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1. Introduction

1.1. Preface by the co-chairs

Satellite Earth Observation (EO) technologies allow us to 'look back in time' as far as the 1970s[1], offering valuable insights into the state of the natural environment and the impacts of human activities. This long-term, global coverage provides a unique perspective for measuring, monitoring and understanding environmental dynamics that are critical to addressing today's greatest challenges, particularly in advancing the sustainability agenda. Even Antarctic glaciers have recently been named after their 'satellite heroes'[2], acknowledging the role of EO in revealing the effects of human activities and a changing climate on these fragile landscapes.

The challenge lies in making sense of the vast volumes of satellite data. Artificial Intelligence and Machine Learning (AI/ML) are uniquely positioned to (1) share the cognitive load, scaling the automation of repetitive analytical tasks. (2) Detect complex or subtle patterns often beyond human perception, from hyperspectral signatures of minerals to the changing signals of an infected crop field. (3) Complement human intuition, recognising that automation and information extracting alone are not enough. An effective human - AI synergy is essential to transform raw data into actionable insights. Together, EO and AI/ML offer a scalable, global perspective on Earth's complex processes, opening the door to innovative solutions that advance the UN Sustainable Development Goals.

This document presents an overview of AI/ML initiatives led by the global space agencies that make up CEOS, highlighting recent advancements in applying these technologies to EO. To frame this landscape, it includes a brief introduction to EO sensor data, key AI/ ML concepts and illustrative applications that integrate AI/ML with EO. Emerging and cutting-edge topics, such as the move from task-specific AI models to foundation models are also briefly explored.

This document is not intended to be exhaustive. Instead, it serves as a living document, a central reference point for tracking the rapidly evolving intersection of EO and AI/ML. Contributions from the community are warmly encouraged and welcomed: if you would like to expand or update any section, please share your suggestions or content via GitHub repository or contribution form. All inputs will be considered for review alongside analysis of key developments in EO and AI/ML. The document is intended to be updated annually to reflect the latest advancements.

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[1] First civilian EO satellite Landsat-1 launched in 1972. https://landsat.gsfc.nasa.gov/satellites/landsat-1/

[2] https://www.bbc.com/news/science-environment-48547803

We especially encourage contributions from space agencies and institutions in the Global South to help ensure diverse perspectives and equitable representation across the global EO and AI/ML community. In future editions, in addition to incorporating community contributions and highlighting major EO and AI/ML developments, we aim to organise dedicated workshops to capture a coordinated roadmap and concrete recommendations on how CEOS agencies can strengthen collaboration in this rapidly evolving domain.

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This document has been developed by the members of the Technology Exploration Interest Group (TEIG) of Committee on Earth Observation Satellites (CEOS) Working Group on Information Systems and Services (WGISS).

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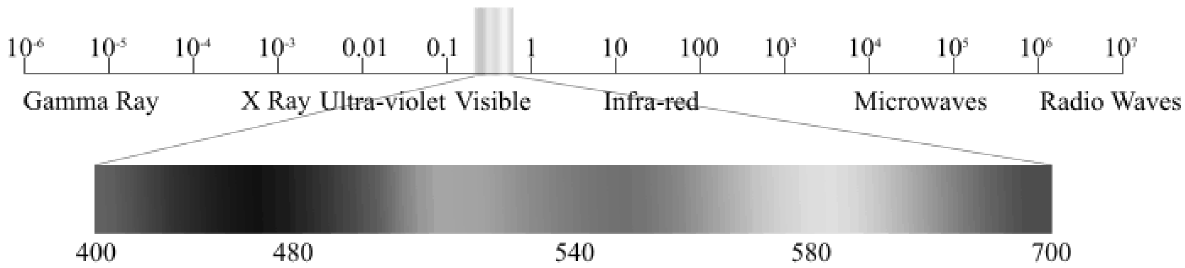
2. Background

2.1. Overview of Earth Observation[3]

Observation is the process through which mankind is able to collect factual data about their physical surroundings. While **Earth Observation** per se comprises any observation that targets the Earth and anything in on or around it, the most prominent of its sub-domains is probably 'remote sensing', of which a significant part is carried out using satellites. Satellite EO can be thought of as a modern day 'macroscope'. Whilst traditional microscopes enabled us to study our world at the micro scale, satellite EO is enabling a global-scale view of the Earth and its processes.

The term **remote sensing** refers to the fact that we can observe properties of phenomena from a larger distance usually without any mechanical connection or interaction. It is useful to distinguish this type of observation from those done at smaller, for the observation negligible, distance, which often are referred to as **in-situ**. Any observation requires a signal to carry information about a phenomenon to the sensor. If mechanical interaction (such as in seismics and sonar, which might validly be called remote sensing as well) is neglected here, only two types of signal carriers remain, gravitational and electromagnetic fields. The by far most used type of signals in remote sensing on which we are hence focussing, are **electromagnetic (EM) waves**.

Electromagnetic waves have an almost unlimited range of wavelengths, called the **Electromagnetic Spectrum** , stretching from atomic to galactic dimensions, part of which is shown in **Figure 2.1-1**. Depending on their wavelength they interact with physical phenomena such as matter at very different scales. Of practical use in remote sensing are wavelengths ranging from some tenth of a micrometre (10^{-6}m) revealing molecular structure and micro-particles, up to several meters reacting to macroscopic properties like object's surface roughness or dielectric properties (water content).



[3] Content modified and adapted with permission from the Satellite Applications Catapult Whitepaper by Kalaitzis et al. (2022) : State of AI for Earth Observation.

Figure 2.1-1: Electromagnetic spectrum as measured in micrometers. Visible wavelengths (lower bar) are in nanometres. Passive optical satellite instruments measure light in the Visible to Infrared parts which arrives either as reflected sun-light or thermally emitted. In contrast, Synthetic Aperture Radar satellites are active , they generate and detect their own signal in the Microwave region. Source : CTAHR.

