Artificial Intelligence in Climate Science: A State-of-the-Art Review (2020–2025)

Vikas Ramachandra
Research Scientist
Vikas.Ramachandra@jacobs.ucsd.edu

Introduction

Climate change is intensifying extreme weather events and posing complex challenges to human and natural systems. In parallel, rapid advances in artificial intelligence (AI) and machine learning (ML) offer new tools to tackle climate science problems. AI can analyze vast climate datasets, improve forecasts, and optimize climate solutions at scales and speeds beyond traditional methods. For example, recent analyses estimate that scaling AI applications could help reduce 5–10% of global greenhouse gas emissions by 2030. At the same time, AI can bolster climate adaptation and resilience by enhancing predictive models and decision support systems. This review surveys the state-of-the-art (2020–2025) in applying AI to climate science across five key areas: **(1)** extreme weather prediction and nowcasting, **(2)** carbon emissions tracking and estimation, **(3)** climate change adaptation and mitigation planning, **(4)** climate model emulation and downscaling, and **(5)** climate-related decision support systems. For each subtopic, we highlight recent developments, AI/ML methods (e.g. deep learning, graph neural networks, transformers, physics-informed models), important datasets and benchmarks, performance metrics, and technical challenges such as data sparsity, interpretability, and generalizability. Cross-cutting themes and future research directions are discussed. The goal is to provide a comprehensive, technical yet accessible overview of how AI is transforming climate science, and to identify opportunities and hurdles on the path toward robust, AI-enhanced climate solutions.

AI for Extreme Weather Prediction and Nowcasting

Accurate forecasting of extreme weather events (such as heavy rainfall, hurricanes, heatwaves, and storms) is critical for early warnings and disaster preparedness. However, traditional numerical weather prediction (NWP) models face limitations in predicting localized, high-impact phenomena on short timescales. AI-based approaches have made remarkable strides in this domain by learning complex patterns from historical data and supplementing or even emulating physical models. **Nowcasting** – forecasting up to a few hours ahead – has been a focus of deep learning models that ingest radar and satellite observations. Notably, DeepMind's *deep generative model of rainfall* (DGMR) used a generative adversarial network (GAN) to produce probabilistic precipitation nowcasts from radar images. DGMR was shown to generate realistic

0–90 minute rain forecasts that outperformed traditional optical-flow advection methods, and in a blind evaluation by 50 expert meteorologists it was ranked **first** in accuracy and usefulness in 89% of cases compared to two existing nowcasting methods. This demonstrated that data-driven "physics-free" models can capture complex, non-linear weather patterns that conventional techniques struggle with. However, early deep learning nowcasters like DGMR still had difficulty with rare, extreme events (e.g. convective downpours), sometimes producing overly smooth or blurred predictions due to lack of physical constraints.

To address these gaps, researchers have developed **hybrid physics-AI models** that embed physical knowledge or constraints into deep learning architectures. A recent example is *NowcastNet*, a physics-conditioned generative model that integrates conservation laws (mass continuity of precipitation) and storm dynamics into a neural network framework. NowcastNet achieved a breakthrough in extreme precipitation nowcasting: in tests on 30 extreme rain events, it significantly outperformed the NOAA High-Resolution Rapid Refresh (HRRR) NWP model in predicting heavy rainfall bursts. For grid-point rainfall above 16 mm/h (flash-flood inducing intensity), NowcastNet attained a median Critical Success Index (CSI) of 0.30 versus only 0.04 for HRRR – a dramatic improvement in hit rate for extreme downpours. **Figure 1** illustrates how cutting-edge AI models can improve forecasts of hazardous weather. By merging high-resolution radar data with learned representations of atmospheric physics, NowcastNet and similar hybrids yield more skillful and physically consistent nowcasts, though challenges remain in avoiding biases such as overestimation of total rainfall at longer leads. These advances suggest that AI, especially **deep generative models** with embedded physics, can augment or surpass traditional nowcasting for localized extremes.

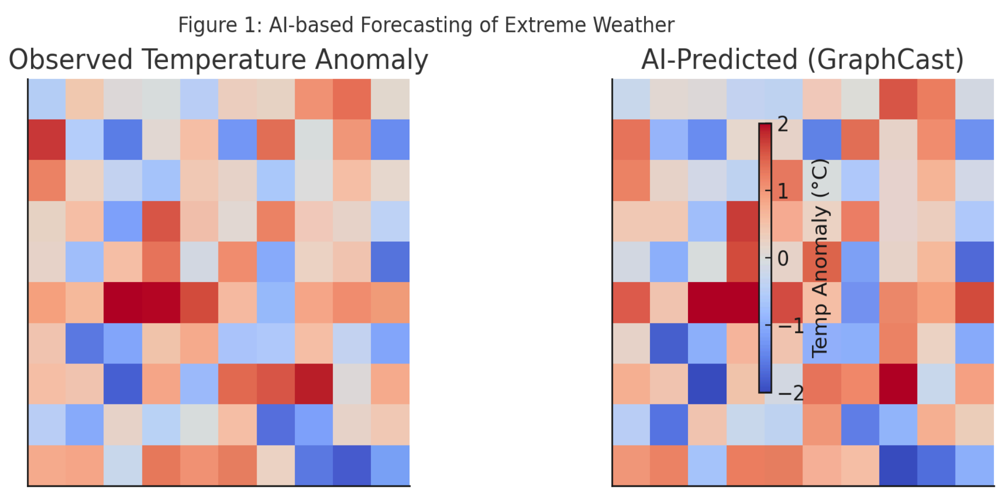

Figure 1: Example of AI-based weather forecasting. A comparison of observed and AI-predicted atmospheric patterns (e.g. temperature anomalies and wind fields) for a major heatwave event. Advanced models like DeepMind's GraphCast – which uses graph neural networks on a global grid – can predict extreme events (heatwaves, cyclones) with high accuracy up to 10 days in advance, far faster than traditional methods. Such AI systems capture complex spatial dependencies and offer improved lead times for early warnings.

