whether such interventions measurably alter the global energy balance [138]. To strengthen equity and social protection, ERB-derived indicators could be coupled with socio-economic data to target adaptation finance toward vulnerable communities and ensure fair-transition measures in high-risk regions.

IV. Critical Assessment of AI/DL Limitations for ECVs

Building on the three examples highlighted in the previous section, it is clear that advanced analytics have already demonstrated potential for advancing the monitoring of ECVs. By enabling the integration and processing of large, diverse EO datasets from multiple platforms, these techniques indirectly contribute to more comprehensive and reliable ECV estimation within key international programs. The AI for Earth Observation (AI4EO - $https://ai4eo.eu/$) project develops applications of ML and DL to detect patterns, anomalies, and trends in climate-related variables such as atmospheric composition, sea surface temperature, and land-use change, while Destination Earth uses AI to build a digital twin of the Earth for high-resolution climate simulations. Similar efforts include NASA's Radiant Earth, which provides open repositories of training datasets and ML models, and China's CASEarth ($https://www.cbas.ac.cn/en/research/CASEarth/$), part of the Big Earth Data Science Engineering initiative. In Europe, the Space for Climate Observatory (SCO -$https://www.spaceclimateobservatory.org/$) and DATA TERRA ($https://www.data-terra.org/$) emphasize the integration of EO data and advanced analytics to address pressing climate challenges. Despite these successes, the rapid adoption of such methods also raises critical questions. This section turns to a critical assessment of these limitations, examining where current approaches may fall short and what challenges must be addressed to ensure robust and trustworthy use of AI for ECV monitoring.

AI/DL approaches have achieved significant advances. However, their operational deployment within this context is constrained by fundamental limitations, including:

- **Transferability across regions** remains problematic, as demonstrated in urban heat monitoring where neural networks trained on specific cities (e.g., Mannheim) achieve 97% accuracy locally but show degraded performance in different climatic zones or urban morphologies. Models trained on TWS data from temperate regions often fail in arid or tropical environments due to domain shift and covariate bias.
- **Interpretability** remains a challenge for both scientific understanding and regulatory acceptance in Earth science applications. This is clearly seen in the ERB, where ML models effectively correct for degradation in instruments measuring TSI —such as the fading of radiometer cavity coatings caused by UV/EUV exposure. However, because the ML/DL algorithms act as a "black box," they fail to provide physical insight into the underlying degradation mechanism. The "black box" nature of the ML/DL algorithm limits scientific trust and regulatory acceptance for climate policy applications [139].
- **Dataset bias** emerges from uneven global coverage of training data, temporal gaps in historical records, and systematic sensor differences across satellite missions. For instance, GRACE/GRACE-FO gap-filling algorithms trained predominantly on continental hydrology may perform poorly in coastal regions or ice-dominated areas.

These limitations are especially critical for policymakers who require robust, explainable tools with quantified uncertainties. Current validation procedures often rely on limited ground truth data (such as sparse weather station networks for urban heat or delayed GRACE products for TWS) and may not capture model performance under extreme climate conditions or in data-sparse regions where ECVs are most needed. Table I gives an overview of different challenges and limitations to monitor some ECVs related to the algorithms used and the dataset.

Historically, AI models for Earth science were built for specific, narrow tasks. Trained on large and multi-source datasets, foundation models (FMs) can now fuse satellite imagery, climate model outputs, and textual reports to learn core representations of the Earth system. FMs open new applications for transfer learning across multiple ECVs and regions, potentially addressing domain adaptation challenges. Recent developments include Aurora, trained on over one million hours of geophysical data and demonstrating superior performance in air quality, ocean dynamics, and weather forecasting [140], and specialized EO foundation models like Prithvi-EO for flood segmentation [141]. However, their effectiveness remains limited by the availability of large, well-curated (certified) EO datasets and the need for specialized pre-training on geophysical data rather than natural language or images [142].

Generative AI and Diffusion Models: A notable omission in many ECV applications has been the recent progress in generative AI, particularly diffusion models. GenCast [143], developed by Google DeepMind, demonstrates that diffusion-based ensemble forecasting can outperform the ECMWF's operational ensemble (ENS) on 97% of evaluated targets while generating 15-day global forecasts in 8 minutes. Unlike deterministic models, diffusion approaches capture the inherent uncertainty of atmospheric evolution by generating multiple plausible trajectories. Physics-informed neural ODEs such as ClimODE [144] embed advection principles directly into the network architecture, enforcing value-conserving dynamics while learning transport patterns from data. These approaches suggest a path toward models that are both data-efficient and physically consistent.

Further recent advances demonstrate diffusion models' effectiveness for climate downscaling with superior fine-scale accuracy [145], while maintaining spatiotemporal coherence for probabilistic climate projections. Unfortunately, these models struggle with physical consistency and may generate unrealistic extreme values critical for climate applications. Evaluation approaches must incorporate domain-specific metrics beyond standard ML benchmarks, including physical checks, conservation law adherence, and performance on rare climate events.

