In collaboration with
the MIT Media Lab

Charting the Future of Earth Observation: Technology Innovation for Climate Intelligence

WHITE PAPER

SEPTEMBER 2024

Images: Getty Images

Contents

Foreword

Sebastian Buckup
Head, Network and Partnerships; Member, Executive Committee, World Economic Forum

Dava Newman
Director, MIT Media Lab; Apollo Program Professor of Astronautics, MIT

With escalating temperatures, increasingly severe weather events and unprecedented levels of greenhouse gas emissions, the world stands at a crossroads. Scientific consensus underscores that immediate measures are essential to mitigate the most catastrophic impacts of climate change. In this new paradigm, Earth observation (EO) technology and innovation are championing a new era for climate intelligence, offering unprecedented insights and solutions to address these urgent challenges. Recent EO innovations, combined with the growth of synergistic technologies (technologies that enhance each other's effectiveness), are eliminating barriers to the effective use of EO at scale. Today's transformational technologies, including advanced satellite sensors, algorithms and artificial intelligence (AI), are proving to be the "enablers" we need, broadening our understanding of our changing environment. At the same time, the launch of additional EO satellites from many nations – and an increasing number of private sector EO data providers – has widened access to images and observable measurements from satellites with the highest revisit times (satellites that visit certain geographic regions more frequently). In turn, this provides more detailed remotely sensed data relating to various elements of climate change.

This white paper, written in collaboration with the Massachusetts Institute of Technology (MIT) Media Lab, highlights the transformative potential of EO for climate intelligence and forecasting. By combining the research capabilities of the MIT Media Lab with the global platform of the World Economic Forum, the paper identifies technology pipelines accelerating the processing and analysis of satellite EO data to provide unparalleled insights into climate change. The paper also highlights the need for accessible and inclusive climate insights, especially for communities most vulnerable to the effects of climate change. We hope this publication will serve as a valuable resource on technology pipelines in EO to address the pressing challenges of climate change.

Executive summary

Earth observation technologies and advanced data processing are revolutionizing climate intelligence, offering unprecedented insights for proactive action.

Systemic challenges have historically prevented EO data from being fully integrated into climate solutions, primarily due to its large volume and complexity. Rapid technological advancements in satellite and sensor technologies are addressing these systematic issues alongside new and open artificial intelligence (AI) algorithms, machine learning (ML) techniques and advanced data visualization platforms. These synergistic technologies have allowed the processing of an immense volume of data in almost real time, transforming raw satellite imagery into actionable climate insights in minutes. These advancements are driven by:

More insightful data than ever before: Recent advancements in satellite EO sensors drive improved global coverage, resolution, accuracy and a wider array of observable measurements. This enables monitoring of larger swaths of land and more frequent revisit rates. These advancements assist the detection and analysis of climate-related events in regions that were traditionally hard to map in detail.

Unprecedented data processing speeds: Sophisticated AI and ML algorithms enable more detailed climate impact assessments (such as those used in post-disaster management) in hours or minutes. This task can take weeks when using traditional models or on-site inspections. Climate ML-based models trained on existing data can produce the same predictions at approximately 1,000 times the speed of traditional models. These improvements in data processing speeds enable timely decision-making, which is particularly relevant in situations requiring real or near-real-time insights, such as rapidly changing weather conditions.

Evolution of large and small EO satellites: EO satellite systems have advanced on two opposite fronts. The rise of small satellites and miniaturization of EO sensor technology have enabled more nations and small- and medium-sized enterprises (SMEs) to launch their own satellites, increasing the volume of publicly available EO data. At the same time, there is an increase in the development of larger, more sophisticated satellite platforms. These platforms can host larger sensor instruments and power facilities to meet the growing demand for reliable and continuous EO data transmission.

Higher resolution climate forecasting: Climate ML-based models and foundation models are increasing the resolution of climate and weather forecast models twelvefold. These enhanced weather predictions help communities and policy-makers plan targeted mitigation and adaptation strategies to improve climate resilience.

Contextual data for end-user needs: Data immersion through augmented reality (AR) and virtual reality (VR) are transforming complex EO datasets into interactive models that help users understand the data and intuitive visual insights that improve decision-making. Digital twins use advanced analytics, ML and AI to analyse data from multiple sources and simulate complex “what if” scenarios. These intuitive technologies allow users to explore and interpret climate data more effectively in a way customized to their needs.

Key next steps include:

– Expanding EO data access for climate-vulnerable communities

– Investing in technology pipelines to drive further innovation in EO-derived climate insights

– Integrating EO data into decision-support systems and climate policies to enable informed, actionable and accountable climate strategies.

– Enabling cross-sector collaboration

Introduction

Integrating complementary technologies with satellite EO converts complex data into actionable climate insights.

By 2032, satellite EO is expected to generate over 2 exabytes of data cumulatively.

Since 1980, the US has experienced 391 weather disasters causing damages of over $2.755 trillion,[1] including severe storms, hurricanes, floods and wildfires. The World Meteorological Organization (WMO) estimates the global socioeconomic benefits of weather forecasting at no less than $158 billion per year.[2]

Earth observation (EO) is critical to monitoring and responding to these climate challenges. It involves the collection of data on Earth's physical, chemical, biological and human systems using remote-sensing and in-situ data methods from an array of sensors and sources. Remote-sensing data is acquired via platforms such as satellites, piloted aircraft, high-altitude platform stations (HAPS) and drones. Conversely, in-situ data is gathered through GPS-enabled devices, the internet of things (IoT) sensors, and a range of various human-operated or automated measurements. While other remote sensing technologies (such as drones and HAPs) are valuable, over 50% of the essential climate variables (ECVs), can only be measured effectively from space. Therefore, satellite EO offers unparalleled advantages in terms of global coverage, scalability, longevity, and continuous and regular monitoring.

Climate intelligence refers to the gathering, analysis and application of historical, current and predictive data about Earth's systems to manage and mitigate climate risks. Next-generation technology pipelines in satellite EO technology, in combination with synergistic technologies such as artificial intelligence (AI), machine learning (ML) and deep learning (DL), are laying the foundation for transforming large datasets into actionable climate insights. By democratizing access to critical climate data, these technologies promote informed decision-making from governments, the private sector and civil society organizations. Such access is pivotal to addressing climate change both nationally and globally, preparing for a future where the full potential of EO data can be harnessed for climate intelligence.

By 2032, satellite EO is expected to generate up to 2 exabytes (2 billion gigabytes) of data cumulatively, accounting for approximately 86% of the total data produced by the space application segment for the forecast period.[3] However, the full potential of satellite EO data in managing climate impacts remains underutilized. This is partially due to the inherent complexity of large satellite EO datasets that require extensive processing and analysis to convert data into actionable climate insights, as well as experts and others requiring ongoing technical training. This complexity can limit its accessibility and timeliness, reducing the effectiveness of climate and disaster response applications.

Advancements in technology within the space industry, such as improved sensors and satellite edge computing, are enhancing EO with higher spatial and temporal resolution as well as on-board processing capabilities for near-real-time climate-related disaster insights. Trends in EO satellites are evolving in two distinct ways: firstly, new entrants are increasingly launching smaller satellites with EO capabilities. This is due to decreasing launch costs that lower the threshold to entry for many nations with emerging space capabilities and small- and medium-sized enterprises (SMEs). Secondly, there is a trend towards developing larger satellites with advanced and sophisticated EO sensors.

In parallel, the development of synergistic technologies is also laying the ground for advanced data processing, analysis, visualization and communication of climate insights. The increased integration of AI with these technologies is enhancing data processing capabilities at a previously unattainable pace and scale. The expanded development of digital twins for generating and testing various climate scenarios, immersive AR/VR data-decision platforms and data cubes allows users to contextualize and tailor EO data based on their specific needs and requests. In addition, the ability to fuse satellite EO and in-situ data through these platforms helps support global to local-level preparedness and response efforts.

1 Bytes to insights

Revolutionizing real-time climate intelligence for disaster response and management with advanced EO technologies.