Sensors are key elements of any observation, as they record the signal and transform it into data. Each sensor thereby inherently takes a ‘snapshot’ of the observed target, which is a **sample** in space, wavelength (spectral or other signal), and time. There is no generally acknowledged **taxonomy of EO sensors** or techniques, but several attributes can be combined to distinguish the most important types in which sensors observe (or sample) phenomena across these dimensions.

In the **spatial dimension** sensors can measure just a single sample, generate 1D coherent profiles, or 2D coherent rasters, being labelled as sounders, profilers, or imagers respectively. Of primary interest to the user is of course the spatial size of the individual sample, also called ‘pixel’. The measured sample size is closely related to the capacity of the sensor to picture the target with a certain detail, often referred to as **spatial resolution**. Spatial resolution is mostly expressed in meters as the size of the pixels which in most cases is roughly identical to their distance.

In EO spatial resolution can range from centimeters to kilometers and is often divided into classes from ‘very high’ (VHR), to ‘high’ (HR), ‘moderate’ (MR), and ’low’ (LR) without internationally applied norms. A relatively detailed and widely used resolution scale is the one used in the Copernicus programme, displayed in **Figure 2.1-2.**

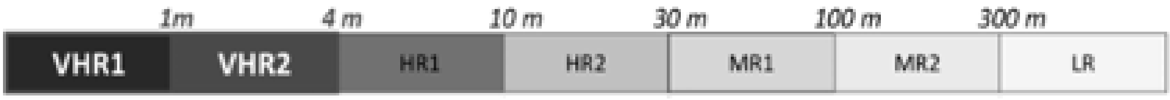


Figure 2.1-2: A common scale to categorise the spatial resolution of EO sensors in the range from below 1m to beyond 300m. Source: ESA.

Equally important is the **spectral dimension**, i.e. which part of the electromagnetic spectrum, often called **band** or **channel**, a sensor is sampling and whether it works only with a single band or multiple such bands. Especially in the optical range most sensors are not working with just a single band (‘monospectral’ or ‘monochromatic’), but with a multitude of bands according to which they are called either **multispectral** (‘multiband’) for a few to tens of bands or **hyperspectral** if the number of bands exceeds roughly a hundred. If the bands are spectrally continuous one would also speak of a **(imaging) spectrometer**. The width and distance of the individual spectral band passes also determines the **spectral resolution** of the sensor.

Another primary characteristic of a sensor is whether it just registers a signal received from the target, then called **passive** sensing, or whether it emits that signal to register the response after interaction with the target, defining **active** sensing.

Finally, in the **temporal dimension**, as most observations need to be done repeatedly, the attribute used to characterise sampling is **revisit time, repeat frequency,** or **cadence**. If the sensor is mounted on a satellite revisit time is usually very regular and often done such that the local (solar) time of the observation is the same on different days (**sun-synchronous**) in order to maintain observation and target conditions which have diurnal cycles.

The relationship between the spatial resolution and the temporal resolution is plotted for selected satellite missions in Figure 2.1-3.

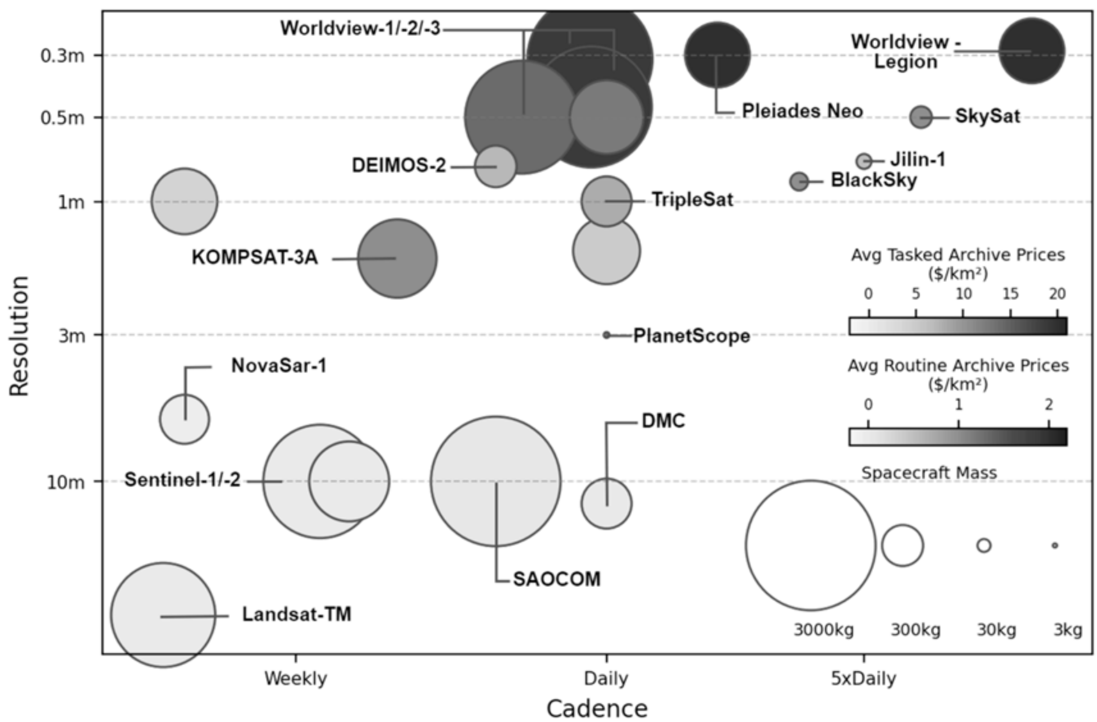


Figure 2.1-3: Revisit period vs. spatial resolution of selected optical and SAR satellite missions.
Source: Kalatzis et al. (2022) © Satellite Applications Catapult.

For AI/ML applications in Earth Observation, it is of paramount importance to understand that most of the desired environmental information cannot be **directly** assessed by EO sensors, which depend primarily on electromagnetic signals. However, spectral, spatial, and temporal variations in these signals contain a wealth of **indirect** information. This can be extracted if there is a physical link between the observed signal and the target variable — such as the relationship between photosynthesis and its characteristic light absorption.