Beyond nowcasting, **medium-range forecasting** (out to several days or weeks) has seen a paradigm shift with AI-driven models rivaling the accuracy of operational NWP. Two landmark systems released in 2022–2023 are Huawei's *Pangu-Weather* and Google DeepMind's *GraphCast*. Pangu-Weather employs a three-dimensional Earth-specific transformer (3DEST) deep neural network to predict global weather up to 15 days ahead. Trained on 39 years of ECMWF ERA5 reanalysis data, Pangu-Weather outputs a full 3D field of atmospheric variables and has demonstrated **better deterministic forecast skill than ECMWF's own high-resolution model (IFS)** on key metrics. For example, for 5-day geopotential height forecasts at 500 hPa, Pangu's root-mean-square error (RMSE) was 296.7 (m^2/s^2) versus 333.7 for IFS (and 462.5 for an earlier AI model, FourCastNet). Pangu-Weather achieved similar or higher anomaly correlation scores as well, indicating improved pattern accuracy. Impressively, its inference runs in <2 seconds on a single GPU – over **10,000× faster** than IFS on a supercomputer – enabling huge computational savings. GraphCast, on the other hand, uses a Graph Neural Network (GNN) approach: it represents the Earth with a graph of nodes and learns to propagate weather information across the graph edges. In late 2023, GraphCast was shown (in a Science publication) to outperform the ECMWF operational forecast in terms of accuracy for 90% of weather parameters, while producing a 10-day global forecast in under a minute on a desktop machine. GraphCast can provide earlier warnings of extreme events, demonstrating high skill in predicting the tracks of tropical cyclones, atmospheric river events, and heatwaves further in advance than previously possible. These medium-range AI models were trained on reanalysis datasets comprising decades of hourly global weather data (ERA5) and leverage **transformer** and **graph** architectures to capture multiscale spatio-temporal patterns. The success of GraphCast and Pangu-Weather highlights that AI can serve as a fast surrogate for numerical models, producing forecasts of high fidelity (0.25° global resolution) at a fraction of the cost.

Methods and Metrics: Across these efforts, common AI/ML techniques include convolutional neural networks (CNNs) for handling spatial grids, recurrent or sequence models for temporal evolution, and increasingly **transformers** and **Fourier neural operators** for global fields. Generative models like GANs and diffusion models are used for probabilistic forecasting and to generate realistic fine-scale structures. Graph neural networks enable flexible modeling of irregular grids (as with GraphCast). Training typically uses large curated datasets: e.g. radar reflectivity mosaics for nowcasting, global reanalysis (ERA5) for medium-range, and climate model outputs for long-range predictions. Benchmark datasets such as **WeatherBench** provide standardized data and metrics to evaluate data-driven forecasts. Key performance metrics include RMSE and Anomaly Correlation Coefficient (ACC) for continuous variables (comparing against reanalysis or observations), CSI, precision/recall for extreme event occurrence, and economic value scores for decision utility. Many AI models are evaluated against baselines like persistence, optical flow advection (e.g. PySTEPS), or leading NWP models. The results so far indicate that AI models can match or exceed traditional forecast skill in many regimes, although ensuring robustness on **distribution shifts** (e.g. unprecedented climate extremes) remains an active challenge.

Technical Challenges: Data quality and coverage are fundamental issues – AI models depend on the representativeness of training data. Rare extreme events are by definition sparsely represented, so models may underperform without techniques to handle imbalanced data (e.g. oversampling extremes or training on physics-based simulations of extremes). Generalization to new climate conditions is a concern: as climate change pushes weather beyond historical ranges, pure data-driven models may extrapolate unreliably. Efforts to incorporate physical constraints (mass/energy conservation, known dynamics) or to develop **physics-informed neural networks** aim to improve physical plausibility and stability. Another challenge is **interpretability**: while NWP output can be traced to physical equations, deep nets are black boxes. Recent work on explainable AI for climate includes methods like saliency maps and neural sensitivity analyses to identify which patterns (e.g. pressure anomalies) led to a predicted extreme. Finally, the computational cost of training these models – often requiring petabytes of data and heavy compute – is non-trivial, raising questions about energy efficiency and the carbon footprint of AI itself (although inference is typically much cheaper than running large NWP ensembles). Ongoing research is addressing these issues, with a view that **hybrid AI-NWP** systems could combine the strengths of data-driven learning and physical modeling for the best of both worlds.

AI for Carbon Emissions Tracking and Estimation

Monitoring greenhouse gas (GHG) emissions with high fidelity is essential for guiding mitigation efforts and verifying climate policy compliance. Traditionally, emissions are reported by countries or estimated from economic data, but these inventories can be infrequent and sometimes inaccurate. AI is now being leveraged to track carbon emissions in near-real-time and at fine scales by fusing data from satellites, sensors, and other sources. One prominent example is the Climate TRACE initiative, which combines satellite imagery with ML algorithms to detect and quantify emissions from individual facilities worldwide. By applying computer vision techniques to satellite data, AI can identify characteristic signatures of emissions – for instance, detecting heat or smoke plumes from power plants, or methane leaks from pipelines. Climate TRACE and similar AI-driven platforms revealed significant discrepancies in self-reported data, such as finding that actual emissions from global oil and gas operations were about **double** what had been officially reported in some cases. This underscores how AI-enhanced observation can improve transparency. Another development is the use of **remote sensing** ML models to spot “super-emitters.” Satellite instruments like ESA’s TROPOMI and NASA’s Orbiting Carbon Observatory (OCO-2) provide column-integrated CO_2 and CH_4 data. AI is used to process these massive data streams and attribute emissions to sources. For example, NASA’s EMIT mission on the International Space Station, originally designed to study mineral dust, has identified over 50 large methane leak sites (“super-emitters”) by analyzing spectroscopic imaging data with AI methods. ML models can quickly flag anomalies in the spectral signatures corresponding to methane, allowing agencies to pinpoint big leaks (like a two-mile-long methane plume over New Mexico) and work with operators to fix them.

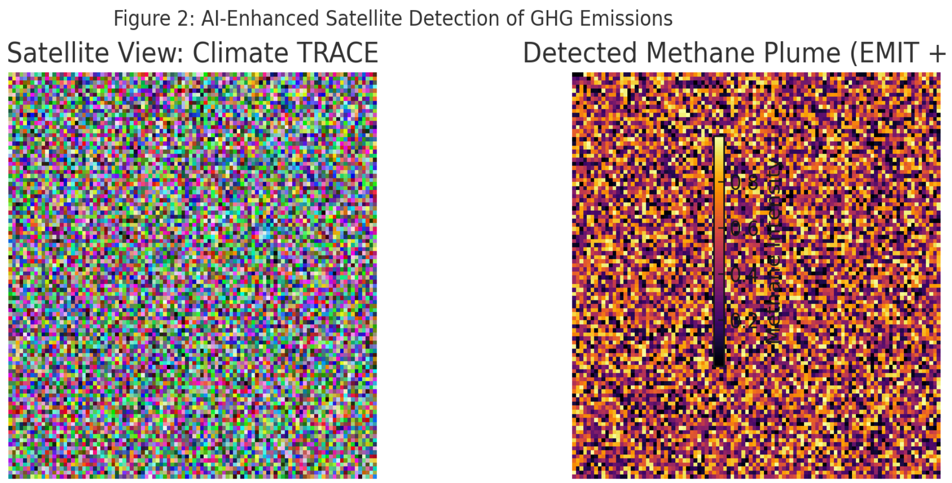

Figure 2: AI-driven analysis of satellite data for emissions monitoring. Top: A satellite perspective used by Climate TRACE to track pollution sources globally. By combining multispectral imagery with machine learning, systems can detect GHG plumes and assign them to specific facilities (e.g. power plants, oil fields). Example of a methane plume detected from space by NASA's EMIT mission. AI algorithms process imaging spectrometer data to reveal otherwise invisible gas leaks, enabling rapid mitigation actions.