Real-time data tools that track climate-related events can monitor changes in weather conditions and help predict a disaster's path. In a disaster response situation, where accurate and fast data analysis is crucial for timely decision-making, EO data decreases in value as it ages. However, emerging technology innovations are driving new opportunities to provide EO-enabled near-real-time climate-related disaster insights.

1.1 Enhanced resolution and diversification in sensing capabilities

Satellites with high-resolution and diverse sensing capabilities are more capable of accurately detecting and monitoring climate-related disasters. For example, in wildfire scenarios, being able to detect new fires and hot spots with satellites every few hours (or less) at a high resolution greatly enhances disaster response and provides better operational guidance to first responders.

Technology pipeline: New developments in satellite EO sensor technology

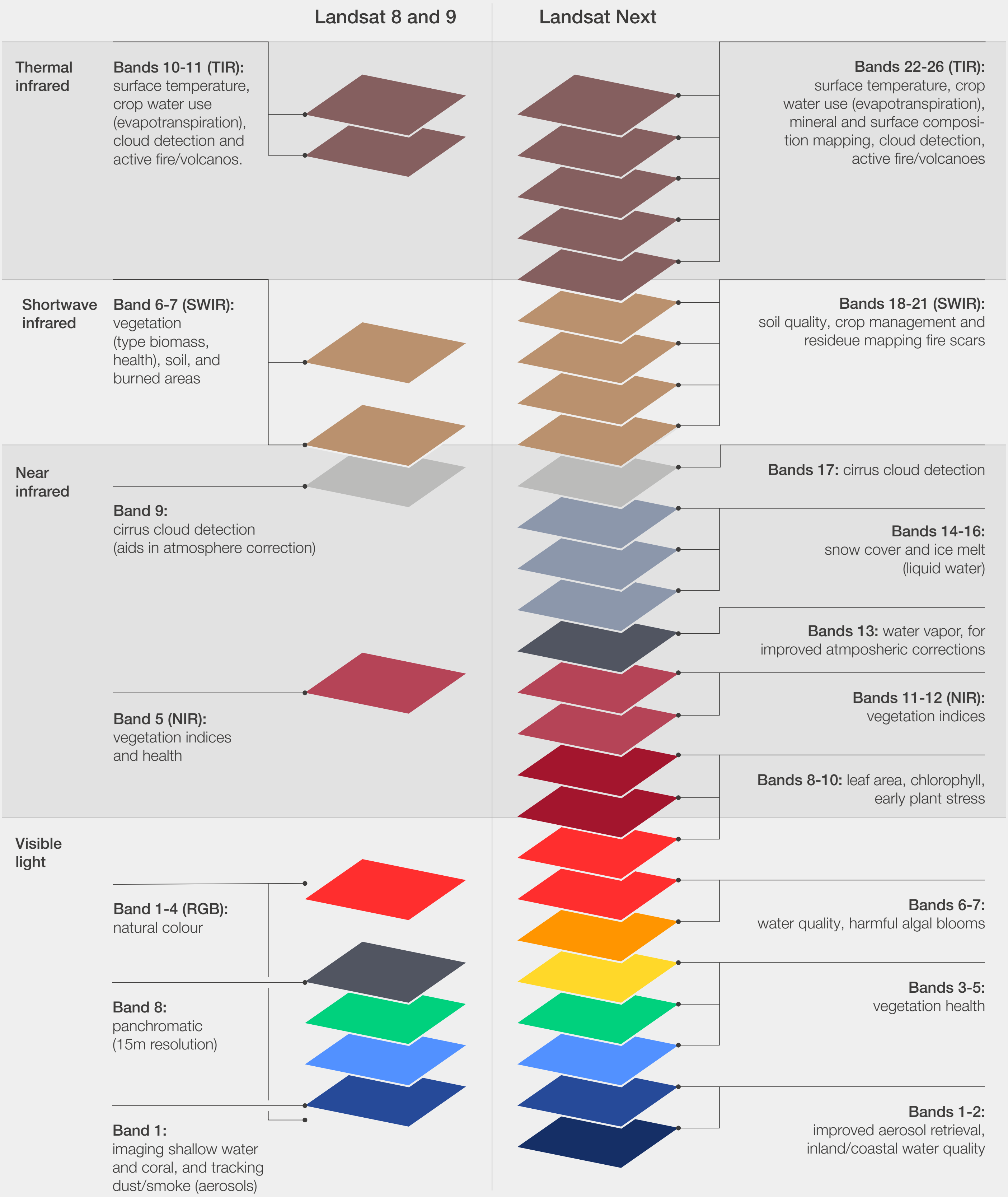
Driven by the rapidly expanding market opportunity and increasing number of potential customers and applications, the potential economic value of EO is expected to exceed $700 billion by 2030.[4] This increasing demand for data has driven advancements in satellite technology (e.g. increasing temporal, spatial and spectral resolution of EO satellite sensors), allowing for better monitoring and analysis of environmental changes, as well as the detection and recording of disasters such as wildfires, floods and droughts.

In 2024, satellite start-up Albedo raised a total of $97 million in early investments (series A-1 funding) to build and launch its first fleet of 24 high-resolution Earth imaging satellites into very low Earth orbit. The company intends to offer high-resolution electro-optical satellite imagery (10cm) and thermal imagery (2 metres). This means that each pixel in the electro-optical imagery represents an area of 10x10 cm on the ground, providing a level of detail previously only available from aeroplanes or classified reconnaissance satellites.[5] South Africa and Belgium-based EO optical imaging solution company Simera Sense raised $15 million in 2024 to accelerate the development of higher resolution and advanced short-wave infrared camera products to match the rising demand from EO satellite manufacturers.[6]

Building on the success of the Landsat program, NASA is also expanding its array of sensors for EO satellites. The Landsat Next mission, slated for launch in 2030, is designed to collect all 26 "superspectral" bands, compared to the 11 "multispectral" bands of previous Landsat missions. Multispectral satellite imagery typically captures 4-12 bands of the electromagnetic spectrum ranging from visible to non-visible light. Superspectral imagery will capture even more bands, enabling more detailed and refined data. LandsatNext's superspectral bands will produce 2-3 times the temporal, spatial and spectral resolution.[7]

FIGURE 1 | **Spectral comparisons between Landsat 8/9 and Landsat Next**

Increased spectral coverage with Landsat Next will support emerging applications



Source: NASA Landsat Communications and Public Engagement Team. (2023). *Spectral Comparison of Landsat 8-9 and Landsat Next*. United States Geological Survey (USGS). https://www.usgs.gov/media/images/spectral-comparison-landsat-8-9-and-landsat-next.

> Integrating AI and edge computing into EO platforms is revolutionizing data processing and analysis.

Muon Space, a start-up developing small satellites to monitor Earth's climate, announced a partnership with the non-profit Earth-Fire Alliance to build a constellation of 50 satellites focused on wildfire prevention and monitoring. The first phase of the three satellites will be launched in 2026 and is equipped with six-band multispectral infrared instruments that provide high-fidelity data to detect fires faster than on-the-ground observations. The multispectral infrared instruments will differentiate genuine wildfire events from false positives and enhance wildfire detection and assessment of fire intensity. FireSat will operate in low Earth orbit with an observation swath of 1,500 kilometres and an average ground sample size of 80 metres. This will allow it to detect fire ignition sites as small as 25 metres squared (m^2) with a revisit time of 20 minutes. This can significantly improve initial response and monitoring, especially in remote areas. For comparison, NASA's Fire Information for Resource Management System (FIRMS) uses satellite observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) instruments to detect active fires and thermal anomalies. MODIS typically detects both flaming and smouldering fires of 1,000m^2 in size. In very good conditions, high-quality observations can detect fires one-tenth of this size (100m^2), and under optimal and extremely rare conditions, even smaller fires of 50m^2 can be detected.[8] FireSat provides a 100% improvement over MODIS under optimal conditions and up to 300% in good conditions.

