How can real-time monitoring and assessment of the effects of climate change be enhanced using artificial intelligence and satellite data?

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Abstract:

Satellite imaging using data sources including Earth observation systems, climate modelling, and remote sensing is a prime example of a data-driven solution in the field of climate change. Including satellite data in climate monitoring assessments has improved its spatial resolution, which helps to extract critical information at scale. Artificial intelligence models find patterns and trends in enormous datasets to predict how different locations may be influenced by climate change. This paper aims to address the ethical concerns of using satellite imaging for climate data collection. The role of data and statistics is emphasised as it remains at the core of training AI models and quantifying climate variables. This paper also discusses Earth's digital twin, an AI-focused solution that can be leveraged to create a replica of earth using satellite data.

Keywords: Data-driven solutions, Earth observation systems, Spatial resolution, Remote sensing, Earth's digital twin

1.0 Introduction

In 1959, as part of the US-Soviet space race, the first weather satellite was sent into orbit with only rudimentary computing power and a primitive ability to measure cloud cover as it orbited the earth. Since then, over 150 satellites have been deployed by NASA and the European Space Agency to orbit above Earth. With the help of this vast satellite network in orbit, scientists can obtain continuous data and analysis on climate change anywhere on Earth, even in remote areas that may be challenging for them to reach. (Anderson, Kara, 2023) It is necessary to gather environmental data across several decades (30 years or more). However, satellites typically have an average lifespan of a few years to a decade. Because satellites have a limited lifespan, data can be collected over a long period of time by satellites carrying sensors from previous missions. Records known as Essential Climate Variables (ECVs) offer vital evidence of climate change.

2.0 Literature Review

2.1 Current applications

Artificial Intelligence has created new avenues for gathering and analysing climate data globally, spanning the oceans, land, and atmosphere. For instance, tracking and identifying waste from the sea using satellites. Artificial intelligence (AI) models have been developed to identify certain types of plastic, as well as to detect floating plastic particles and submerged plastic rubbish by combining AI with drones. The sensitivity of AI models can guarantee that the most minute variations in humidity and wind speed may be recognized and studied by AI, while human analysts may overlook such details.

Table 1.1 - How different technologies in AI have successfully aided in the detailed detection and prediction of wildfires.

Deep Learning Model	Examples	Performance
Convolutional Neural Networks (CNN)	- Detecting wildfire through satellite imagery- Identifying smoke plumes and flames through real-time video analysis	Achieved an accuracy of 97% in detecting wildfires from satellite images (Oh et al., 2020)
Recurrent Neural Networks (RNN)	- Predicting wildfire intensity and spread based on weather patterns and historical data—Analysing sensor data to predict the likelihood of a wildfire event	Outperformed traditional regression models by up to 12% in predicting wildfire spread (Mohan et al., 2021)
Generative Adversarial Networks (GAN)	- Generating synthetic wildfire images to aid in training CNN models- Creating simulated wildfire scenarios to test emergency response strategies	Generated high-quality synthetic images with a 50% reduction in data requirements (Park et al., 2020)

2.3 Current challenges

The UN Environment Programme (UNEP) examined the SDG indicator framework in March 2019 and found 93 indicators that have an environmental focus. As per the review, only 30 environmental indicators were evaluated formally on a global scale because of insufficient data. “Much of the critical data used to track climate change and its impact on Earth is collected by satellites in space. But all that data needs to be better analysed in order to better cope with the climate crisis” Ellen Stofan, undersecretary for science and research at the Smithsonian Institution (Erwin). Yet while modern space technology provides us with terabytes of useful climate information, sifting through and translating this data into effective statistics and analysis is where AI can step in. The Intergovernmental Panel on Climate Change (IPCC) released its assessment report, outlining the mounting evidence of the global crisis. The paper highlights Earth observation satellites as a crucial instrument for monitoring the causes and effects of climate change(ESA, 2021). For AI systems to generate forecasts and suggestions, a lot of data is required. But biassed input can produce biased outputs when AI systems are trained on it. An AI system trained solely on historical data from particular groups of people or locations can lead to biased outputs.