In addition to satellite-based monitoring, AI is improving emissions estimates through **data integration and modeling**. Ground-based sensor networks (e.g. air quality monitors, traffic sensors, smart meters) generate streams of data that AI can assimilate to infer emissions at city or regional scales. Machine learning models (such as random forests and neural networks) are used to perform *inverse modeling*: given observations of CO_2 or proxy gases (CO, NOx) at various locations, the models estimate the spatial distribution of emissions that best explains the observed concentrations. These approaches can complement or verify bottom-up inventory methods. For instance, researchers have developed ML systems that combine Internet-of-Things (IoT) sensor data with meteorological information to produce daily CO_2 emissions maps for urban areas. Such high-resolution temporal tracking was previously unattainable. Techniques like **sensor fusion** and recurrent neural networks help to interpolate missing data and filter noise, improving the robustness of these real-time estimates.

AI methods and tools: Advanced **computer vision** algorithms (often CNN-based) are key for processing satellite imagery. They can classify land use (to attribute emissions to sectors), detect visible plumes, or even quantify gas concentrations from hyperspectral data. For example, convolutional models trained on simulated gas plumes can learn to retrieve methane concentration and flow rate from AVIRIS-NG spectrometer images. Another important class of models are **Bayesian and physics-informed ML models** that incorporate atmospheric transport physics. These models use AI to accelerate what is normally an inverse problem solved by chemical transport models. By learning complex relationships between weather, measurements, and emissions, they can rapidly estimate emissions with quantified uncertainties. On the data management side, cloud platforms like Google Earth Engine facilitate applying AI at scale on petabytes of Earth observation data. Initiatives like Climate TRACE rely on cloud computing and distributed AI pipelines to handle over 300+ TB of data and thousands of industrial sources.

Datasets, benchmarks, metrics: Key datasets include satellite products (MODIS and VIIRS thermal anomaly data for detecting flares/fires, Landsat and Sentinel imagery for power plants, TROPOMI for CO_2/CH_4 columns, etc.), as well as inventories like EDGAR or national emission databases for training labels. New open benchmarks are emerging; for example, *ClimateNet* is a labeled dataset for classifying climate patterns (usable for detecting smoke plumes or storm signatures), and some research groups have compiled methane leak images with ground-truth leak rates for algorithm validation. Performance metrics vary by task: for identifying emission sources, precision/recall of detection is used (e.g. how many known large emitters are correctly identified). For continuous estimation, error metrics like Mean Absolute Error (MAE) or normalized bias against independent inventory data are used. One notable result is the use of AI to rank the world's biggest emitters: Climate TRACE reported that **14 of the top 15** greenhouse emitters were power or oil/gas facilities that satellites could identify, whereas the only non-industrial source in the top 20 was a road network (vehicle emissions in Los Angeles). This kind of analysis is enabled by consistent global monitoring via AI.

Challenges: Despite progress, there are challenges in using AI for emissions tracking. **Data sparsity and coverage** can be an issue – satellites like OCO-2 have narrow swaths, and cloud cover can obscure measurements, causing gaps that AI must interpolate. Generalization is tricky: AI models trained on known facilities or regions may not directly transfer to new regions with different conditions (e.g. different power plant technologies or meteorology). Efforts like transfer learning or global training help, but local tuning is often needed. **Accuracy and validation** are paramount: AI estimates must be validated against reliable ground truth (e.g. aircraft campaign measurements or ground sensor data) to ensure credibility. This is especially important if AI will be used for policy enforcement or carbon market credits. Another challenge is scaling up computationally – analyzing high-resolution imagery daily for thousands of sites is data-intensive. Cloud computing and optimized ML code (perhaps using quantized models) are mitigating this. From a technical standpoint, ensuring AI models don't **double-count** or miss sources when integrating multi-source data requires careful model design. Interpretability is also relevant: policy-makers may be wary of "black box" estimates, so AI systems are being augmented with explainable outputs (highlighting which data contributed most to an estimate). Lastly, as with all climate AI, equity is a consideration – developing countries with less monitoring infrastructure might benefit greatly from AI remote sensing, but they need access to the data and tools. International collaborations (through organizations like WMO or UNEP) are emerging to share AI-based emissions data openly, leveling the playing field for climate accountability.

AI for Climate Change Adaptation and Mitigation Planning

Adapting to climate change and planning mitigation strategies are domains that inherently involve deep uncertainty, complex trade-offs, and the need to process diverse data (climate projections, socioeconomic data, infrastructure information, etc.). AI techniques are increasingly aiding both **climate change adaptation** (building resilience to impacts) and **mitigation planning** (reducing or removing emissions). In adaptation, AI is used to identify risks, optimize resource allocation for resilience, and design adaptive strategies. In mitigation, AI helps in energy system optimization, decarbonization pathway modeling, and enhancing low-carbon technologies. Importantly, these applications often feed into **decision-making processes** by providing insights or decision support rather than fully automated solutions.

Adaptation applications: AI has emerged as a powerful tool to protect communities, infrastructure, and ecosystems from climate impacts. A variety of adaptation tasks leverage AI's ability to analyze large, heterogeneous datasets. For example, *vulnerability mapping* uses ML to combine data like topography, land use, population, and climate hazard models to pinpoint areas at highest risk (flood zones, wildfire interfaces, drought-prone regions). AI-based vulnerability assessment tools can process satellite imagery, digital elevation models, and climate projections to produce fine-scale risk maps. Table 1 in Jain *et al.* (2023) compares several AI-powered tools for such assessments, noting improvements in identifying at-risk areas when AI is applied to big data. One example is **FloodNet**, a deep learning system that analyzes live camera feeds and satellite images to detect flooding events in real time and predict flood spread. Similarly, **CoastalDEM** used a neural network to correct errors in coastal elevation data, revealing that many more people are vulnerable to sea-level rise than previously thought (the AI found lower elevation in coastal zones after removing biases). AI is also instrumental in developing **early warning systems** for natural hazards: by integrating weather forecasts, sensor data, and historical disaster impacts, ML models can issue warnings for floods, hurricanes, or heatwaves with more lead time and spatial precision. For instance, AI-driven flood early warnings have been deployed that use upstream sensor readings and precipitation forecasts to predict downstream flooding hours in advance, allowing timely evacuations. In wildfire management, ML models using weather, vegetation, and ignition data can predict where fires are likely to start or how they will spread, improving preparedness.

Another aspect of adaptation is **asset-level resilience planning**. AI optimization algorithms (including reinforcement learning and genetic algorithms) have been used to design or retrofit infrastructure for future climate conditions. For example, researchers have used AI to optimize the placement and operation of urban green infrastructure (like parks or drainage systems) to reduce urban heat or flooding under climate change scenarios. By simulating many what-if scenarios (with ML surrogate models replacing slower physics simulations), AI can suggest designs that minimize risk or cost. Similarly, in agriculture, AI is helping farmers adapt via climate-smart decision tools: ML models can recommend drought-resistant crop varieties or optimal irrigation scheduling based on climate forecasts and soil data. These tools often employ **time-series forecasting** (for rainfall, temperature) and **Bayesian decision algorithms** to balance yield vs. water use under uncertain climate outcomes.