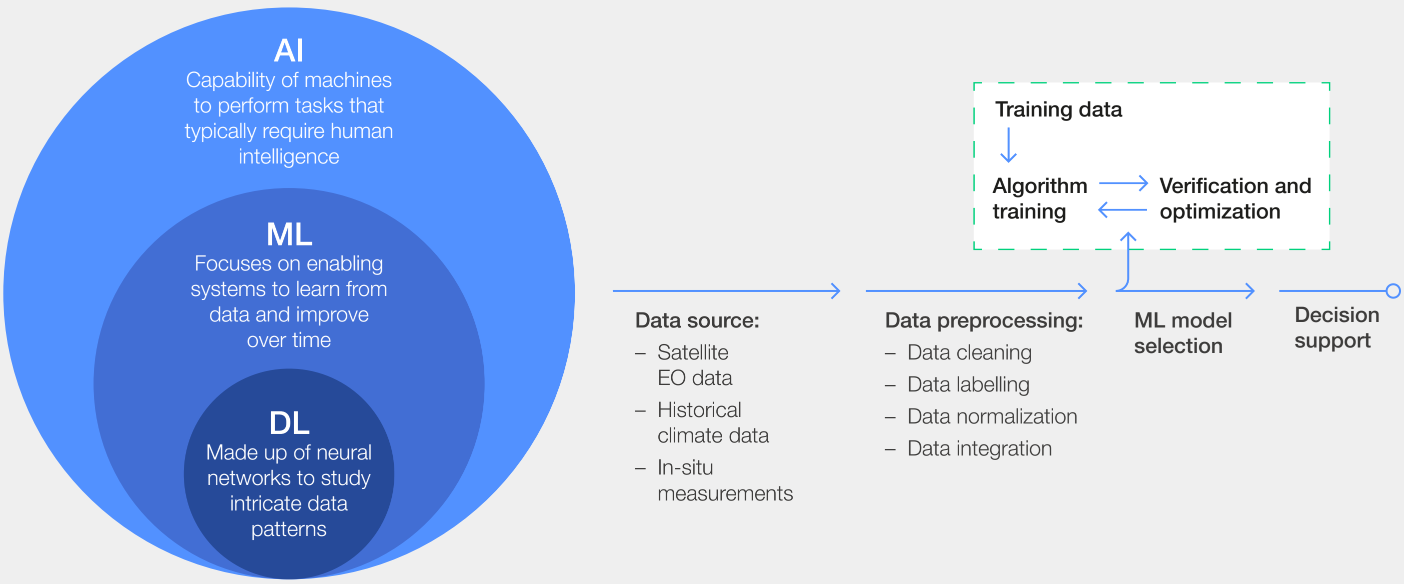
1.2 Reduced EO data processing time to enable near-real-time climate response

With increasing global demand for timely climate intelligence, the time between data acquisition and actionable insights needs to be significantly reduced. Integrating AI and edge computing into EO platforms is revolutionizing data processing and analysis. These advances greatly increase computational efficiency and enable real-time analysis to improve the speed and accuracy of climate-related decision-making.

Technology pipeline: AI, machine learning and deep learning models

The increased availability and complexity of high-resolution EO data has called for the use of advanced AI, ML and DL. In the context of satellite EO data, AI executes the broad analysis of data, while ML, a subset of AI, focuses on the recognition of patterns and anomalies within large EO datasets. A further subset is DL, which facilitates the extraction of detailed features from high-resolution satellite imagery. These algorithms can process large amounts of complex EO data in almost real time, resulting in less time between data collection and the generation of insights. By improving computational efficiency, ML technologies overcome several limitations of traditional data processing methods.

FIGURE 2 **Data processing framework – using AI to transform EO data into actionable climate insights**



AI = artificial intelligence, ML = machine learning, DL = deep learning

In post-disaster events, where there is an urgent need to accelerate damage assessments, high-resolution EO data and ML models use "semantic segmentation" to categorize each pixel of a satellite image, not unlike object recognition.[9] This allows detailed and accurate damage assessments that once took weeks to be completed in hours or minutes. Traditionally, geospatial damage assessments take 30 seconds per structure, which means evaluating 4.1 million structures after a disaster like Hurricane Ian would take one person 16 years. In the case of Hurricane Ian, ML algorithms were used, resulting in rapid evaluation and $80 million in expedited assistance for disaster survivors.[10] Recently, for example, Microsoft partnered with Planet to use AI models and satellite EO imagery to assess the extent of damage from Hurricane Beryl in Carriacou, Grenada. Microsoft trained a change detection model that analysed both pre- and post-event EO imagery and intersected this data with building footprint layers from an incomplete OpenStreetMap dataset. While the analysis only covered a portion of the affected area, this approach allowed the model to quickly identify 888 damaged buildings out of 1,937 in the area analysed.

FIGURE 3 **Post-disaster building assessment in response to Hurricane Beryl in Carriacou, Grenada**

Note: Pre-disaster satellite EO imagery (top) and damage assessment visualizer showing AI-predicted damage layer in red overlay (bottom).

Source: Esri World Imagery. (2024). *Microsoft AI for Good - Damage Assessment Visualizer for Hurricane Beryl in Grenada (July, 2024)*. https://satelliteimagerydemostg.z5.web.core.windows.net/damage-assessment/hurricane_beryl_grenada_07_02_2024.html

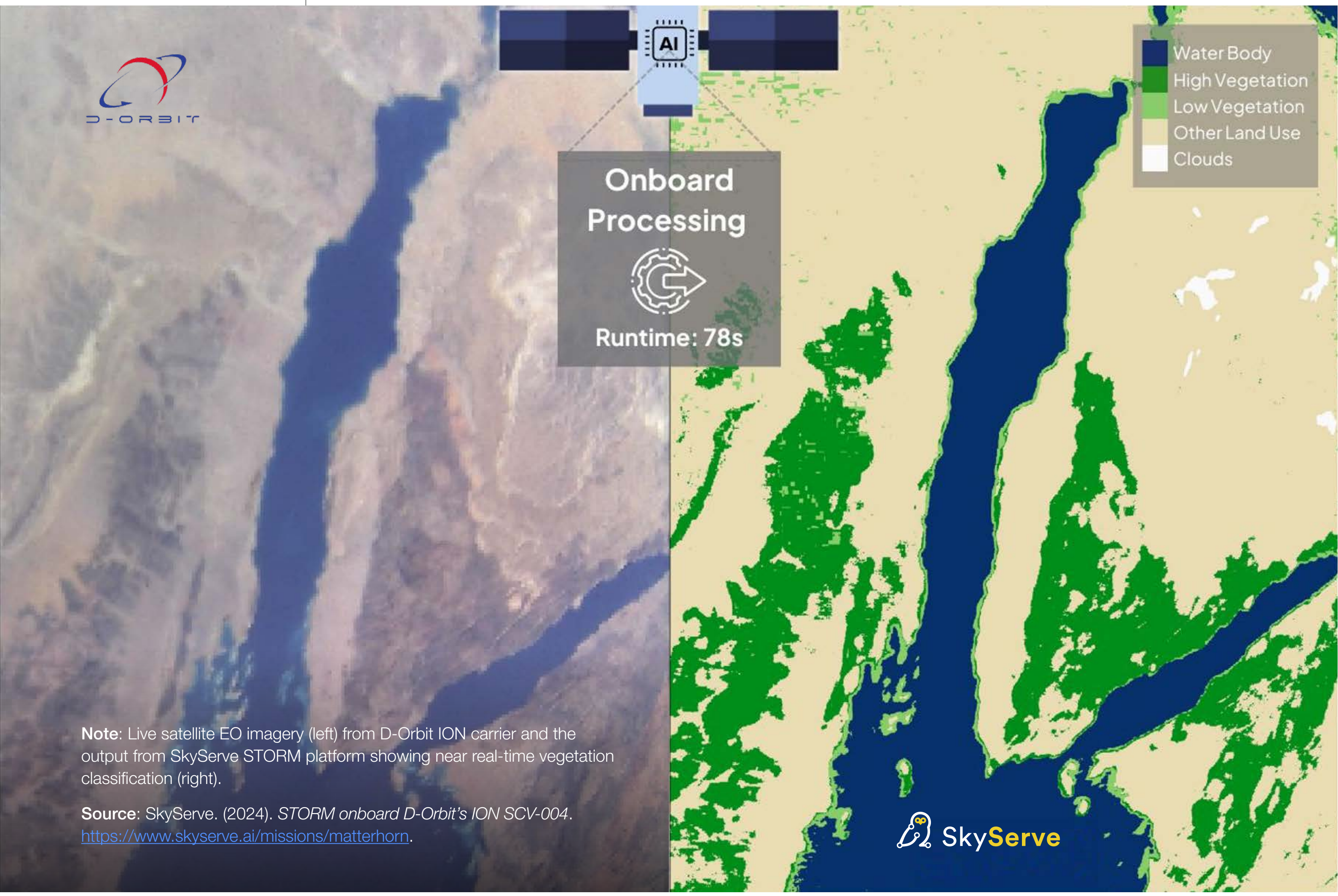
Technology pipeline: In-orbit data processing with satellite edge computing