These links can be exploited using **physical (parametric)** models, which require a detailed understanding of the underlying phenomena, or through **non-parametric, often stochastic** methods such as AI/ML, which rely on sufficient training or reference data. However, the ability to infer information is inherently limited when the desired variable is not — or not reliably — encoded in the observed signals. For example, a sufficiently resolved set of optical and microwave data may enable estimates of tree number, size, density, and condition or even species, but it often does not reveal how the land is being used — whether for forestry, agriculture, or recreation.

2.1.1. Optical EO satellites

Examples of optical multispectral sensors are plotted along with their bands in **Figure 2.1.1-1**. and some more along with their mission duration and spatial and temporal resolution satellites in **Figure 2.1.1-2**. All these sensors are passive imagers. The more bands they have, the more subtle spectral signatures of different surfaces on the ground can be detected. Similar to human fingerprints, different ground surfaces interact with light and have their own unique signature. For example, vegetation and iron-rich surfaces have a unique signature in the very-near-infrared (VNIR), other surfaces such as clay minerals have a signature in the longer wavelengths, in the short-wave infrared (SWIR).

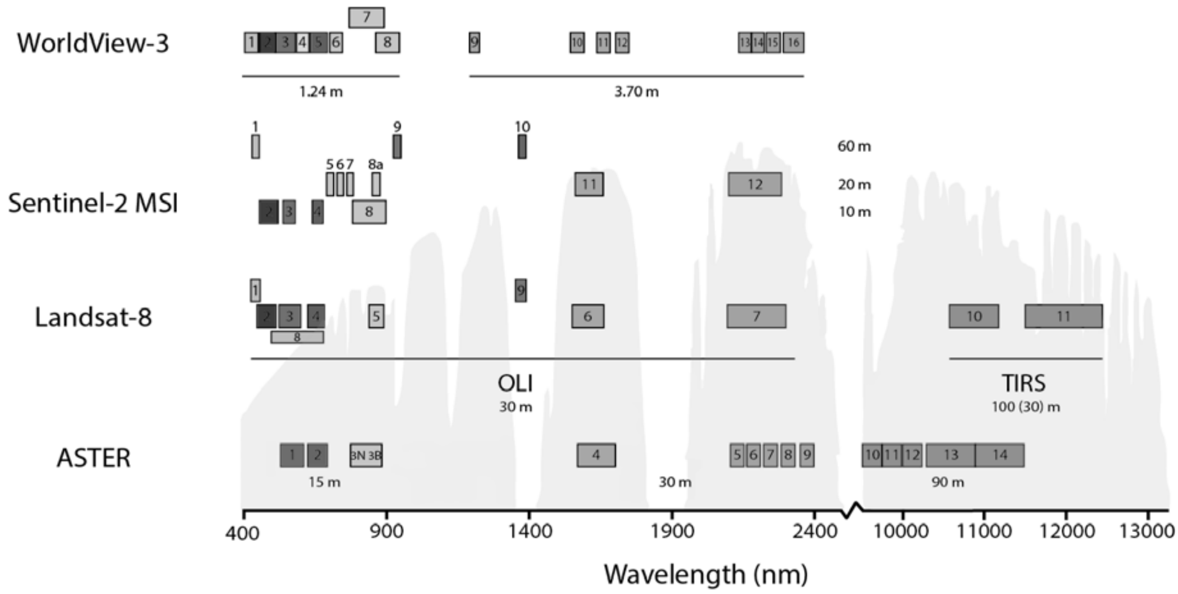


Figure 2.1.1-1: Spectral and spatial resolutions of common multispectral optical sensors. Atmospheric windows are shown in grey. These are wavelengths thorough which light from the Sun cannot penetrate the Earth’s atmosphere. Spectral bands are shown in colored rectangles, and their numbers correspond to the band ID of their instrument.

Source: Cardoso-Fernandes et al. (2020).