3.0 Methodology and analysis

3.1 Mobilising Data-Closing the environmental data gap

This includes satellite imagery, remote-sensing data, astronomical data, space weather data, space-based navigation and communications data. Satellites take the top spot as the main mode of climate data collection as more than 50% of essential climate variables are measurable only from space (WEF Space for Net Zero). A World That Counts, a seminal report published in 2014, outlined the need for a data revolution to address sustainable development concerns. It refers to data as "the lifeblood of decision-making," without which effective policies are nearly impossible. Kevin Trenberth, a senior researcher in the U.S. The National Center for Atmospheric Sciences in Boulder said, "We cannot manage what we can't measure." This places a strong emphasis on quantifying climate observations, which will help us uncover new climate variables and make tracking progress easier. The cost of obtaining satellite data has decreased due to technological advancements. Public access to satellite operators' climate data is becoming increasingly common around the world. Some institutions have implemented free and open data policies, such as the European Space Agency and the U.S. Geological Survey. Another example would be that a large portion of space data is multipurpose by nature in ways that "regular data" typically isn't. For example, monitoring smoke from Canadian wildfires as it moves across the United States can aid in weather pattern analysis, air quality forecasting, and warning people to take preventative measures. This is because the climate extends beyond political boundaries. Though gathering data isn't very productive unless it's transformed into insightful statistics and paired with AI technologies—which will be discussed further in this paper.

3.2 Deployment and Enhancing Current AI tools

The AI technique ‘reinforcement learning’ is used to detect and track features on the Earth's surface such as to better control the orientation of the spacecraft, and detecting forests using deep learning (“ESA - Artificial intelligence in space”). This also improved the image quality, unlocking new methods to employ deep learning on the spacecraft.

Table 1.2- Outcomes of AI and Deep Learning when trained on satellite and climate data.

AI Technology	Purpose	Input Data	Outcomes	Example Applications	Reference
Machine Learning	Predicting future climate patterns and changes	Climate models, historical climate data, satellite imagery	Projections of future temperature, precipitation, and other climate variables	Informing climate policy, guiding adaptation strategies	(Linardos et al., 2022)
Deep Learning	Analysing satellite imagery to detect changes.	Satellite imagery, climate data.	Identification of changes in patterns	Monitoring deforestation, guiding land use planning	(Catani, 2021)

Combining historical and current datasets with geolocated real-time data improves the accuracy and efficiency of AI algorithms. There are three basic methods that researchers are utilising AI for climate modelling. The first strategy entails creating emulators that are machine-learning models that mimic the output of traditional models without requiring tedious mathematical computations. Furthermore, the National Geospatial-Intelligence Agency (NGA), a US intelligence agency and the largest purchaser of satellite imagery on the market, has made it apparent that data analytics will replace plain data as its primary strategy. Citing Robert Cardillo, Director at NGA: "I envision the future where we will move from analysing Big Data towards realising the potential of Fast Data. We'll buy basic imagery analysis as a commodity – much like we buy foundation data today".

In a 2023 study, climate scientist Vassili Kitsios at the Commonwealth Scientific and Industrial Research Organisation in Melbourne, Australia, and his colleagues developed 15 machine-learning models that could emulate 15 physics-based models of the atmosphere. They used the surface air temperature forecasts from the physical models up to the year 2100 for two atmospheric carbon concentration pathways—a low and a high carbon emission scenario—to train their system, named Quicklime. It took around thirty minutes on a laptop to train each model. The outcomes closely matched those of the traditional models based on physics. A proposed approach suggested by many scientists is to create hybrid models by integrating machine learning components into physics-based models. The ultimate objective is to develop AI-powered computer representations of Earth's systems that are able to quickly and accurately replicate every facet of the weather and climate, down to the kilometre scale.