What Can and Cannot Be Addressed: It is useful to distinguish three categories of challenges: (i) *What is being addressed*: transferability via foundation models, uncertainty via diffusion ensembles, physical consistency via physics-informed architectures; (ii) *What needs further research*: robust out-of-distribution detection for non-stationary climate, hybrid physics-AI architectures with full interpretability, computationally efficient deployment; (iii) *What remains infeasible without workarounds*: perfect generalization to unprecedented climate states (workaround: scenario-conditional training), full interpretability of deep networks (workaround: physics-guided

TABLE I: AI/DL Applications for Essential Climate Variables: current status and overview of some limitations. Note that model selection (e.g., CNN vs. U-Net) is often empirical and depends on available training data and computational resources. Emerging architectures such as diffusion models and foundation models may supersede these choices as the field evolves.

ECV	Primary EO Sources	AI/DL Models	Validation Data	Known Gaps
LST/T	MODIS, Landsat, VIIRS	CNN, Random Forest, Neural Networks	Weather stations, Flux towers	Cloud contamination, Urban bias
TWS	GRACE/GRACE-FO	ICA, Bayesian CNN, XGBoost	Well data, Hydrological models	1–3 month latency,Temporal data gaps, Coarse resolution, Coastal errors
ERB	CERES, MODIS, TSI radiometers (TIM, PMO6)	Regression ML, DL	Radiometer intercomparisons, ground radiometers	ML can correct instrument drift and fill gaps but must preserve absolute calibration
Soil Moisture	SMAP, SMOS, Sentinel-1	LSTM, CNN, Gaussian Process	In-situ networks, Cosmic-ray probes	Vegetation effects, Frozen soil
Precipitation	GPM, TRMM, IR satellites	U-Net, RNN, Ensemble methods	Rain gauges, Weather radar	Extreme events, Orographic effects
Sea Surface Temperature	VIIRS, MODIS, AVHRR	Deep Learning, Physics-informed NN	Argo floats, Ship measurements	Diurnal variations, Polar regions

constraints, post-hoc attribution), removing sensor-level biases through AI alone (workaround: maintain FRM infrastructure). These distinctions help set realistic expectations for AI-enhanced ECV products.

Further limitations include computational requirements that restrict operational deployment, limited interpretability compared to process-based models, and fundamental uncertainty about generalization to future climate states not represented in historical training data [16].

V. From Observation to Action: The Data Infrastructure Driving Global Climate Policy

Moving from the technical challenges of monitoring the ECVs, we now focus on the structural foundation that translates any observation into global commitment: the data infrastructure. One clear example of how climate data informs international policy is the global goal of limiting warming to 1.5°C, as outlined in the Paris Agreement [136]. The achievement of this goal depends on a coordinated system that includes data collection, analysis, and policy development. The time series (or data set) of the ECV provides critical input for evaluating environmental challenges, including those posed by extractive industries such as mining and fossil fuel production, which contribute significantly to greenhouse gas emissions, pollution, and biodiversity loss. Comprehensive analyses based on ECV data can help quantify the impacts of mining and resource extraction across the value chain, enabling stakeholders to mitigate harm and align actions with sustainability goals [146].

A key asset is the WIGOS platformed developed by the WMO, supporting technological advances in climate monitoring by providing robust data quality control mechanisms. It encompasses both operational and research-based surface and space observation subsystems, with physical infrastructure located on land, at sea, in the air and in space. Interoperability and data compatibility are achieved through internationally recognized standards, recommended practices, and rigorous processes for system design, evolution, and performance monitoring. Operational since 2020, WIGOS integrates diverse observational networks and delivers reliable data sets through initiatives such as the Global Basic Observing Network (GBON) and Regional Basic Observing Networks (RBON):

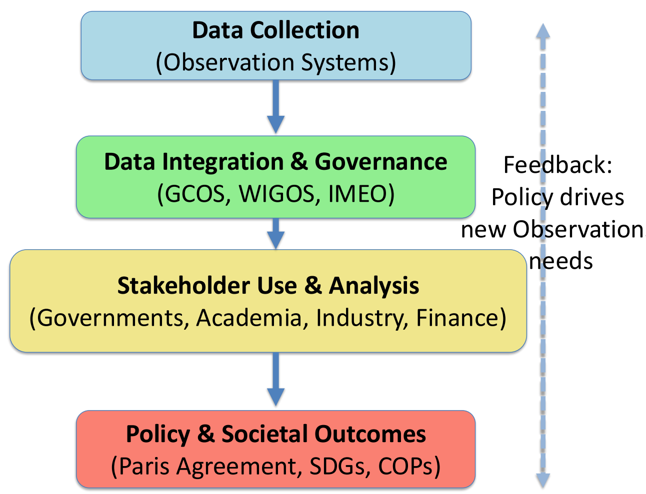

Fig. 6: Conceptual flow of climate observation data into policy. Data are collected globally through standardized networks, integrated by governance bodies, and applied by stakeholders to inform policy and sustainability actions. Feedback from policy outcomes drives improvements in observation needs and data governance frameworks.