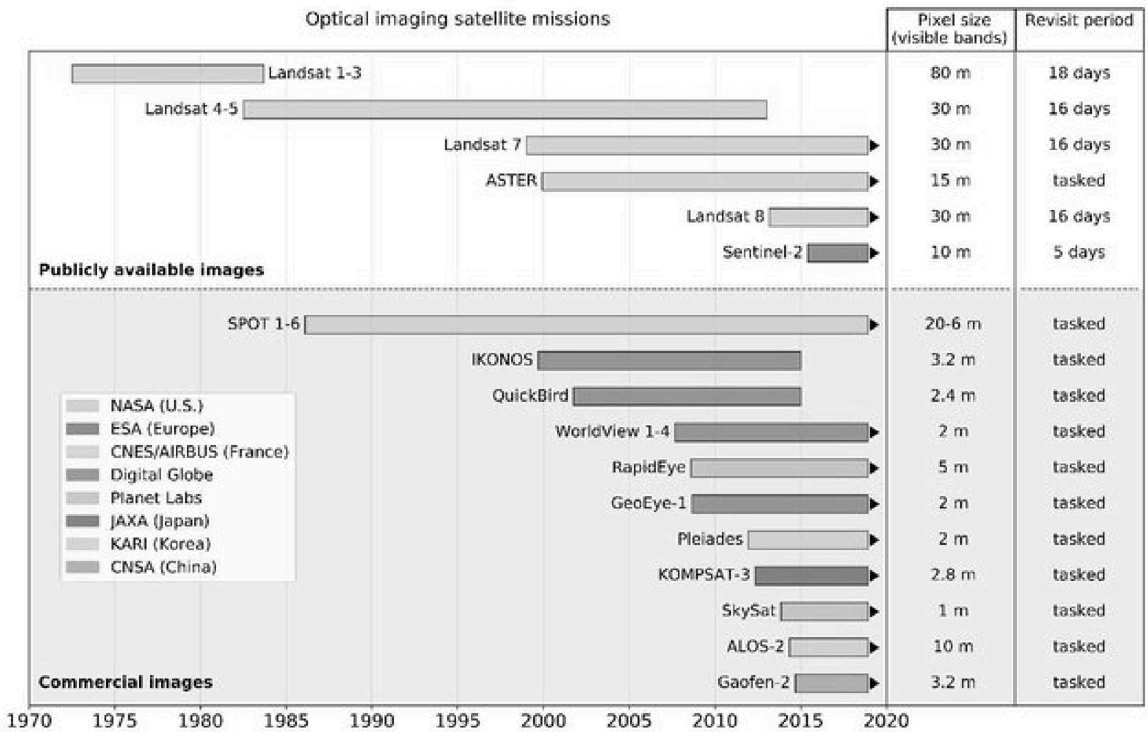


Figure 2.1.1-2 : Years of operation, spatial resolution, and revisit period of optical satellite missions. The term 'tasked' refers to the fact that the satellite may return to the same place on Earth if it is requested by the satellite operators or the users. This means, the revisit is not guaranteed. Source: Vos et al. (2019)

2.1.2. SAR

Synthetic Aperture Radar (SAR) sensors are active microwave imagers mostly operating in one single band. Their data is often referred to as the **amplitude**, and the **phase** of the signal which is proportional to the time taken for the signal to return to the satellite. The SAR signal is sensitive to the structure of the object on the ground. The signal measured by the SAR sensor is called **backscatter**. Man-made structures such as buildings or ships in the sea act as strong reflectors - returning more of the signal back to the satellite. In contrast, other surfaces such as calm water causes most of the signal to randomly scatter away - returning much less signal back to the satellite. Therefore, SAR is sensitive to the scattering mechanism of the object it interacts with. This property is enhanced by emitting and detecting the signal at different polarisations. For example, the development of agricultural crops ('growth stages') are tracked in this way and can help in prediction of yield. As crops grow, the dominant scattering mechanism may change so that vertically polarised signals may interact more with the vertical structures of the crops, such as stems and thus result in a higher signal return. In vegetated and rural areas, SAR backscatter is also highly dependent on the Vegetation Water Content (VWC), with higher backscatter returns for higher moisture content (**Figure 2.1.2-1**). To be noted, different wavelengths interact with different parts of the vegetation, with larger wavelengths, e.g. L-band, capturing the bottom part of the vegetation and potentially the soil level for low density forests, and smaller wavelengths, e.g. C-band, capturing the top of the canopy (**Figure 2.1.2-1**).

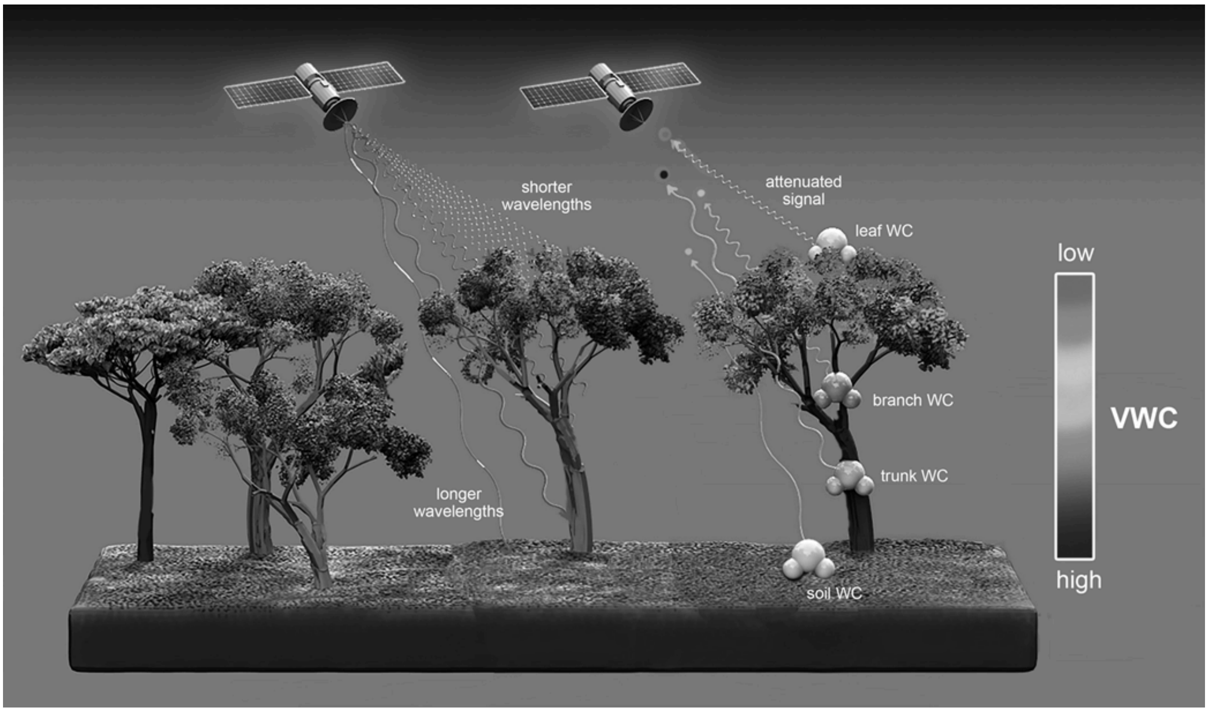


Figure 2.1.2-1: SAR signal interaction with vegetation. Transmitted signal is shown in red and the returned signal is shown in blue. The returned signal strongly depends on the vegetation water content, with higher backscatter for higher moisture. Source: Konings et al. (2021).

2.1.1.1. InSAR

The interferogram between two SAR images contains information on the phase difference between the acquisitions and is referred to as **InSAR** (SAR **interferometry**). Whilst SAR data refers to the raw satellite data, InSAR refers to the processing chains of techniques used to estimate ground deformations and/or topographical height using the phase difference detected in SAR acquisitions. In satellite InSAR, successive acquisitions in time are obtained by the same satellite or a constellation of satellites with similar instrumental and orbital characteristics scanning the area of interest. Several processing schemes are feasible and interferometry is based on the production of interferograms, involving the use of the phase difference between acquisitions (i.e. at different times) to estimate the movement of the ground surface and its elevation.