In-orbit data processing represents a significant advancement in the management and use of EO data. Satellite edge computing processes EO data directly onboard the satellite, integrating advanced computational capabilities. Edge computing can also facilitate spike-based processing, whereby the satellite processes and downlinks data only when its sensors detect a change in the surrounding environment. This helps in extracting higher performance on low power and storage, increasing the per orbit efficiency by smart capture, processing and dissemination. By shifting data processing from ground stations to the satellites themselves, this approach greatly reduces latency and the need for data download.

SkyServe, an Indian space technology start-up focused on onboard AI and edge computing for satellites, recently demonstrated the delivery of real-time insights using optical imagery on their [Mission Matterhorn](https://www.skyserve.ai/missions/matterhorn). The SkyServe STORM system was successfully deployed in orbit aboard D-Orbit's ION Satellite Carrier, a fleet of orbital transfer vehicles. Using D-Orbit's live EO data feed, on-board computer and data distribution resources, the STORM satellite edge computing system showcased its ability to process live images using DL models for real-time vegetation classification. This demonstration is crucial for disaster response as it significantly enhances the efficiency and speed of data processing, allowing faster transmission of vital information to emergency responders.

SkyServe is further scaling the solution for multi-sensor fusion of multispectral and hyperspectral data from space by partnering with Loft Orbital. SkyServe's Mission Denali will install the SkyServe STORM platform on the YAM-6 spacecraft, Loft Orbital's first spacecraft capable of performing "virtual missions". By decoupling the concepts of "satellites" (a platform with payload hardware) and "missions" (an objective executed by the payload), the SkyServe STORM platform aims to scale the practical application of in-space data processing by executing geospatial AI models on a whole host of satellites.

FIGURE 4 **Demonstration of satellite edge computing with EO data**



Note: Live satellite EO imagery (left) from D-Orbit ION carrier and the output from SkyServe STORM platform showing near real-time vegetation classification (right).

Source: SkyServe. (2024). *STORM onboard D-Orbit's ION SCV-004*. https://www.skyserve.ai/missions/matterhorn.

1.3 Parallel evolution of small and large EO satellites

EO satellites have evolved on two fronts: the miniaturization of sensor capabilities and the development of larger, more sophisticated satellite platforms. Miniaturized sensors, as well as reduced manufacturing and launch costs, have enabled more nations to manufacture and launch their own EO satellites and increase publicly available EO data. This revolution democratizes access to timely, high-quality climate insights for a range of stakeholders – from individuals to local decision-makers and non-governmental organizations (NGOs) – where they previously might have been unattainable due to costs or technical constraints.

Conversely, the rise of larger satellites highlights a trend towards greater reliability and capability of EO satellites to host advanced sensors, data processing power and power facilities for continuous data transmission. These larger platforms can house instruments such as multispectral and hyperspectral imaging, synthetic aperture radar (SAR) and advanced radiometers.

Technology pipeline: Miniaturization of EO sensors

The proliferation of small EO satellites and progress in the field of material science has spurred the development of EO sensors that are not only compact and lightweight but also possess enhanced capabilities to perform complex observations compared to their predecessors. Advancements in microelectronics and semiconductor technologies have integrated greater processing power into smaller chips, facilitating data analysis on the sensor hardware itself. Advancements in 3D printing manufacturing methods have enabled the fabrication of miniaturized sensors at a lower cost. The miniaturization of sensors could create opportunities for high-altitude platform stations (HAPS) offering consistent monitoring over specific areas.

Optical monitoring is already possible with HAPS, but advancements in SAR and other sensors, such as thermal infrared remote sensing, could be revolutionary for monitoring disasters such as wildfires.

WildFireSat, the Canadian Space Agency's (CSA) wildfire monitoring satellite mission, uses a new type of infrared sensor based on 10 years of development of microbolometer technology.[11] With the ability to function at room temperature, these infrared sensors represent a major advancement over previous large-scale and resource-hungry sensors that required cooling to extremely low temperatures. Without the reliance on heavy equipment and high energy demands, sensors continue to become smaller and more efficient. This is particularly relevant for developing nations or SMEs who are looking to operate their own EO satellite at low costs.

Technology pipeline: Embracing larger satellite designs for advanced capabilities

The addition of larger EO satellites is a new trend for many EO satellite operators, who have been focused on small satellites over the past decade. This change is partly driven by anticipated reductions in launch costs for heavier payloads, facilitated by new launchers entering the market. As a result, priorities are shifting from satellite mass to capacity, performance, operational lifetime and the need for robust, high-performing and continuous EO solutions. For example, companies like Planet and Capella Space are adding to their fleet of EO satellites with significantly larger satellite bus designs. While Planet continues to provide near-daily, 3-metre monitoring via the Dove constellation, it is also expanding its offerings to larger satellite designs, such as the Pelican and Tanager systems, weighing between 100 to 200 kilograms.

BOX 1

New radio frequencies allocated

Governments and regulators have previously taken measures to ensure the availability of Earth Exploration Satellite Service (EESS) passive bands for crucial weather prediction activities and improved imaging activities. Recently, member states of the International Telecommunication Union (ITU) allocated additional radio spectrum for climate monitoring, weather prediction, and other scientific and satellite missions. However, the World Radiocommunication Conference (WRC) 2023 was only a partial success for EO activities. While it provided more spectrum for passive EESS, enabling advanced measurements of ice clouds for better weather forecasting and climate monitoring, it also identified critical frequencies for the measurement of sea-surface temperature (SST) to mobile phone networks (i.e. 5G). This forced the EO community to study the feasibility of SST in other frequency bands. The upcoming ITU WRC in 2027 will consider the introduction of new mobile phone networks, such as 6G, in the X band. The X band operates in the 8-12 gigahertz range and is the primary spectrum for downlinking satellite EO data. If allocated to 6G, the X band could restrict EO ground stations to remote areas, thereby reducing the resilience of the EO sector and the reliability of data transmission.

2

New era in climate forecasting for adaptation and resilience

Accurate weather and climate predictions strengthen community preparedness for future climate challenges.

An ML-based model trained on existing data can produce the same estimates approximately 1,000 times faster than traditional models.

Satellite EO data, combined with evolving synergistic technologies, offers valuable insights for forecasting future climate scenarios and their global and local impacts. While AI and ML have been in development for over 25 years, their advancements have only accelerated in the last decade, making AI and ML applications increasingly competitive with traditional numerical methods. Systemic data-driven and digital technologies provide critical insights to enable climate adaptation and build resilience in communities and businesses.[12] Looking ahead, several key trends are set to transform weather and climate forecasting even more in the years to come. The move from artisanal to industrial-grade data science will make it easier and more efficient than ever for climate scientists to build and deploy large-scale AI models.[13] This will allow AI models to enhance the scalability and efficiency of climate predictions. The rise of customized AI models will allow for more tailored and precise forecasting solutions, addressing the requirements of specific regions and sectors. In addition, the integration of multimodal capabilities, like those seen in the most recent generative AI models, will enable the concurrent processing and analysis of diverse data types,[14] improving the quality and reliability of climate models.