- GBON defines the mandatory minimum set of surface and upper-air observations that every country must provide at internationally agreed standards and intervals. Its goal is to ensure the foundational data needed for global Numerical Weather Prediction (NWP), climate monitoring, and early warning systems.
- RBON, on the other hand, complements GBON by addressing region-specific observing needs. It strengthens observational coverage in areas with specific climatic, geographic, or socioeconomic vulnerabilities, ensuring

regional relevance and resilience.

These datasets are critical for informing both local and global climate strategies, improving climate risk forecasting, and supporting the efficient deployment of renewable energy systems. For example, the upper air temperature, one of these ECVs, plays a critical role in detecting atmospheric warming. Observations of this variable are gathered through a global network of measurement platforms organized under the WIGOS. In addition, local measurement networks—particularly in urban areas—are expanding. In Section III, we presented an example of how AI can be innovatively applied to enable continuous spatially real-time monitoring of upper air temperature in cities, contributing to more resilient urban planning and improved public information. This approach directly supports the SDG 11 (Sustainable Cities and Communities), which aims to make cities inclusive, safe, resilient, and sustainable. Moreover, in the same section, we investigated the ERB, providing critical information on the planet's energy balance, which underpins our understanding of climate dynamics. Accurate ERB data directly supports SDG 13 (Climate Action) by informing mitigation strategies, while also indirectly contributing to SDG 11 by guiding climate-resilient urban design and early warning systems for extreme weather events.

Beyond these case studies, the monitoring of ECVs is linked with a wide range of environmental and socioeconomic domains that are central to sustainable development. For instance, ECVs such as soil moisture, precipitation, and surface temperature are vital for assessing agricultural productivity and informing adaptive farming practices [147], [148]. These datasets enable early warning systems for droughts and floods, directly supporting food security and resilience. In the context of biodiversity conservation, ECVs like land cover, vegetation indices, and ocean surface temperature provide information for tracking ecosystem health and species distribution shifts [149], [150]. Continuous observation of these variables allows for the identification of climate-sensitive habitats and the formulation of evidence-based conservation strategies. Furthermore, ECV monitoring enhances decision-making in integrated land–water–energy management, helping stakeholders balance competing demands on natural resources. This cross-sectoral applicability ensures that climate data not only guides mitigation and adaptation in urban environments but also strengthens rural livelihoods, agricultural sustainability, and ecosystem preservation. Collectively, these applications reinforce the interconnected nature of the Sustainable Development Goals—particularly SDG 2 (Zero Hunger), SDG 14 (Life Below Water), and SDG 15 (Life on Land)—demonstrating how comprehensive climate observation systems like WIGOS contribute to a truly global sustainability framework. Figure 6 is an illustration of how data monitoring ECVs are collected through global observation systems (e.g., WIGOS, GBON, RBON), integrated within governance frameworks (GCOS, IMEO), and utilized by diverse stakeholders to inform climate risk analysis, environmental assessments, and sustainability reporting, ultimately supporting international climate policy and the SDGs. Although WIGOS provides the infrastructure for collecting global observational data, especially meteorological, hydrological, and environmental, GCOS defines the climate monitoring requirements and specifies what ECVs are needed. They are connected together with their common data policy based on reliance on infrastructures, systems that ensure long-term, reliable observations. Without such foundations, it would be impossible to produce the information needed for effective climate policy and environmental decision-making.

A. Conclusions

This review study emphasizes the importance of ECV monitoring and analysis in advancing our understanding of climate systems and supporting informed decision making facing many challenges related to global climate change. High-quality traceable data sets are critical for identifying climate trends, predicting future conditions, and ensuring actionable policies. Advances in physics-informed DL algorithms (and AI) are revolutionizing the analysis of big data related to ECV datasets, enabling improved prediction, near-real-time monitoring, and gap-filling in observational data. The integration of AI with robust data quality standards should ensure consistency, accuracy, and reliability across various observation platforms.

By controlling the quality of the datasets and employing standardized calibration and validation procedures, scientists can better address challenges related to inconsistencies and data interoperability. This convergence of technology and methodology provides policymakers with reliable, actionable evidence needed for informed decision-making. These robust data standards offer critical support for global observation initiatives such as the GCOS and WIGOS, which are essential for developing resilient climate policies.

Furthermore, the alignment of ECV monitoring with policy frameworks highlights the essential role of data-driven strategies in fostering sustainable development and climate adaptation. Policies informed by these data, such as those that underpin initiatives (e.g., the UNEP Methane Emissions Observatory, GEO-7), exemplify how ECVs translate scientific understanding into specific targets and regulations designed to reduce greenhouse gas emissions and transition to sustainable resource management. Policymakers therefore rely on the consistent and transparent monitoring of ECVs to mandate and enforce the necessary changes for global climate resilience.

In the future, interdisciplinary collaboration and the integration of emerging technologies (as, e.g., quantum computers and quantum algorithms) will play a key role in advancing the utility of ECVs for climate science and policy.

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