2.2. Core ideas in Deep Learning[4]

Machine Learning research is experiencing its biggest growth spurt in the history of the field. With groundbreaking ideas being published several times a year, how can one keep up with the field? The good news is that the useful set of foundational ideas is updated only every few years. Below, we describe a subset of those ideas at an intuitive level, and why they matter for EO.

2.2.1. Architectures

2.2.1.1. Convolutional Neural Networks (CNNs)

Convolution is the backbone of modern computer vision and remains central to AI4EO applications. CNNs rely on *location invariance*, the idea that features such as a building's footprint can be recognized regardless of where they appear in an image. This makes CNNs efficient: instead of relearning the same building features across multiple locations, the network generalizes them across the image.

Traditional CNNs operate on 2D images (X and Y), but the approach extends naturally to 3D datacubes. In EO, the extra dimension often represents *time*, enabling 3D CNNs to learn spatio-temporal patterns such as land cover change.

2.2.1.2. Recurrent Neural Networks (RNNs)

RNNs introduce a notion of *memory* by feeding outputs back into their own inputs. This allows them to capture temporal or sequential dependencies. An example is seasonal vegetation changes from EO time series. While powerful, RNNs are limited by their ability to retain information over very long sequences. Examples of recurrent neural network structures include LSTM (Long Short Term Memory) blocks or GRU (Gated Recurrent Unit)

[4] Content modified and adapted with permission from the Satellite Applications Catapult Whitepaper by Kalaitzis et al. (2022) : State of AI for Earth Observation.

blocks. Each of them have a temporal element which maintains some historic data and holds that forward to the next timestep, so that the previous values will impact the future outputs.

2.2.1.3. Attention and Transformers

Originally developed for natural language processing, Transformers (built on stacked attention layers) are increasingly used in vision tasks. Attention mechanisms dynamically learn *contextual relationships*: e.g., recognizing a road may require connecting distant pixels along a line, whereas recognizing crops may require local context. Unlike CNNs, Transformers can adaptively decide what to focus on. Early adoption in EO was slowed by computational costs. For example, in a 100 x 100 image, the model needs to deal with 10, 000 pixels which does not fit in GPU memory. So, more practical implementations had to be devised for images by limiting the attention span of each pixel to a certain radius.

2.2.2. Degrees of Supervision

Weakly-supervised learning — EO datasets rarely fits perfectly into the supervised learning paradigm. Expert annotations are expensive to produce. Weak supervision is effectively a compromise in the level of detail of the ground truths that allows for faster and cheaper annotation. For example, it is pointless to fully annotate and delineate the exact shape of water bodies in a river network for hundreds of kms, when a ML model requires only fragments of it to learn to segment rivers. Another example of weak-supervision is to train segmentation and object detection models with annotation at the image level but not at the pixel level.

Semi-supervised learning — It is common for EO datasets to be partially annotated. For example, many crop fields in a region might lack annotation, yet these regions contain temporal spectral signatures that obey the same physical laws. Crop fields with similar spectral signatures are likely to represent the same type of crop, regardless of annotation. The main idea of weak-supervision is that even a non-annotated spectral signature is a valuable feature that can guide the learning and prediction of the annotated ones.

Active learning — The problem of learning is not just about ‘what’ to learn, but also ‘when’ to learn it. In the typical supervised learning paradigm, an ML model is allowed to plough through thousands of labelled data points whose individual contribution to the overall learning can be dubious. This is obviously inefficient when time is of the essence. With Active Learning, the labelling process occurs with an ML model in the loop, that tells the human which datapoint to label next. This can speed up the learning process of a model by orders of magnitude.

Transfer learning — This type of learning makes sense when there exists a database of general-purpose models pretrained on very large datasets. These might perform well enough on average, but they might not necessarily fit the needs of an individual use-case. For example, an end-user might have a bespoke and probably expensive dataset that they cannot share beyond their local network (for legal reasons). In this case, instead of uploading and adding their data to a bigger corpus, they can download one such pre-trained model and fine-tune its parameters to their data.

Self-supervised learning — SSL is the most promising approach to unsupervised learning. To appreciate the simplicity of SSL, it helps to view it in the light of supervised learning. In Computer Vision all images share the same "DNA"—a conglomeration of oriented lines, curves, color gradients, and other low-level spatial configurations—all ubiquitous in what the human eye could reasonably perceive. With that in mind, SSL defines its own ML tasks on a use-case. We can easily do so by altering a dataset of images in a consistent manner while retaining the originals. Then we can train a ML model to 'repair' altered images to their original state and because we kept the originals we can do this with good-old supervised learning. Such tasks whose ground-truths are produced programmatically are known as *pretext tasks*, see **Table 2.2.2-1**.

Pretext task	Image degradation	Reconstruct from
Inpainting / infilling	remove center patch	rest of the image
Spectral interpolation	remove the RED band	other bands
Time extrapolation	remove final **revisit** from time-series	past revisits
Colour restoration	remove colour / convert to monochrome	monochrome image
Super-resolution	reduce spatial resolution	low-resolution image

Table 2.2.2-1: Real examples of pretext tasks in SSL. Each degradation implies a reconstruction task.

The running theme here is to guess the *missing* parts from the *observed* parts, and the best part is that they all depend on ground-truth whose generation is trivial to automate. The point of all this is that regardless of the pretext task, a similar set of low-level visual features will be learned (the hypothetical 'DNA'). This observation leads to the main hypothesis of self-supervision, written here as a question:

Since any given ground-truth might not be the exclusive enabler for the learning of low-level features, why allow the absence of expertly annotated ground-truths be the information bottleneck to learning?