Technology pipeline: Climate ML-based models

Climate ML-based models use ML to process and learn from large datasets derived from traditional physics-based models to rapidly assess the uncertainties and risks of climate extremes. These models mimic physical processes by identifying statistical patterns in model inputs and outputs. Once trained, the ML-based models substitute specific parts of traditional models to reduce the computational demand while maintaining the model's accuracy. Traditional Earth system models are computationally intensive and can be unfeasible for localized studies due to the need to process petabyte-scale datasets. Climate models that integrate physics-informed ML can overcome these challenges, using multiscale ML-based operators to deliver accurate and fast predictions. For example, traditional weather models allocate 30-80% of their computation time to estimating the movement of solar energy through the atmosphere. An ML-based model trained on existing data can produce the same estimates approximately 1,000 times faster than traditional models.

DL has emerged as an innovative approach to climate emulations due to its ability to process large datasets and improved emulation of weather forecasts at high spatiotemporal resolutions and low computational costs. Recent developments in generative adversarial networks (GANs) and diffusion models have created photorealistic imagery of faces, animals, satellite views and street-level flood scenes. However, climate disaster planners and responders need more than photorealistic images; they also need physically reliable information.[15] The Climate Pocket is an innovative climate education simulation that harnesses fast ML-based climate models to illustrate the localized flood impacts of global climate policy decisions. It integrates physics-informed ML and EO data with physics-based models to provide reliable, physics-consistent predictions. The tool combines GANs with climate science models to produce photorealistic, synthetic and localized climate estimates for any location on Earth for the next 70 years.

FIGURE 5 | **Photorealistic visualization of AI-generated flood risk**

Note: Pre-disaster EO satellite imagery (left) generated flooding post-disaster using physics-informed Generative Adversarial Networks (GANs) (right).

Source: Earth Science. (n.d.). *Earth Intelligence Engine*. https://climate-viz.github.io.

Technology pipeline: Geospatial AI foundational models

Foundation models can use ML to process and analyse large amounts of satellite EO data, which allows them to capture complex patterns within the climate system. These models develop a comprehensive understanding of atmospheric dynamics by learning from diverse datasets, enabling them to perform a wide range of tasks with accuracy and efficiency. They enable localized studies that would be unfeasible through traditional Earth system models and could significantly reduce computational demands while maintaining precision.

Developed by a team of researchers at Microsoft, Aurora is a cutting-edge AI foundational model that can forecast global levels of six key air pollutants – carbon monoxide, nitrogen oxide, nitrogen dioxide, sulphur dioxide, ozone and particulate matter – in under a minute. These predictions extend up to five days and are achieved at a significantly lower computational cost compared to traditional models. By using large EO datasets to develop general-purpose representations, Aurora is set to generate high-resolution weather forecasts for up to ten days, surpassing both traditional simulation tools and specialized DL models. According to its developers, Aurora is about 5,000 times faster than state-of-the-art numerical integrated forecasting systems.[16]

As an example of a public-private partnership (PPP), NASA and International Business Machines (IBM) Research have developed the Prithvi-weather-climate model, an AI foundation model aimed at applications for shorter-term weather and longer-range climate forecasts. The geospatial foundational model, developed with NASA satellite data, will be publicly available on the AI platform Hugging Face. It will be among the largest models uploaded to Hugging Face while being one of the first open-source ML models built in partnership and collaboration with NASA. Trained using Harmonized Landsat Sentinel-2 (HLS) satellite data, the model was originally built for flood and burn scar mapping. However, it can also track deforestation, predict crop yields and monitor greenhouse gases. The MERRA-2 dataset, known for integrating space-based aerosol observations, provided the training foundation for the model, which has since been fine-tuned to enhance climate model resolution twelvefold.[17] The model employs downscaling techniques to generate high-resolution outputs from coarse data at low computational costs.

Climate ML-based models and geospatial AI foundation models – what, why and how do they relate?

Climate ML-based and foundation models serve distinct but complementary roles in climate forecasting, harnessing ML capabilities to address different aspects of climate data processing. Climate ML-based models approximate specific selected physical processes within traditional climate models by identifying and using the statistical patterns in large datasets. They are effective for local studies and quick, high-resolution predictions at low computational costs. They are most useful for applications that need to iterate quickly and often, such as forecasting localized extreme weather.

At the other end of the spectrum, geospatial AI foundational models are designed to detect high-level patterns from large amounts of satellite EO data. These models are trained on many different datasets in a self-supervised way, learning patterns from data without labels, enabling the models to understand atmospheric dynamics. geospatial AI models perform well across a wide range of applications and are suitable for both global and local scales, providing high-resolution views of climate events. They can create highly accurate models of global patterns while remaining computationally efficient by incorporating advanced ML methods to process and normalize data.

TABLE 1 | **Enhancing data visualization and decision-making – ML-based vs geospatial AI models**

	ML-based models	Geospatial AI foundational models
What are the primary applications and what type of outputs do they generate?	Uses classification, regression and clustering techniques to make localized predictions, scenario analysis and risk assessments	Produces global predictions, multiscale models and general-purpose representations
How do they enhance data visualization and decision-making?	Heatmaps, 3D models and dashboards	Interactive maps, simulation tools and AR/VR experiences

> Digital twins use advanced analytics, ML and AI to analyse data from multiple sources, predict environmental changes and simulate complex "what if" scenarios.

The use of EO data in ML-based and foundational models can decrease the build time of a flood map by as much as 80%,[18] helping to convert data into more precise predictions of floods. EO data was proven to increase the accuracy of predicting flood susceptibility by up to 20%,[19] and using EO data with ML algorithms has led to a near-100 times larger dataset when modelling storms and hurricanes compared to traditional methods.[20]

In flood forecasting, these models could help city planners recognize flood-prone areas and prioritize the deployment of temporary designs like sandbags and other immediate flood defences. Longer-term measures, such as improved evacuation strategies, may simultaneously be implemented.

In the case of flash flooding, a 12-hour lead time can potentially reduce damage by up to 60%. In comparison, just a one-hour advance lead time can reduce damage by 20%.[21,22] Better flood vulnerability maps facilitate preventative action that can reduce the cost of a major flood. Annual investments in flood defences of $50 billion for coastal cities could cut expected losses in 2050 from up to $1 trillion a year to $60-63 billion,[23] with a further $12-71 billion required by 2100 to address sea-level rise.[24] AI-driven, detailed flood mapping and accurate forecasting can help direct resources to the most vulnerable regions.

While ML has significantly improved weather forecasting, a challenge remains in applying the same techniques to long-term climate predictions of more than 10 years. Climate systems are more complex with longer timescales, requiring more advanced models that can capture the intricate feedback mechanisms and long-term trends. Additionally, the lack of transparency in foundation models remains an issue compared to traditional weather and climate models. Combining these models through physics-informed neural networks (PINNs) might allow users to achieve the best of both worlds, integrating the advanced pattern recognition of foundation models with the interpretability and physical consistency of traditional models.

Technology pipeline: Digital twins

Digital twins represent an advanced simulation model that integrates EO data to simulate various climate scenarios. These models can be used by city planners and policy-makers for simulations of possible strategies and their impacts on the virtual outcome. Digital twins use advanced analytics, ML and AI to analyse data from multiple sources, predict environmental changes and simulate complex "what if" scenarios. They achieve this by creating a dynamic, digital replica of the Earth's system. This novel approach enables high-fidelity climate simulations, providing a crucial sandbox for testing and refining climate-related strategies.

The Destination Earth (DestinE) initiative from the European Commission is an example of the pioneering efforts in developing a detailed digital twin of the Earth. Using advances in high-performance computing, EO data and ML techniques, DestinE will provide predictions of global environmental change scenarios and their impacts, drawing from capabilities of the European Centre for Medium-Range Weather Forecasts (ECMWF), the European Space Agency (ESA) and the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). The first prototype has been delivered at EuroHPC LUMI Supercomputer Centre in Kajaani, Finland.[25] Currently in its second phase, DestinE's Open Core Service Platform offers a user-friendly, secure cloud-based digital modelling and open simulation platform to complete a full digital replica of Earth by 2030.