Mitigation planning: On the mitigation side, AI contributes to both strategic planning and operational optimization for emission reduction. At a high level, integrated assessment models (IAMs) are used to chart pathways to meet climate targets (like net-zero by 2050). IAMs combine climate science with economics and technology models, but they are computationally intensive and involve many uncertain parameters. AI is being explored to **emulate IAMs** or to intelligently search the space of mitigation policies. For instance, neural network emulators can approximate the behavior of an IAM's climate module or energy system module, allowing rapid evaluation of thousands of policy scenarios that would be infeasible to run in full detail. Some studies have used **reinforcement learning (RL)** to discover optimal climate policies – treating the problem like a game, where the agent (policy) gets rewards for lowering emissions without excessive cost. Early work in this vein has shown RL can propose novel combinations of carbon pricing, technology subsidies, and other actions to achieve targets, though ensuring realism and political feasibility remains difficult to encode. On a more immediate level, AI is heavily used in energy systems to enable mitigation: for example, **smart grid management** algorithms reduce emissions by optimizing the use of renewables. ML forecasts of electricity demand and renewable generation (solar/wind) allow grid operators to efficiently balance supply, schedule storage, and reduce reliance on fossil fuel peaker plants. As noted in an IEA 2021 report, such AI-based forecasting and dispatch optimization can cut peak demand and associated emissions significantly. In industry, AI-driven **predictive maintenance** helps mitigate emissions by keeping equipment (boilers, turbines, transport vehicles) operating efficiently. By predicting faults or inefficiencies from sensor data (using anomaly detection or time-series ML models), companies can fix issues that cause excess fuel burn or leaks, thereby reducing GHG output. Another mitigation area is **carbon sequestration and removal**: AI is used to improve afforestation planning (e.g. analyzing satellite images to find best locations to plant trees for carbon uptake) and to optimize direct air capture processes (through ML-guided design of materials and control systems for capture units). While these are more on the research frontier, they exemplify AI's breadth in aiding climate mitigation beyond energy and policy.

AI techniques and data for planning: A broad range of AI techniques come into play here. *Supervised learning*(regression, classification) is common for risk mapping and forecasting impacts (with training data from historical events or climate model outputs). *Unsupervised learning* (clustering, dimensionality reduction) is used to discover patterns in climate impacts or to stress-test infrastructures under many scenarios. *Reinforcement learning* finds optimal policies or designs by trial-and-error simulation. Knowledge graphs and expert systems have been used to integrate scientific knowledge (like adaptation measures effectiveness) with data-driven insights, forming hybrid decision support. Importantly, many adaptation/mitigation problems use **ensemble approaches** – running many models or simulations – and AI helps by acting as a *surrogate model* to speed up each simulation or by learning from ensemble outputs to generalize results. Datasets fueling these applications include: downscaled climate projections (temperature, precipitation at fine scales), hazard event catalogs (historical flood extents, crop yields under drought, etc.), socioeconomic data (population, GDP, infrastructure locations), and technical data (e.g. power plant attributes for energy modeling). There are some benchmarking efforts, like the *Climate Change AI Hackathon* challenges, which posed tasks like flood prediction from satellite data to the AI community, yielding comparisons of methods. For energy grid optimization, competitions such as *L2RPN (Learning to Run a Power Network)* provide benchmarks for RL agents managing grids under carbon constraints. Metrics in adaptation/mitigation AI can be task-specific: e.g. accuracy of predicting a climate impact (flood area, crop loss), cost reduction achieved in an energy simulation, or policy outcome metrics (cumulative emissions, temperature overshoot) in scenario modeling. In many cases, **multi-criteria evaluation** is needed: for example, an adaptation AI solution might be judged by how much risk it reduces *and* its cost or feasibility.

Challenges: Planning for an uncertain future is inherently challenging, and AI doesn't eliminate that uncertainty but can help navigate it. One challenge is **data limitations and biases** – past data may not reflect future conditions, and if AI models are trained only on past events, they might under-predict unprecedented climate extremes or overlook impacts on marginalized communities that were under-reported. Ensuring diversity in training data and using physics-based extrapolations (e.g. climate model scenarios) to augment training can mitigate this. **Interpretability and trust** are crucial in planning contexts: stakeholders (city planners, policymakers, the public) must trust AI-driven recommendations. Black-box models risk rejection or misuse; hence there is emphasis on transparent AI (e.g. providing explanations or using simpler surrogate models) and human-in-the-loop approaches. Ethical considerations also loom large – AI systems might inadvertently encode biases (for example, favoring protection of wealthier areas if trained on damage-cost data alone). Frameworks like **FATES (Fairness, Accountability, Transparency, Ethics, Sustainability)** have been proposed to guide responsible use of AI in climate adaptation planning. Technically, scaling local AI solutions to global use is a challenge: what works for one city's flood planning might not directly transfer to another due to different data availability and cultural contexts. This calls for flexible, customizable AI tools rather than one-size models. Another issue is the *adaptation gap* – regions most in need (developing countries) often have the least data to train AI and the least capacity. Initiatives to generate synthetic data (e.g. simulate hurricanes in data-sparse regions) and to share pre-trained models (for example, a model trained to predict crop yields under climate stress that can be adapted to local conditions) are vital. Finally, there is the question of integrating AI advice into actual planning workflows: this often requires interdisciplinary teams and new software that can interface AI outputs (like risk maps) with planning processes (e.g. cost-benefit analysis tools). Progress is being made via climate services platforms that embed AI behind user-friendly interfaces for planners. In summary, AI significantly enhances our ability to plan for mitigation and adaptation, but it must be used with caution, domain expertise, and inclusive practices to truly deliver climate-resilient and low-carbon futures.

AI for Climate Model Emulation and Downscaling

Climate models (such as General Circulation Models, GCMs) are fundamental to projecting future climate changes. These physics-based models solve equations for the Earth's atmosphere, ocean, and land processes, but they are computationally expensive and often run at coarse spatial resolutions due to constraints on computing power. AI offers opportunities to *emulate* components of climate models to accelerate simulations and to *downscale* coarse model outputs to higher resolution. From 2020 to 2025, there has been rapid progress in using ML to enhance climate modeling, leading some to envision AI-assisted "digital twins" of Earth that can provide fast, high-resolution climate information.