SSL allows us to leverage as much unlabelled data as we can store, to learn ‘jack-of-all-trades’ features useful for common vision tasks, like classification. Then we can specialize (fine-tune) them in a supervised way through our limited ground-truths. Regardless, industry and science practitioners of SSL will be the first to agree on the importance of pretext task design. For example, in agriculture when it comes to classifying crops, we expect seasonality to be a key differentiator of temporal crop signatures[1]. Here, once again the real-world is reminding us that there is no replacement for creativity and subject-matter expertise, and that intuitions gained from ImageNet eventually do hit a wall.

Foundation Models — Foundation models are a more recent development within the field of machine learning. They leverage the benefits of self-supervised learning and of transfer learning. In these models, a large scale model is developed using some SSL task, such as a masked auto-encoder, using a massive quantity of data. Once these models are trained, to represent the SSL task, they are then modified and *transferred* to a different task, known as fine-tuning. This fine-tuning is the application of the pre-trained foundation model to a different downstream task, using principles of transfer learning. It has been shown that these foundation models learn the inherent structures within the data they are aiming to represent and can then be fine-tuned on new tasks with much less data that would be required to build a model from scratch, improving the performance on a weakly-supervised task.

The role of ground-truth in unsupervised learning — If there is one takeaway from the success stories of unsupervised learning, it is that an obsession with nailing the end-task alone misses the point of learning and can even hinder a model from reaching its full potential. On the other hand, regardless of the type of unsupervised learning being used, the importance of the availability of expertly annotated ground-truths cannot be overstated. Ultimately, a successful application of ML must be demonstrably predictive of the end-task. This means, ground-truth labels, whether acquired by manual annotation or from expensive bona-fide physics simulations, will always be in high demand. Even if they serve merely as a sanity check, or a unit-test.

3. Research trends in AI4EO

The rate of progress in AI4EO is primarily driven by advances in hardware and sensor design first, and then by ML software—research-grade code born out of academic papers that eventually makes it into production-grade **GIS** dev tools. The comoving **SOTA** in ML then translates into new model specifications per use-case. For example a new SOTA in semantic **segmentation** will be immediately translated into a solution for segmenting agricultural parcels. This publication pattern occurs enough times in a year to keep practitioners on their toes. The good news is that the useful set of foundational ideas is extended at least every few years. We covered those in section **4. Core ideas in Deep Learning**.

3.1. Venues of cross-disciplinary research

The following is a brief overview on top-tier academic conferences, for the readers who are interested in staying up to date with the SOTA in ML. Key journal publications include: JMLR[2], TPAMI [3], FTML[4], TMLR[5]. Key conferences include: NeurIPS [6], ICML, ICLR[7], CVPR[8], AAAI[9], AISTATS[10]. Aside from the main proceedings, each conference also hosts satellite academic workshop events catered to researchers working in specific basic and applied research domains. In the context of AI4EO, the following AI4EO workshops are staples in most annual iterations of the aforementioned conferences: EarthVision[11], AI4Earth[12], MLPS[13], CCAI[14]. Because of their interdisciplinary nature, some of these events are supported by IEEE technical committees which also host their own conferences, like IGARSS[15].

The development and publication of ideas in AI4EO follow a common trajectory:

1. A new SOTA is published at a conference, typically on a problem unrelated to EO.
2. EO practitioners discover the new ML paper and translate it to their problem.
3. Occasionally, the translation of the new paper will be successful and the EO researchers will publish their preliminary results in a EO workshop or symposium, such as AGU[16], EGU[17], LPS[18]. This is a good opportunity to receive early feedback from the EO research community.
4. Finally, the new ML application makes it into a EO or RS journal.

Note that at step 1 of this workflow the new ML methods are not benchmarked on EO datasets. This status quo is perpetuated by much of the ML community framing the advancement of the **SOTA** only with respect to traditional benchmarks for image classification, segmentation, object detection—like ImageNet [19], CIFAR[20], COCO [21]—while EO tasks are not yet featured in the standard regiment of benchmarks. However, an increasing number of larger and larger scale datasets are starting to pop up, like those of the SpaceNet competitions[22].

3.2. From sensing to applications

Table 3.2-1 provides a detailed breakdown of most of the work in AI4EO in various verticals. Here are the main takeaways:

- Most of the works in AI4EO investigate optical data since it is the most abundant.
- **CNN** architectures have recently become the most ubiquitous architecture as they allow for the discovery of shift-invariant patterns not only in space, but also in time (**3D-CNNs**). They are also easier to train than **RNNs**, hence the latter are starting to be used less frequently. Therefore, CNNs are recognised as a natural fit for segmentation and classification problems in EO.
- **SAR** data is becoming increasingly available, with many interesting use-cases emerging for InSAR.
- With a heterogeneous array of sensors, it is clear that learning to **fuse** instruments harmoniously is key to complementing the observation gaps in isolated instruments.
- The majority of use-cases in EO are framed as **segmentation** problems, to identify the spatial extent of an object, or regression / nowcasting / forecasting of continuous quantities, like crop yield.
- Scientific fields have all found uses of ML to embed data into physical models (data assimilation), or fine-tuning physical models through data (parameter retrieval), or forming digital-twins of large-scale phenomena for cheaper simulation and at finer resolutions (down-scaling, subgrid-parametrization).
- Agriculture is becoming the most frequent user of EO data (after intelligence / reconnaissance users), both in the environmental / sustainability front, like food-security, and commercially, for crop yield forecasting, monitoring, and asset management.
- Understanding the type of some surface on the Earth (LULC) is a problem that cuts across many disciplines, and ties naturally with **classification** and **segmentation** ML tasks and **architectures**.