In another demonstration of PPPs, Lockheed Martin and NVIDIA are advancing AI-driven EO digital twins for the National Oceanic and Atmospheric Administration (NOAA). Through Lockheed Martin's open Rosetta 3D for AI-driven data fusion and NVIDIA's Omniverse Nucleus for seamless data sharing, these digital twins are increasing the precision of environmental monitoring by integrating diverse data from NOAA's extensive collections on the cryosphere, land, atmosphere, space weather and ocean domains. Both satellite EO and ground-based observations are used to create an exact representation of the Earth at high resolution.

3 Democratizing climate insights

Providing accessible climate intelligence empowers diverse stakeholders to make informed decisions.

Democratizing climate insights means overcoming technological and accessibility barriers to empower a range of stakeholders – from policy-makers to local communities – to use and act on critical climate. This involves a more inclusive and informed approach using innovative technology tools and platforms that translate raw climate data into meaningful, contextual climate insights.

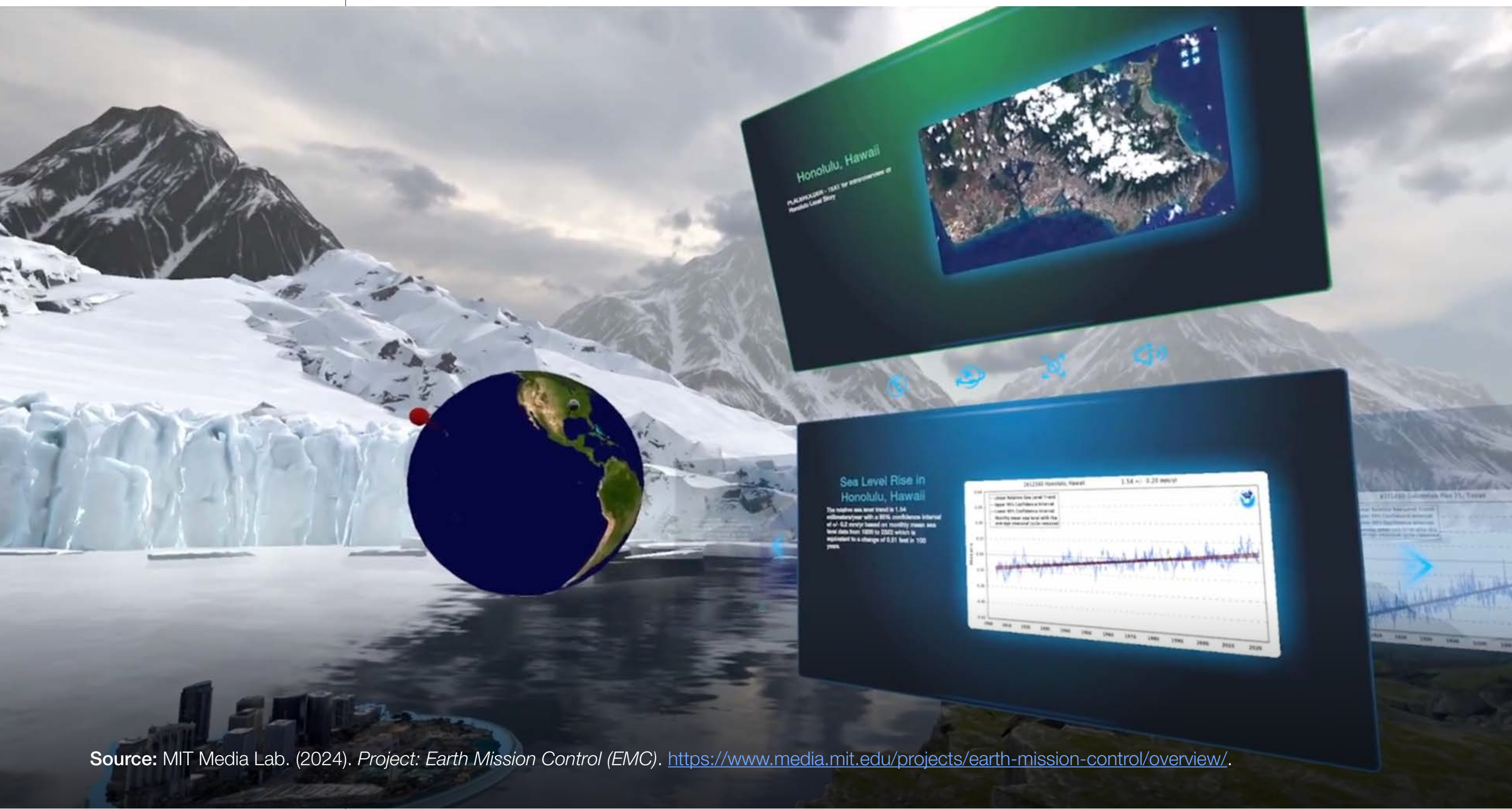
Data visualization and decision support tools, particularly those built on open-source platforms, are transforming how we understand and respond to climate threats. Advancements in AR, VR and data cube technologies enhance data accessibility, support informed decision-making and promote collaborative solutions to climate challenges. These tools translate complex EO datasets (in combination with in-situ data) into visual formats, enabling all stakeholders – regardless of their technical expertise or background knowledge – to easily understand crucial climate insights. While AR and VR technologies provide users with an immersive experience to interact with digital representations of climate data in a more intuitive way, Earth system data cubes are a novel approach for addressing data interoperability. They achieve this by integrating multiple data dimensions (such as spatial, temporal and variable grids) for analysis at various scales and complexity levels.

Technology pipeline: AR/VR data immersive platforms

AR and VR are transformative tools that provide immersive experiences, allowing users to interact with digital environments. When combined with EO data, these technologies turn complex multidimensional EO datasets into comprehensible and interactive models. These Earth system models immerse users as if they are experiencing a situation firsthand, encouraging a nuanced and holistic understanding of climate issues. They achieve this by employing intuitive, interactive visual data presentation alongside depth of information while encouraging data literacy.

A leading example is the Massachusetts Institute of Technology (MIT) Media Lab's Earth Mission Control (EMC). EMC's purpose-built interactive environment enables the exploration and analysis of complex climate data, facilitating more informed decision-making on a broad array of topics. It also enriches analysis and climate decision-making, deepening the user's understanding of various climate projects and policies. Through hyperlocal storytelling components and spotlighting the human impact of climate change, EMC provides users with the insight to make proactive climate decisions and the agency to advocate for climate action. In its current beta phase, EMC includes a location-based decision table, information dashboards and global data projections on a sphere. These modules provide users with powerful insights focusing on hyperlocal features using EO data. By layering EO data with AI and user-friendly interfaces, EMC democratizes access to critical environmental information, providing powerful tools for environmental and socioeconomic advocacy as well as strategic planning for climate resilience.

FIGURE 6 **MIT Media Lab's EMC immersive AR/VR platform**



Source: MIT Media Lab. (2024). *Project: Earth Mission Control (EMC)*. https://www.media.mit.edu/projects/earth-mission-control/overview/.

BOX 2 **ESA unveils AI-driven EO assistant**

ESA's planned development of an "Earth observation digital assistant" (a ChatGPT-style text-based enquiry with EO data) is a key demonstration of generative AI and EO. Designed to accept natural language questions and process them through advanced EO foundational models, ESA's envisioned digital assistant will also generate responses through images, making complex EO data more accessible.

Technology pipeline: Data cubes

EO open data cubes represent a transformative approach to managing and analysing multidimensional EO data. They allow access to EO data through coordinates rather than traditional file names or directory structures, resulting in easier and more efficient access to the large archive of satellite EO datasets, particularly when using cloud-based computing infrastructures. The popularity of EO data cubes has increased in recent years as the structured format allows for more complex analysis and understanding of environmental processes, patterns and trends.

A major barrier identified by users of EO data is the high effort required for data preparation. To increase the usability of EO data, initiatives such as the Committee of Earth Observation Satellites Analysis Ready Data (CEOS-ARD) are helping countries and international organizations overcome this barrier by offering EO data that has been processed to a minimum set of requirements. This data is formatted to enable immediate analysis with minimal additional user effort, as well as interoperability with other datasets.