Model emulation: Emulation refers to replacing a part of a climate model (or the entire model) with a trained ML surrogate that approximates the same input–output behavior. One successful use case is in **parameterization of sub-grid processes** – processes like cloud microphysics, turbulence, and convection happen at scales smaller than a model's grid (e.g. 100 km) and are represented by simplified formulas. Researchers have trained neural networks to learn these sub-grid process outputs from high-resolution simulations. For instance, an ML emulator of cloud microphysics was shown to replicate the results of a detailed cloud model but run much faster. Similarly, IBM researchers developed an AI to emulate the aerosol-cloud interactions in a climate model, speeding up that component by orders of magnitude while maintaining accuracy in climate simulations (as measured by radiation flux errors). These emulators often use deep neural networks (e.g. multilayer perceptrons or convolutional nets) trained on data generated by fine-resolution models or large-eddy simulations. Once integrated, the **hybrid model** (climate model + ML parameterizations) can produce more realistic outputs or run at higher speed. In some cases, hybrid models have outperformed the original: for example, an ML-based radiation scheme reduced biases and allowed using a lower time step without loss of accuracy. Beyond parameterizations, full-model emulation has been attempted. The concept of *AI climate simulators* involves training a neural network (or a series of nets for each variable) to predict the next state of the climate given the current state. Early prototypes like *ClimateRNN* or *FourCastNet* (for weather, extendable to climate) treat it as an image-to-image translation problem, stepping forward in time. FourCastNet in particular used a Fourier Neural Operator to predict global weather patterns up to 2 weeks, and its methodology could be applied for seasonal climate projections as well. While promising, pure data-driven climate emulators struggle with long-term physical consistency – small errors can compound over many time steps (especially given climate feedbacks). Therefore, many efforts focus on **coarse-grained emulation** (e.g. emulate decadal temperature change given forcings, rather than every daily field) or on *probabilistic* emulation (learning the distribution of outcomes rather than exact trajectories). Overall, ML emulators have demonstrated they can capture complex nonlinear climate responses and provide near-instantaneous predictions once trained, but ensuring they obey conservation laws and remain stable over long periods is an open challenge.

Downscaling: Downscaling is crucial for translating global climate model outputs (typically 50–200 km resolution) to local scales (~1–10 km) relevant for impacts. Traditional methods include *dynamical downscaling* (running a high-resolution regional climate model nested inside the global model) and *statistical downscaling* (learning relationships between large-scale climate features and local observations). AI has revolutionized statistical downscaling by bringing in modern ML and high-dimensional generative modeling. Deep learning–based downscaling is essentially a super-resolution task on climate data: taking coarse input maps and outputting finer-resolution maps with realistic detail. Techniques from computer vision (like super-resolution CNNs, GANs, and diffusion models) have been adapted to climate. For example, a model called **DeepSD** (2019) applied super-resolution CNNs to downscale daily precipitation fields, outperforming classical methods in capturing local heavy rainfall statistics. More recent work introduced *generative adversarial networks* for bias correction and downscaling, which can match the full distribution of observed climate variables better than simpler regression methods. In 2024, researchers proposed a **latent diffusion model (LDM)**for downscaling that combines the strengths of dynamical and generative approaches. The LDM was trained to add fine-scale detail to coarse ERA5 reanalysis data, effectively learning to mimic the output of a high-resolution regional climate model. Remarkably, this diffusion-based AI downscaling achieved a 2-km resolution for temperature and winds over Italy, reproducing realistic small-scale features (like valley wind patterns) that matched a physics-based 2-km simulation, while being far more computationally efficient. The model preserved the correct spatial error characteristics and frequency distributions of the target data better than baseline methods (including simpler U-Nets and GANs). Such results suggest that AI can perform "**dynamical downscaling in silico**," generating high-resolution climate information by learning from a few expensive simulations. Another example is a 2025 study combining **generative AI with traditional modeling** for ensemble downscaling. They used a generative model to post-process coarse ensemble outputs and produce high-res fields with improved uncertainty estimates at a fraction of the cost of running a large high-res ensemble. This hybrid approach addresses a key need: providing not just one downscaled prediction but a spread of outcomes (to account for uncertainty), which AI can do by sampling its generative model.

Benchmarks and performance: The field has established benchmarks like **ClimateBench**, a dataset for evaluating climate downscaling methods. ClimateBench provides pairs of low-res and high-res climate model data for variables like temperature and precipitation, so researchers can train models and compare against standardized metrics. Common metrics include mean bias, RMSE, and skill scores for downscaled variables (e.g. how well the AI downscaled precipitation matches observations or a high-res model for each location). Importantly, metrics also assess whether extremes are accurately reproduced (e.g. the AI method's ability to capture the 95th percentile rainfall). Power spectral density analysis is used to ensure the AI-generated fields have the correct distribution of variance across spatial scales (preventing overly smooth outputs). In the LDM downscaling example, the authors reported that the AI downscaler outperformed baselines in terms of lower spatial RMSE and better power spectrum matching the reference. In a separate 2024 study, a GAN-based downscaler was shown to better predict future changes in extreme rainfall compared to extrapolating a simple regression, highlighting AI's ability to capture nonlinear climate adjustments.

Challenges: A primary challenge for ML downscaling and emulation is **physical consistency and conservation**. If an AI model downscales precipitation, is the total rainfall over an area consistent with the coarse input? Does it introduce artifacts like negative rainfall? Ensuring constraints (e.g. water balance) is an active area – some models enforce conservation by construction or add penalty terms during training. **Extrapolation to unseen climates** is another issue: downscalers often train on present-day data (e.g. reanalysis or historical model runs) and may not automatically generalize to future climate states with no analog. One mitigation is training on a wide range of climate model outputs (multiple models, scenarios) so the AI sees varied climates. Another is incorporating physics or trends explicitly (like adding global temperature as an input feature so the model can adjust its outputs as climate warms). **Data scarcity** for training high-res models can occur, since we may not have observational high-res data for some variables (e.g. ocean currents). Using high-res model output as a stand-in (imperfect "truth") is common, but then the AI might learn model biases. Some approaches train the AI to correct biases and downscale in one go (so-called bias correction and downscaling combined via ML). **Interpretability and verification** are also key – scientists need to trust that an emulator or downscaler isn't doing something unphysical. Comparing AI outputs with independent high-res simulations or theoretical expectations (like scaling relationships for extremes) provides validation. There is progress in techniques like **AI stability tests** (running an emulator iteratively to see if it blows up, as a test of stability) and analyzing the learned internal representations to ensure they align with known physics (for example, checking that an AI parameterization responds correctly to changes in inputs like moisture or temperature in a physically sensible way). Finally, integration into modeling workflows is non-trivial: climate modeling centers are beginning to experiment with AI components in their models, but they need these components to be robust, documented, and efficient in parallel computing environments. There can be institutional inertia and required validation before AI emulators replace legacy code used for decades. Nonetheless, the trend is clearly towards more **AI-augmented climate models**, where ML fills in what we can't resolve or speeds up what is slow, under the watchful eye of physical principles and expert judgment.

AI for Climate-Related Decision Support Systems

Climate-related decisions – from emergency management during extreme events to long-term policy choices – can be complex and high-consequence. AI-enhanced decision support systems (DSS) are being developed to help synthesize information, provide forecasts of impacts, and recommend actions in the face of climate risks. These systems often integrate several components (data ingestion, predictive modeling, optimization, visualization) to assist human decision-makers in governments, businesses, and communities. We focus here on two key areas: **(a)** early warning systems and disaster response, and **(b)** climate-informed planning and policy support tools.