3.3 Digital twin of Earth

Creating a digital twin of Earth has become a newly growing consensus in this field with many government and private companies sprinting towards developing the most advanced AI systems that are breaking accessibility and technological barriers. A digital twin of Earth has the following characteristics: dynamic forecasting models, impact assessment capabilities, and a digital representation of the planet's past and present states. The ability to imitate planetary activity is enhanced by machine learning, under both default and customised situations. The digital duplicate offers a precise depiction of the system's current condition and is fed by frequent, focused, and varied observations. One of the primary objectives of this suggested method is to simulate hypothetical scenarios in order to prevent disasters. Advanced computational powers, Machine Learning (ML), and Surrogate Modeling enable forecasting, which offers real-time or almost real-time prediction of future system states.

Finally, investigating "what-if" situations is now possible with the generation of impact assessments. With their help, we will be able to forecast Earth Science events, such as severe weather, and comprehend the relationships between different systems. Moreover it assists in identifying abnormal situations (outlier identification). In March 2024, NVIDIA unveiled its digital twin cloud platform for Earth-2 climate, which allows for unparalleled scale in weather and climate simulation and visualisation ("NVIDIA Announces Earth Climate Digital Twin | NVIDIA Newsroom"). The AI can swiftly sort through masses of meteorological and climate data thanks to its extensive training; it can generate hundreds upon thousands of possible outcomes and eventually determine the likelihood of a certain weather event in a given area.

With the use of this model, scientists can reliably enter current data and simulate both the best- and worst-case scenarios for natural disasters in various environments throughout the world. For instance, circumstances and hazards related to landslides can be simulated and observed as if they were occurring in real time. Based on the knowledge gained from each test, this could help with readiness for future occurrences that could be detrimental. This initiative is a prime illustration of how cutting-edge satellite missions and the scientific community may work together.

3.4 Ethics

Protecting privacy and preventing the misuse of personal information requires the ethical use of data; however, this may not apply to climate monitoring; rather, it may only apply to high-resolution imagery used for mapping and navigation or satellite-based surveillance. Therefore, it is likely that space data ethics does not place as much emphasis on subject protection (e.g., with climate data, where the data isn't so much about individuals).For example, if surveillance is conducted by drones or unmanned aerial vehicles (UAVs) within a territory's airspace, it may be governed by local laws. However, space-based intelligence, surveillance, and reconnaissance (ISR) can be exempt from local laws because space itself is beyond national borders. Boundless global coverage is necessary to guarantee unbiased data. Climate monitoring using AI can benefit low economic countries who are unable to conduct climate research on a local scale due to factors such as inaccessibility to expertise and infrastructure. Climate data would typically come under unobtrusive data collection when data collection is made possible by satellites without posing any threats to national security. Recognizing that outer space is a global common, space data ethics give distinct weight to sovereign autonomy (beyond control of a state's own space objects), including sovereign authority of data pertaining to their borders (NASA Space Data Ethics).

Conclusions

Collaborating collaboratively to develop systematised approaches for data interchange and analysis is necessary to ensure the effectiveness of satellite imaging. These models are anticipated to get more accurate as the environmental data gap narrows. This is leading to the development of a comprehensive platform that can handle real-time satellite data and convert it into advantageous insights like the digital twin of Earth. The optimal way to train models for machine learning is to use a variety of scenarios, including extreme and edge instances, so that the complete influence of each variable can be assessed. Ethical concerns remain less of a threat and the focal point of climate monitoring using satellites due to data not being related to individuals. Environmental machine learning models are mostly restricted to the last few decades, since high-quality satellite data has only been accessible for a little over sixty years. There aren't any datasets from significant ice ages or interglacial eras available to study how the environment might alter in more extreme circumstances. Our current technology may not be able to provide predictions for longer time frames, like 100 years into the future, but it will be sufficient to construct models and projections for the next 50–75 years.

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