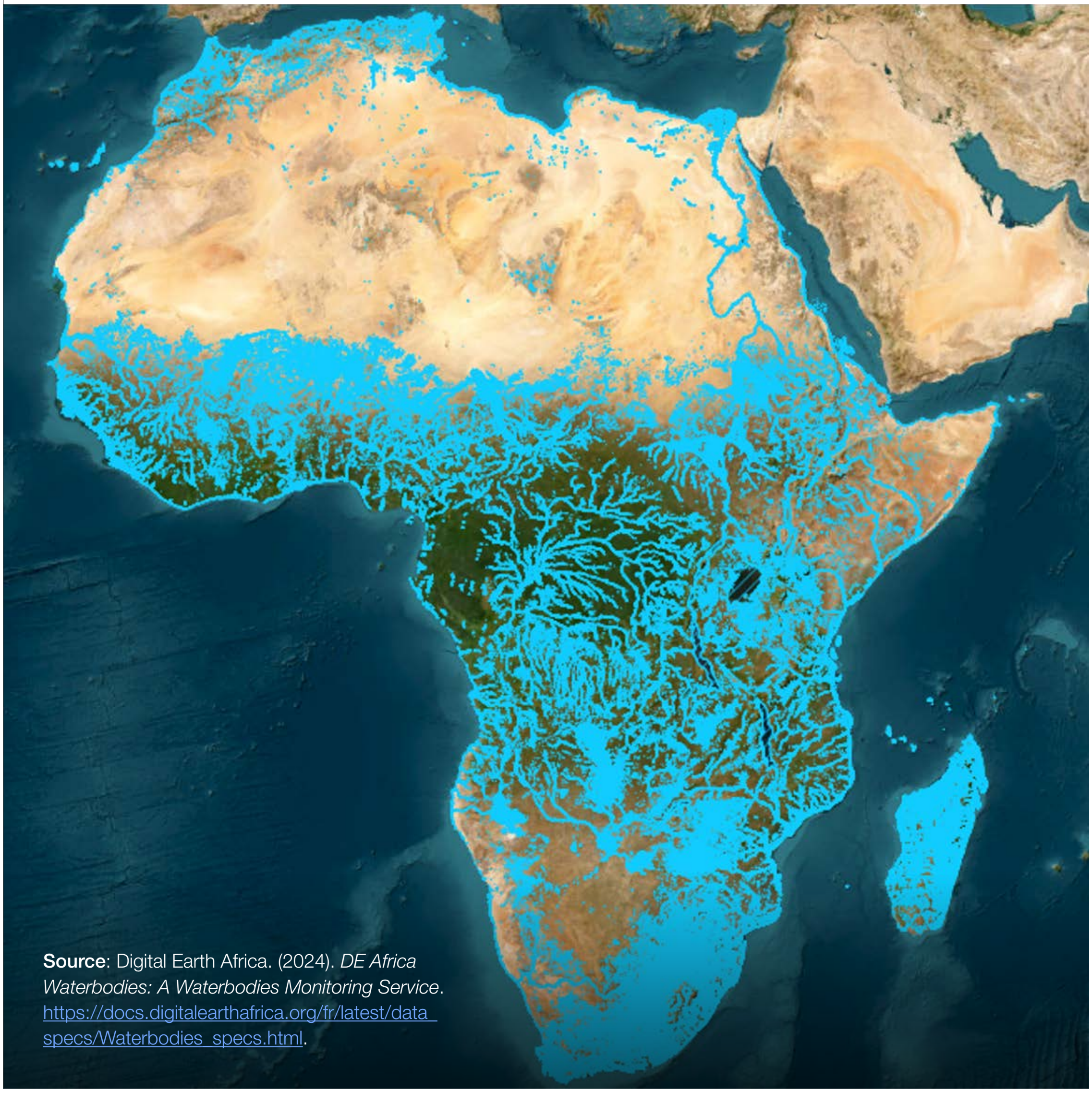
Digital Earth Africa (DE Africa) is an initiative that aims to use satellite EO data for developmental purposes across the African continent. It uses

Open-source AI platforms are also able to quickly process new data and feed it into early warning systems.

the open data cube technology to organize large amounts of satellite imagery into multidimensional arrays (i.e. sorting data by time, location or spectral bands), making it easier to extract and analyse useful insights. DE Africa announced the release of the Waterbodies Monitoring Service (WMS) in 2024. WMS is a tool that delivers a dynamic time series of wet, dry and unobserved surface area as a proportion of the historical water body extent. Overall, it does this for over 700,000 unique water bodies across the African continent on a weekly basis. It is projected that the amount of urban land at high risk from frequent flooding could rise by 270% in North Africa and by as much as 800% across southern African zones; mid-latitude areas could see a dramatic increase of nearly 2,600% by 2030.[26] Open-source AI platforms are also able to quickly process new data and feed it into early warning systems.[27]

Clay, an open-source and non-profit project, is democratizing access to complex Earth analysis by developing large-scale foundation models on satellite-borne data, starting with Sentinel-1 and Sentinel-2 imagery. The outputs of these models are called vector embeddings, which effectively compress the relevant spatial and temporal signals of EO data cubes to be accessed through simple point-and-click web interfaces. While there are several open EO foundational models, Clay's approach to open-source mission-specific product development, coupled with its non-profit status, sets it apart. It assembles donated compute resources to train the largest open models, sets meaningful benchmarks to assess model quality and publishes gold-standard, easily accessible training data.

FIGURE 7 **DE Africa WMS for over 700,000 waterbodies across Africa**



Source: Digital Earth Africa. (2024). *DE Africa Waterbodies: A Waterbodies Monitoring Service*. https://docs.digitalearthafrica.org/fr/latest/data_specs/Waterbodies_specs.html.

Conclusion

EO data is pioneering climate intelligence and disaster response with increased levels of accuracy, efficiency and timeliness. As both EO and synergistic technologies such as AI, ML, advanced sensors and data visualization continue to evolve, so will the way EO data is processed, analysed and used. This transformation will allow practitioners at all levels to grasp climate-specific problems and will enable relevant actors to make data-informed, proactive decisions.

Addressing the complexities of climate change requires a collaborative approach. Governments, private sector entities and academic institutions must work together to support the rapid development of EO and synergistic technologies. They must prioritize a human-centric approach that includes making critical climate insights more accessible, understandable and intuitive. This will require investment in infrastructure, promotion of data sharing and the development of the necessary skills to use these advanced tools. Increased PPPs and research collaborations are needed to continue to stimulate innovation, share expertise and accelerate the uptake of EO-based solutions. Equally important is the need to prioritize community engagement, education and capacity development around climate insights, particularly for those in regions most vulnerable to the impact of climate change.

Moving forward, the emphasis should be on building a strong, data-driven ecosystem around climate. This includes establishing a support system for rapid data collection and integration, championing collective efforts in analysis and exploratory solutions, and ensuring scalable, open-source platforms for accessing curated datasets. These design principles can also act as a bridge to fill the gap between raw EO data and actionable climate intelligence, paving the way for a more resilient and informed response to climate challenges.

The integration of satellite EO data and next-generation technologies will enable a future whereby climate intelligence is more actionable and aimed at empowering communities with the agency, tools and knowledge they need to prepare and react to climate change. Through continued development of technology pipelines and collective commitment, it is possible to transform the approach to climate action, ensuring a sustainable future for generations to come.