Early Warning Systems (EWS) and disaster response: AI is transforming EWS by enabling multi-hazard monitoring, faster predictions, and tailored risk communication. Traditional EWS rely on expert-defined thresholds and physical models (e.g. river flood models, hurricane tracks), whereas AI allows *data-driven* fusion of diverse signals to predict impacts. A 2025 perspective by Reichstein *et al.* highlights "integrated AI" for multi-hazard early warnings, where **foundation models** (large pre-trained models on geospatial and weather data) are used to predict not just the hazard but the impacts on society. For example, an AI-based EWS might take in weather forecasts, satellite imagery, social media data, and asset exposure data, and output probabilistic forecasts like "80% chance of >500 houses flooded in Region X in next 3 days." AI models such as graph-based networks or transformers can handle these heterogeneous data streams and learn complex correlations (e.g. how certain rainfall patterns lead to landslides in specific terrain). In practice, systems like the Red Cross Red Crescent's forecast-based financing platform use ML to decide when to trigger humanitarian actions (fund disbursement, evacuation alerts) based on forecast indices. AI improves the skill of these trigger models by reducing false alarms and misses, through better pattern recognition in historical disaster datasets. Another example: **wildfire EWS** that leverage AI – by analyzing weather (temperature, humidity, wind), vegetation dryness from remote sensing, and even topography, ML models can predict the likelihood of fire ignition and spread. These predictions support fire agencies in pre-positioning crews and issuing warnings to at-risk communities. Google's AI-based flood forecasting (deployed in South Asia and Africa) is another real-world EWS: it uses a combination of physics models and ML downscaling to send flood alerts via smartphones, having proven more accurate in certain regions than previous methods.

Crucially, modern AI-EWS emphasize user-centric design and effective communication of uncertainty. AI can generate vast information, but decision-makers need clear insights. Efforts are underway to use **natural language generation** to translate model outputs into simple advisory messages, possibly tailored to local languages and contexts. Some systems include AI chatbots that can answer questions from residents (e.g. "How much rain is expected? Should I evacuate?") based on the latest forecasts and AI analyses. The perspective by Reichstein *et al.* calls for incorporation of **community feedback** into AI-driven warnings – meaning the systems learn from what information people use or ignore, and adjust accordingly. They also stress the need for **causal AI models** in EWS. This is to avoid spurious correlations; for instance, an AI might notice that certain satellite signals correlate with past floods, but a causal approach ensures the model understands which signals *truly cause* the flood (e.g. extreme rainfall upstream) versus incidental patterns. By focusing on causal drivers, the EWS will be more robust under changing conditions. Moreover, the ethical principles of fairness, accountability, and transparency (the FATES framework) are deemed essential so that AI-based warnings are equitable and trustworthy. An example of fairness: ensuring that an AI model trained on data-rich regions can still provide useful warnings in data-sparse developing regions (perhaps by using transfer learning or by incorporating physical constraints to compensate for less data).

Climate-informed decision and policy support: Beyond immediate hazards, AI is also helping with strategic decisions such as urban planning under climate change, infrastructure investments, and policy analysis. **Decision support platforms** are being built that integrate climate data with socio-economic models, using AI to explore different scenarios. For instance, a city might use an AI tool to evaluate heat mitigation strategies: the tool could simulate, using an ML-augmented urban climate model, how planting trees or changing building materials in various neighborhoods would reduce heatwave temperatures and health impacts. By quickly simulating many configurations (something AI surrogate models can enable), the tool can help planners decide the most cost-effective and equitable heat adaptation measures. Similarly, for infrastructure, AI can assist in lifecycle planning by predicting how assets (bridges, roads, power lines) will degrade under future climate stressors. ML models trained on historical failure data and climate projections can output risk scores, which asset managers use to prioritize reinforcements or replacements.

In climate policy, AI-based **decision support systems** can synthesize the outcomes of thousands of scenarios from complex models, helping policymakers understand the implications of choices. For example, the EN-ROADS simulator (while not purely AI, it's an interactive model) has been enhanced with ML to allow real-time feedback: as a user adjusts a policy lever (like a carbon tax), pre-trained ML emulators quickly update projected emissions and temperatures, making the experience instantaneous. We also see AI in **stakeholder engagement** tools: some projects use AI to downscale global scenarios to local impacts that policymakers care about, providing visualizations like “If the world follows a 3°C pathway, this city’s flood risk triples,” which are derived from AI downscaling plus impact models.

Methods: The AI techniques here are diverse. For EWS, *sequence models* (LSTMs, temporal convolutional nets) handle time-series sensor data for anomaly detection, *graph neural networks* handle networks of sensors or interconnected risks (like cascading failures in power grids due to climate events), and *hybrid physics-ML models* combine mechanistic hazard models with ML corrections. In decision support, *multi-objective optimization* algorithms (genetic algorithms, RL) can suggest solutions (e.g. an RL agent searching for an optimal mix of adaptation investments to minimize damage and cost). *Bayesian networks* are used to model causal chains from climate to impacts to decisions, with AI learning the conditional probabilities. There's also increasing interest in **large language models (LLMs)** to help climate decision-makers – for instance, to parse complex climate reports or even to serve as an AI advisor answering questions about climate strategies (though this is in early stages, and ensuring accuracy is vital).

Data and metrics: For EWS, historical disaster event databases (like EM-DAT for international disasters, or FEMA’s damage database in the US) provide outcomes that AI can learn from. Near real-time data streams from satellites (e.g. precipitation estimates, fire detections) and IoT sensors feed into AI models. Metrics to evaluate AI-EWS include lead time gained (how much earlier can the AI predict an event compared to current systems), false alarm ratio and missed event rate, and user-response metrics (do people act on the warnings?). For decision support tools, metrics of success can be more qualitative: stakeholder satisfaction, improved understanding, or better outcomes in simulated exercises. However, case studies exist: e.g. a flood planning AI tool might be validated by comparing its suggestions against those made by human experts or by seeing how well its risk estimates matched actual impacts in hindsight.