proximity	sensor	method	task	application
orbital / satellite [23, 24] aerial [25,26,27, 28, 29, 30, 31] in-situ / ground data [32, 33, 34, 35]	optical [36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 27, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60] SAR [41, 25, 61, 48, 62, 63, 26, 34, 64, 65, 66, 67, 68, 69, 70, 71, 72, 60, 73, 74, 75] lidar [76, 41, 26, 77, 54, 78, 79, 80, 29, 30, 31, 81]	autoencoder [82, 83, 84, 85] attention / transformer [86, 68, 52, 81, 87] Bayesian / probabilistic [32, 33, 88] CNN / U-Net / ResNet [39, 76, 40, 42, 45, 62, 50, 89, 90, 65, 68, 52, 91, 77, 28, 92, 54, 59, 81] ensemble [33, 42] GAN [62, 93, 94, 95] boosting [48] regression [25, 96, 82, 43, 48, 62, 97, 98] MLP [99, 42, 100] random forest [61, 45, 48, 97] RNN [32, 61, 47, 88, 50, 66, 92, 60] SVM [61, 48, 62, 101]	anomaly detection [102, 85] change detection [41, 103, 62, 69, 71, 104, 105] classification [36, 40, 42, 82, 106, 103, 44, 45, 47, 27, 65, 52, 91, 77, 75] data assimilation [96, 82, 88, 107, 108] enhancement / infilling / image translation [103, 66, 109, 110, 57, 93, 94, 98, 95] object detection [39, 106, 103, 50, 101] registration / image matching [111, 112] regression / forecasting [99, 25, 82, 43, 48, 107, 49, 64, 100, 92, 113, 97, 35, 74] search / mining [36, 103, 114, 107, 108, 115, 87] segmentation [36, 37, 39, 76, 40, 42, 82, 44, 116, 50, 90, 117, 57, 60] sensor fusion [41, 42, 82, 103, 88, 26, 108, 52, 113, 80, 81, *118*] surrogate modelling [99, 96, 108, 35] transfer learning [82, 43, 50, 91] unsupervised learning [115, 53, 59]	agriculture [25, 42, 119, 120, 82, 43, 46, 63, 121, 100, 52, 113, 97, 29, 30] climate [99, 122, 88, 48, 63, 49, 53, 92] earth / geo science [99, 96, 82, 88, 63, 107, 123, 108, 31] energy [36, 33, 82, 74] environmental science [82, 61, 34] epidemiology [51] finance / insurance [58, 124] ship / aircraft awareness [39, 65, 73, 75] geology [86, 119, 63, 69, 71, 54, 56] hydrology / hydrography [32, 38, 82, 46, 64, 54] infrastructure / development [36, 37, 40, 49, 102, 69, 70] LULC / forestry [42, 82, 106, 103, 61, 47, 62, 27] livestock [125] maritime [45, 65, 55, 75]

Table 3.2-1: From sensing to application. A breakdown of work in AI4EO in terms of the type of sensor employed, modelling approach, prediction task, and application domain.

									model
task	attention / transformer	CNN	RNN	GAN	MLP	random forest	regression	SVM	Bayesian / probabilistic
change detection anomaly, LULC		[82, 62,85]					[62]	[62]	
classification building, damage, vehicle, hazard, scene, LULC, crop	[52, 81]	[40, 42, 82, 45, 62, 65, 52, 91, 77, 28]	[61, 47]		[42]	[61, 45]	[82]	[61]	
search / mining question answering, relational reasoning, image search	[87]								
Image translation inpainting, infilling, super-resolution, pansharpening, deblurring, denoising, synthetic generation	[68]	[68]	[66]	[93, 94, 95]			[98]		
fusion cross-calibration, harmonisation, optical + optical, optical + lidar, optical + SAR	[52, 81]	[42, 48, 52, 77, 54, 81, 118,]	[32, 88]		[42]				[32]
object detection / counting Infrastructure, vehicle, cattle		[50, 89]	[50]					[101]	
registration / image matching video stabilisation, 3D reconstruction, orthorectification		[111, 112]					[111, 112]		
regression / forecasting water volume, precipitation, temperature, velocimetry, utilisation, biomass, moisture, wind power			[32, 82]		[99, 100]	[48, 97]	[25, 43, 48, 82]	[48, 97]	[32, 33]
segmentation cloud / shadow, vegetation, building, oil slick, LULC, water, rock, road, crop	[86	[39, 76, 40, 42, 82, 50, 89, 90, 54	[50, 60]		[42]		[82]		
transfer learning self-supervised, semi-supervised, zero/few-shot learning, domain adaptation		[91, 59	[50]						

Table 3.2-2: Tasks and models. Selected works in AI4EO grouped by task and modelling approach.

3.3. The future of AI4EO research

The following is a curated but not comprehensive list of promising research directions, aimed at prospective researchers about to enter the field of AI4EO.

Uncertainty — Quantifying uncertainty in computer vision applications can be largely divided into regression settings such as depth regression, and classification settings such as semantic segmentation. Deep learning methods cannot however represent uncertainty in an interpretable manner. Vanilla deep learning models do not allow for uncertainty representation in regression settings for example, and deep learning classification models often output softmax probability vectors, but their predictive uncertainty can be miss-calibrated when the related features are rare. For both settings, uncertainty can be better calibrated with Bayesian deep learning approaches, which offer a systematic and principled framework for modelling uncertainty [126].

AI explainability — During the last decade ML has proven to be extremely successful in a variety of different problems [119], yet it is often used as a black box that does not provide us with any insight besides the final outcome [96]. Given that, the EO community has been reluctant to abandon traditional approaches and adopt ML in all those critical areas that require transparency and trust, such as the Earth sciences. In order to overcome these limitations, recently there has been a great interest in developing methods for explainable AI (**xAI**) [127]. The main goal of this research direction is to increase the understanding of ML models without sacrificing their remarkable predictive power. To this end, several post-hoc model-agnostic explanation methods, that enrich DL and shed some light on how decisions are taken, have been developed [128].

3.3.1. Quality of data products

On the quality of data products derived from ML models, it is fair to revisit conventional approaches of measuring correctness in supervised settings; to question our confidence in a product's closeness-to-reality. Often, the latter is compromised by a generative model's lack of attention to detail, or excessive creativity:

- **Uncertainty maps** [129] — a type of saliency map to visualise what the model does not know. Uncertainty maps should be a standard component of the metadata accompanying a synthetic product, like those produced by fusion and **image-translation** models, like **super-resolution**. Disclosing the margins or errors in the data values would provide transparency and increase the trust by users of analysis-ready products. An exemplary map is displayed in Figure 12.