Contributors

MIT Media Lab

Minoo Rathnasabapathy
Research Engineer, MIT Media Lab; Fellow, Space Technology, World Economic Forum

World Economic Forum

Helen Burdett
Head, Technology for Earth

Valentin Golovtchenko
Lead, Climate Technology

Nikolai Khlystov
Lead, Space Technology

Hazuki Mori
Lead, Space Technology

Acknowledgements

Arthur Anglin
US Specialist Leader, Deloitte

Bethany Baldwin-Pulcini
Lead, Virtual Missions Frameworks, Loft Orbital

Giuseppe Borghi
Head, Φ-lab Division, European Space Agency (ESA)

Joey Couture
Fellow, World Economic Forum;
US Manager, Deloitte

Matteo Emanuelli
Manager, Radar Programs, Airbus Defence and Space

Casper Fibæk
Earth Observation Applications Specialist, European Space Agency (ESA)

Dan Hammer
Co-Founder, Clay

Björn Lütjens
Postdoctoral Associate, Massachusetts Institute of Technology

Ana-Mia Louw
Operations Manager, Simera Sense

Seamus Lombardo
Impact Metric Associate, Planet Labs

Goutam Naik
Founder's Office Executive, SkyServe

Masami Onoda
Director, International Relations and Research Department, Japan Aerospace Exploration Agency

Lisa-Maria Rebelo
Lead Scientist, Digital Earth Africa

Steven Ramage
Executive Officer, Committee on Earth Observation Satellites (CEOS)

Kati Tolomei
Head, Marketing, Loft Orbital

Andrew Zolli
Chief Impact Officer, Planet Labs

Production

Laurence Denmark
Creative Director, Studio Miko

Rose Chilvers
Designer, Studio Miko

Willem Liley
Editor, Studio Miko

Endnotes

1. NOAA National Centers for Environmental Information (NCEI). (2024). *U.S. Billion-Dollar Weather and Climate Disasters*. https://www.ncei.noaa.gov/access/billions/.
2. World Meteorological Organization (WMO). (2020). *The value of Surface-Based Meteorological Observation Data: Costs and benefits of the Global Basic Observing Network*. https://library.wmo.int/records/item/57167-the-value-of-surface-based-meteorological-observation-data-costs-and-benefits-of-the-global-basic-observing-network?offset=681.
3. Analysys Mason. (2023). *The implications of increasing Earth observation data*. https://www.analysysmason.com/research/content/articles/the-implications-of-increasing-earth-observation-data/.
4. World Economic Forum. (2023). *Amplifying the Global Value of Earth Observation.* *https://www3.weforum.org/docs/WEF_Amplifying_the_Global_Value_of_Earth_Observation_2024.pdf.*
5. Albedo. (2022). *A First Look at 10cm Satellite Imagery*. *https://albedo.com/post/albedo-simulated-imagery*.
6. Simera Sense. (2024). *Simera Sense, world leader in Earth observation optical imaging solutions, raises €13.5m in growth investment round.* https://www.simera-sense.com/capital-raise/.
7. NASA Landsat Science. (2024). *Landsat Next: Mission Objectives*. https://landsat.gsfc.nasa.gov/satellites/landsat-next/mission-details/.
8. NASA Earthdata. (2024). *FIRMS Frequently Asked Questions*. https://www.earthdata.nasa.gov/faq/firms-faq.
9. Robinson, C., R. Gupta, S. F. Nsutezo, E. Pound, et al. (2023). *Turkey Building Damage Assessment.* Microsoft Research. https://www.microsoft.com/en-us/research/uploads/prod/2023/02/Turkey-Earthquake-Report-2_MS.pdf.
10. NEMAforyou. (May 4, 2023). *Emerging Earth Observation Technologies and Their Impacts on the Future of Disaster Response*. YouTube. https://www.youtube.com/watch?v=YfkyMU6x9qk&t=583s&ab_channel=NEMAforyou.
11. Canadian Space Agency. (2024). *WildFireSat: Enhancing Canada's ability to manage wildfires.* Government of Canada. https://www.asc-csa.gc.ca/eng/satellites/wildfiresat/.
12. World Economic Forum. (2024). *Innovation and Adaptation in the Climate Crisis: Technology for the New Normal*. https://www.weforum.org/publications/innovation-and-adaptation-in-the-climate-crisis-technology-for-the-new-normal/.
13. Davenport, T. H. and R. Bean. (2024). *Five Key Trends in AI and Data Science for 2024.* MIT Sloan Management Review. https://sloanreview.mit.edu/article/five-key-trends-in-ai-and-data-science-for-2024/.
14. Heikkilä, M. and W. D. Heaven. (2024). *What's next for AI in 2024.* MIT Technology Review. https://www.technologyreview.com/2024/01/04/1086046/whats-next-for-ai-in-2024/.
15. Lütjens, B., B. Leshchinskiy, C. Requena-Mesa, F. Chishtie, et al. (2020). *Physics-informed GANs for Coastal Flood Visualization*. https://www.researchgate.net/publication/344734339_Physics-informed_GANs_for_Coastal_Flood_Visualization.
16. Bodnar, C., W. P. Bruinsma, A. Lucic, M. Stanley, et al. (2024). *Aurora: A Foundation Model of the Atmosphere*. https://arxiv.org/abs/2405.13063.
17. Koehl, D. (2024). *Prithvi-weather-climate: Advancing Our Understanding of the Atmosphere*. NASA Earthdata. https://www.earthdata.nasa.gov/learn/blog/prithvi-weather-climate-foundation-model-background-benefits.
18. Nemni, E., J. Bullock, S. Belabbes and L. Bromley. (2020). Fully Convolutional Neural Network for Rapid Flood Segmentation in Synthetic Aperture Radar Imagery. *Remote Sensing*, vol. 12, issue 16, no. 2532. https://www.mdpi.com/2072-4292/12/16/2532.
19. Yu, H., Z. Luo, L. Wang, X. Ding and S. Wang. (2023). Improving the Accuracy of Flood Susceptibility Prediction by Combining Machine Learning Models and the Expanded Flood Inventory Data. *Remote Sensing*, vol.15, issue 14, no. 3601. https://www.mdpi.com/2072-4292/15/14/3601.
20. Maddy, E. S. and S. A. Boukabara. (2021). MIIDAPS-AI: An Explainable Machine-Learning Algorithm for Infrared and Microwave Remote Sensing and Data Assimilation Preprocessing - Application to LEO and GEO Sensors. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 8606-8616. https://doi.org/10.1109/JSTARS.2021.3104389.
21. CRUE ERA-Net. (2008). *Effectiveness and Efficiency of Early Warning Systems for Flash-Floods (EWASE)*. https://www.academia.edu/31684129/Effectiveness_and_Efficiency_of_Early_Warning_Systems_for_Flash_Floods_EWASE.
22. Rogers, D. and V. Tsirkunov. (2024). *Global assessment report on disaster risk reduction: costs and benefits of early warning systems*. World Bank Group. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/609951468330279598/global-assessment-report-on-disaster-risk-reduction-costs-and-benefits-of-early-warning-systems.
23. Hallegatte, S., C. Greeb, R. J. Nicholls and J. Corfee-Morlot. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, vol. 3, pp. 802-806. http://dx.doi.org/10.1038/NCLIMATE1979.
24. Hinkel, J., D. Lincke, A. T. Vafeidis, M. Perrette, et al. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences of the United States of America*, vol. 111, issue 9, pp. 3292-3297. http://dx.doi.org/10.1073/pnas.1222469111.
25. European Space Agency (ESA). (2024). *A milestone in digital Earth modelling*. https://www.esa.int/Applications/Observing_the_Earth/A_milestone_in_digital_Earth_modelling.
26. Güneralp, B., İ. Güneralp and Y. Liu. (2015). Changing global patterns of urban exposure to flood and drought hazards. *Global Environmental Change*, vol. 31, pp. 217-225. https://doi.org/10.1016/j.gloenvcha.2015.01.002.
27. Nearing, G., D. Cohen, V. Dube, M. Gauch, et al. (2024). Global prediction of extreme floods in ungauged watersheds. *Nature*, vol. 627, pp. 559–563. https://doi.org/10.1038/s41586-024-07145-1.

COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

The World Economic Forum, committed to improving the state of the world, is the International Organization for Public-Private Cooperation.

The Forum engages the foremost political, business and other leaders of society to shape global, regional and industry agendas.

World Economic Forum
91–93 route de la Capite
CH-1223 Cologny/Geneva
Switzerland

Tel.: +41 (0) 22 869 1212
Fax: +41 (0) 22 786 2744
contact@weforum.org
www.weforum.org