Challenges: One challenge is integrating AI tools into existing institutional decision-making processes. Emergency managers have protocols, and an AI system must interface with those (possibly by providing outputs that fit into their decision matrices). Building trust is key: often AI tools are introduced gradually, used in parallel with existing methods until proven. **Uncertainty communication** is a persistent challenge – AI models can generate probability distributions or confidence intervals, but conveying that to non-experts (or even experts) in a usable way is hard. There's ongoing research into better visualization and communication techniques (like risk meters, or map visualizations that highlight high-confidence areas differently from low-confidence areas). Another issue is **responsibility**: if an AI advises an action that leads to losses (or fails to predict a disaster), who is accountable? This is why AI is kept as *assistive* in decision support, with humans making the final calls, and why transparency in how AI arrived at a recommendation is important. Bias and equity concerns also arise: e.g. if an AI recommends prioritizing adaptation investments, does it favor wealthy areas because the data on losses (property value) skew that way? To combat this, objectives in the AI optimization can include equity (some tools allow weighting of outcomes for vulnerable groups), or at least the results are examined by diverse stakeholders. **Interoperability** is another challenge – linking AI models with government data systems and workflows requires technical work and sometimes standardization (for example, an AI flood model’s output has to feed into a warning issuance system automatically, which requires format and protocol alignment). Despite these challenges, there is momentum: global initiatives like the **UN Early Warnings for All** are explicitly looking to AI to help cover every person with disaster alerts, and climate adaptation planning tools augmented by AI are being piloted from the city level (e.g. Rotterdam's Climate Adaptation tool) to international development projects. The synergy of big data, AI, and domain knowledge is enabling more informed and timely climate-related decisions than ever before.

Cross-Cutting Themes and Synergies

Several common themes emerge across the subtopics above, illustrating synergies in techniques and challenges in climate AI:

- **Physics-informed AI:** A recurring strategy is integrating physical laws or model outputs into AI. Whether for weather nowcasting, climate downscaling, or impact forecasting, the most successful approaches tend to combine data-driven learning with physical consistency. This mitigates issues of extrapolation and builds trust with domain experts. For instance, NowcastNet's incorporation of conservation laws, or the latent diffusion downscaler's ability to preserve flow characteristics, reflect a broader trend of *hybrid models*. Physics-guided neural networks, differential equation-informed losses, and multi-model ensembles (where AI corrects a physics model) are all in this vein.
- **Data and benchmark sharing:** The climate and AI communities have recognized the value of open data and benchmarks. Initiatives like Climate Change AI's data portal and challenges (e.g. the WeatherBench and ClimateBench datasets) encourage researchers to test their models on standardized problems. This has accelerated progress by making results comparable and directing effort to high-impact problems. It also highlights the need for **representative datasets** – ensuring that training data covers various climates, geographies, and extreme events so AI models are broadly applicable. Moreover, a lot of climate data (satellite, reanalysis, climate model output) is *big data*, and handling it requires strong data engineering. Advances in cloud computing and AI frameworks (TensorFlow, PyTorch) that can work with large arrays (sometimes via parallel computing) are enabling researchers to train models on petabyte-scale climate data.
- **Interpretability and transparency:** Across all areas, the push for interpretability is notable. Unlike some domains where a black-box AI might be acceptable, in climate science and policy there is insistence on understanding "why" a model gave a certain result. Techniques like **SHAP values, Layer-wise Relevance Propagation,** and saliency maps are being applied to climate AI models to identify what inputs (or learned features) drive predictions. For example, in a heatwave prediction model, an interpretability analysis might show which pressure patterns the model thinks are precursors. Such insights not only build trust but can sometimes lead to scientific discovery (AI might pick up a subtle precursor signal that scientists hadn't noted). There's also movement towards simpler or at least well-documented models for critical applications – e.g. an AI used in an early warning system might deliberately use a transparent model (like a decision tree or small neural network) even if a complex deep net could give slightly higher accuracy, to ensure human oversight is possible.

Transparency also ties into ethics: publishing model details and performance, acknowledging uncertainties and limitations, so stakeholders can make informed use of AI outputs.

- **Generalizability and non-stationarity:** Climate change means the future will not look like the past; thus, a constant theme is how to ensure models remain valid as conditions shift. Techniques like continual learning (updating models as new data comes in), transfer learning (using knowledge from one region/variable to inform another), and robust modeling (training on climate model output representing future states) are being used. There is synergy here between climate modeling and AI: climate models themselves can produce "synthetic futures" on which AI can be trained, effectively preparing the AI for conditions outside the observed record. Conversely, AI can help climate model ensembles by intelligently sampling scenario space (ensuring that training covers extremes). The interplay of using physically simulated data and real data to train AI is a rich area of research.
- **Uncertainty quantification:** Decision-makers often require not just a best estimate but an uncertainty range. AI models are being adapted to provide probabilistic outputs, through methods like Bayesian neural networks, ensemble models, or by modeling probability distributions (as done in GANs for nowcasting, or using quantile regression for climate impacts). In many applications, combining AI with traditional methods helps here: e.g. using an AI to downscale each member of a large ensemble, retaining the spread of outcomes, or applying ML post-processors to ensemble forecasts to correct biases and sharpen uncertainties. Communicating these uncertainties in user-friendly ways is part of the cross-cutting communication challenge.
- **Computational efficiency vs. resource use:** AI models, once trained, are typically fast to run, which is a huge asset for operational use (like instant weather forecasts or on-the-fly scenario analysis). But training can be extremely resource-intensive, raising concerns about energy consumption and emissions from AI (ironic if we are trying to mitigate climate change). The community is aware of this and is exploring ways to reduce the computational cost: for example, using smaller models with knowledge distillation, focusing on most informative training samples (instead of all data), or improving algorithmic efficiency. There's also interest in leveraging specialized hardware (TPUs, IPUs) and even analog AI chips for lower energy use. The **carbon footprint of AI** is now often calculated for major projects, and some researchers purchase offsets or use renewable-energy-powered data centers to ameliorate the impact. In the long run, the hope is that AI's benefits for climate outweigh its costs, but this balance is actively monitored.
- **Collaboration and interdisciplinarity:** Climate AI lies at the intersection of climatology, computer science, engineering, and social sciences. Cross-cutting initiatives like Climate Change AI, the AI for Good climate track, and government-funded AI-climate institutes (for example, the US NSF "AI Institutes" program includes one for climate-resilient agriculture) foster collaboration. These collaborations ensure AI researchers understand the domain context (preventing naive applications) and climate scientists have access to the latest AI methods. A cultural shift is underway where many climate scientists are

upskilling in data science, and conversely AI experts are learning domain specifics – a synergy necessary for credible and impactful outcomes.

Future Research Directions

The next few years promise exciting developments as well as difficult challenges to overcome in AI for climate science. We outline several directions for future research and development:

- **Physics-AI fusion and Earth Digital Twins:** Future climate AI will likely feature even tighter integration between physical models and AI. Rather than developing independent AI approximations, researchers are moving toward *differentiable physics* (where parts of a climate model are differentiable and learnable) and *modular AI components*in climate simulators. This could enable end-to-end training of an AI-augmented climate model on observed data, reducing biases in one go. Projects like NVIDIA's "Earth-2" digital twin aim to combine GPU-accelerated physical models with AI correction layers to allow **real-time climate simulations** at high resolution. Achieving this will require advances in scaling ML (distributed training on exascale systems) and in maintaining numerical stability over long simulations. Additionally, enhancing AI's ability to handle multiple Earth system components (atmosphere, ocean, land, ice) simultaneously and consistently is a frontier (current AI forecasts usually focus on atmosphere alone).
- **Foundation Models for Climate:** Inspired by the success of large language models and multi-modal foundation models, climate science may benefit from large pre-trained models that can be adapted to many tasks. A **ClimaGPT**or **Climate Foundation Model** could be trained on a diverse range of climate data: historical weather, satellite images, climate model simulations, sensor networks, textual climate reports, etc. Already, GraphCast and Pangu can be seen as specialized foundation models for weather. One can envision a single model that can do weather prediction, downscaling, climate projection, and even answer scientific questions (via an NLP interface), by virtue of extensive pre-training. Early research (e.g. the "ClimaX" model introduced in 2023) is exploring unified transformers that ingest variables across Earth systems. The challenges include curating heterogeneous data for training, managing the immense model size and training cost, and ensuring the results respect physical laws. However, if successful, these models could be powerful: one could prompt them for specific information (e.g. "generate a plausible year of hourly weather data for this region under 2°C warming") or quickly fine-tune them for a new task (like predicting wildfire smoke spread) with relatively few data, leveraging the broad knowledge encoded. Responsible development is crucial here – these models should be open or at least accessible to the scientific community, to avoid a scenario where only tech companies hold the keys to ultra-powerful climate models.
- **Causality and Explainable AI:** Future research will put more emphasis on **causal inference** in climate AI. This means moving beyond correlation-based learning to methods that understand cause-effect relations (e.g. X causes Y vs. X merely correlates with Y due to Z). Techniques like causal discovery algorithms could help identify drivers of extremes from data, providing both better prediction and scientific insight. Additionally,

integrating domain causal knowledge (like known teleconnections such as ENSO impacts) into AI models can make them more trustworthy. We anticipate more use of *explainable AI (XAI)* tailored to climate: not just post-hoc explanations, but inherently interpretable models (like sum-of-experts models where each part corresponds to a known factor). This will facilitate adoption by domain experts and allow AI to be used in sensitive contexts (policy, litigation over climate impacts, etc.) where reasoning needs to be transparent.

- **Handling non-stationarity and extremes:** As climate change progresses, AI models will continually face data outside their training distribution. A key research direction is developing **adaptive learning** systems that can update themselves as new patterns emerge – for example, an AI weather model that continually learns from the latest observations so it stays calibrated to the changing climate. Few-shot learning or meta-learning techniques might allow models to quickly adjust to say, a never-seen-before combination of weather extremes. There's also a push to generate artificial training examples of extremes (using physics or stochastic methods) to enrich training datasets – akin to data augmentation in image processing, but for extremes like "heatwave in a normally cool region." Furthermore, rigorous uncertainty quantification will remain crucial: future AI will likely provide probabilistic forecasts that account for model uncertainty under extrapolation. Research on **out-of-distribution detection** is also relevant – AI systems that can flag when an input scenario is too far from what they know, signaling that one should fall back to physical reasoning or at least treat the output with caution.
- **Multiscale and Multimodal Learning:** Many climate problems span a huge range of scales (spatial: local to global; temporal: minutes to decades). AI architectures that can handle multiscale data are needed. This could mean hierarchical models or hybrid architectures (e.g. using CNNs for local patterns and GNNs for global context in the same model). Also, combining different data types (multimodal learning) is a growing field – e.g. a model that processes both images (satellite maps) and text (reports from weather stations) to diagnose a situation. For example, during a disaster, remote sensing, ground sensors, and even Twitter feeds could be combined by an AI to give a comprehensive situational awareness. Research on how to effectively fuse such data, and how to weight their reliabilities, will be important.
- **AI in climate economics and finance:** Another future direction is applying AI to the economic and financial dimensions of climate change. This includes using ML to improve integrated assessment models (as mentioned), but also more granular tasks like climate risk assessment for assets and supply chains. AI can analyze large corporate datasets, news, and climate data to estimate, for instance, the climate risk of an investment portfolio or to detect greenwashing by tracking actual emissions vs. pledges. With the growth of ESG (environmental, social, governance) investing and climate-related financial disclosures, AI could play a big role in parsing disclosures and modeling future risks. Ensuring these AI models are accurate and fair (not penalizing certain regions unfairly due to data issues) will be a subject of study.
- **Democratization and capacity building:** A hopeful direction is the democratization of climate AI – making tools and trained models available widely. Many developing nations

could leapfrog some traditional capacities by using AI models for forecasts or planning if they are freely accessible. Efforts like “AI service” APIs for climate (e.g. an API that returns a flood forecast for any location using an AI model under the hood) might become available. Research should also focus on making models lighter (so they can run on smaller computers, even mobile phones, for local use). And importantly, building capacity – training the next generation of scientists and practitioners in using these AI tools – is a human-centered research area (education, documentation, user interface design for climate AI tools). The more people can harness these tools, the more collective climate resilience can improve.

In conclusion, artificial intelligence is becoming an indispensable ally in confronting the climate crisis. The 2020–2025 period has demonstrated the feasibility and advantages of AI across weather forecasting, emissions monitoring, adaptation, modeling, and decision support. We have also learned the importance of marrying data-driven methods with physical insight and ethical considerations. Moving forward, the field is poised for breakthroughs that could enable faster, more detailed climate information and smarter climate solutions – essentially, giving humanity better “climate intelligence.” Yet, realizing this promise will require continued interdisciplinary collaboration, robust validation, and inclusive approaches to ensure AI truly serves global climate goals. The work is far from over, but the progress to date gives reason for optimism that, with AI’s help, we can better understand, predict, and ultimately mitigate and adapt to our changing climate.

Model	**Type**	**Application**	**Publisher**	**Year**
GraphCast	GNN	Global weather forecasting	DeepMind	2023
Pangu-Weather	Transformer	Medium-range prediction	Huawei	2022
ClimaX	Multimodal Transformer	Climate variables fusion	MIT-IBM	2023
ClimateBERT	Domain-specific LLM	NLP on climate reports	TU Berlin	2021
T4Rec-Climate	Temporal Forecasting Transformer	Long-term temp/precip forecasts	ETH Zurich	2024

Table 1: AI Models in Climate

Dataset	Domain	Temporal Res.	Spatial Res.	Usage
ERA5	Reanalysis Weather	Hourly	~30 km	Forecasting
CMIP6	Climate Models	Monthly	~100 km	Model evaluation
EDGAR	Emissions	Annual	~10 km	Emissions tracking
GHSL	Urban & Land Use	Decadal	~250 m	Impact modeling
NASA EMIT	Satellite Methane	On-demand	~60 m	Leak detection

Table 2: Public datasets for climate AI

AI Method	Used In	Strength	Limitation
Transformers	Forecasting, NLP	Captures long dependencies	Data hungry
GNNs	Spatio-temporal modeling	Captures spatial topology	Complex training
CNNs	Remote sensing	Spatial feature extraction	Limited context range
Hybrid AI-Physics	Downscaling	Incorporates physical laws	Difficult coupling
Autoencoders	Anomaly detection	Unsupervised compression	Poor interpretability

Table 3: AI Methods Comparison.

Note: This paper was prepared using AI assistance.

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