- **Perceptual metrics** [130, 131] have been traditionally applied on the image-translated products, like in **super-resolution** and **pansharpening**. Alternative approaches may consider saliency, which is deeply rooted on the broad concepts of information and uncertainty. While saliency criteria can be also founded on solid perceptual criteria, a purely statistical approach allows to scrutinise not only the output product but the inner layers in neural networks.

- **Distortions and hallucinations** that result from image translation tasks should be evaluated at the model level, either by looking at the internal latent feature representations, studying the effect of convolutional filters, how and when they activate under different stimuli [132].

- **Losses for image-to-image translation tasks** — Existing work in image tasks uses predominantly pixel-based (MSE, MAE, SSIM), kernel-based (KSSIM), perceptual (learned filter-based comparison), adversarial (discriminator + generator minimax game). Research opportunity: losses that operate in Fourier and wavelet domains.

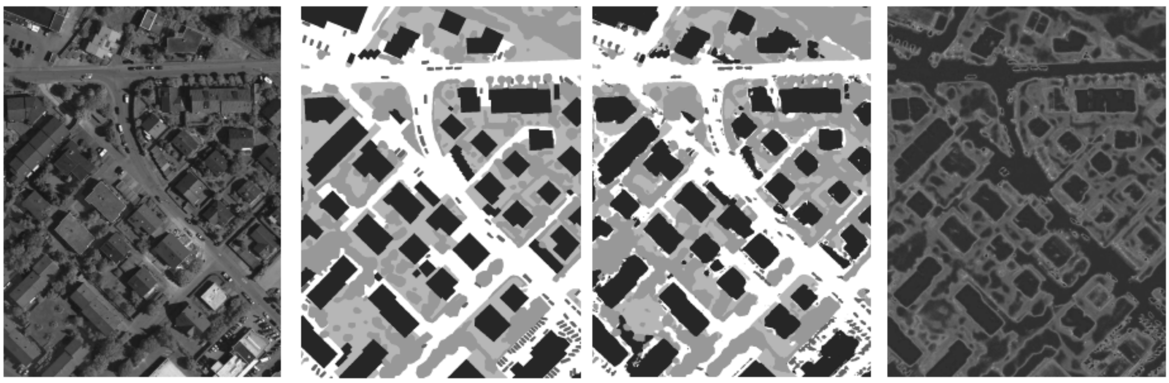


Figure 3.3.1-1: An example of uncertainty map for a CNN-based land cover classification task. From left to right: aerial optical image, its ground truth, the CNN-predicted land cover classes and the uncertainty map. The uncertainties of the predictions are highest at the edges of classes (lighter colour) and lowest at the core of each class type. Source: [133].

3.3.2. Harmonisation

In section **7.2. Data for AI/ML data interoperability** we discussed the main challenges of ML-based harmonisation. Recent advances in Deep Learning architectures imply further room for progress:

- **Attention over time** — Current attention-based architectures attend only on pixels or patches, like the visual Transformer with multiple self-attention heads at the level of tiled patches [134]. There is an opportunity to design an attention over time, for datacubes that involve time-series of satellite revisits.

- **Generative-based harmonisation** — Opportunity to use generative models, like Conditional GANs, to realistically generate missing modalities [95] or to infill missing data, for example due to cloud coverage.

- **Spatial co-registration of products** — End-to-end spatial co-registration during sensor fusion. Satellite inclinations are naturally modelled by projective / homography transformations [135].

- **Spectral registration of optical products** — As of yet, the spectral bands of a pixel are not treated as a longitudinal data series, by which each band is represented by both its reflectance value and its wavelength interval. Instead, only the reflectance value is used, as in most cases all of the training data come from the same sensor, so there is no need to keep track of the exact wavelength intervals of each band. The need for a longitudinal spectral analysis arises in cross-instrumental studies (e.g. sensor-to-sensor mapping, sensor fusion). One way to achieve this could be through "band-positional" encodings that capture correlations of partially overlapping bands between different instruments. The idea is inspired by the (spatial) positional encodings used in the visual Transformer.

3.3.3. AI safety

"Technology is an amplifier of human intent" [136]. The point of this quote is not that technology is inherently neutral; it is not because tech cannot exist in isolation from civilization. Therefore, one would be amiss to think that AI will 'do no evil' [5]. Bias is a key

[5] Artificial intelligence is creating a new colonial world order | MIT Technology Review

ingredient of our ability to learn, therefore AI systems too are inherently biassed. These vulnerabilities can be exploited to concentrate power, or to fool and attack AI-based infrastructure systems.

- **Robustness to adversarial inputs** — Our increasing reliance on EO data will eventually necessitate their safeguarding from malicious signals on the ground. This type of interference is a real concern for situational awareness applications involving InSAR [137].

- **Privacy and ethics** — Indigenous tribes in the Amazon rainforest; villages in rural parts of Darfur, Western Sudan; migrants fleeing violence —are all examples of vulnerable populations that can be compromised en masse through the wrong use of a data API. This problem is actually best addressed not by AI, but with the instilling of ethical practices in school and university curricula. That being said, AI can in fact help, through the systematic collection evidence for acts against humanity [6]. But it can also help to deliberately obfuscate the sensitive information of such communities, like geolocation data and visual indicators of activity in rural regions.

- **Onboard-ML** can also play a role here, through the development of lightweight ML models that can be installed directly on the hardware of satellites, and help with the prefiltering of sensitive data, prior to transmitting them to the Earth [138].

[6] Using AI to scale up human rights research: a case study on Darfur – Citizen Evidence Lab

3.4. MLOps Life cycle and tasks

3.4.1. Background for MLOps life cycle

Machine Learning Operations (MLOps) refers to the idea of best practice managing and operating machine learning systems in production.

Originally, DevOps unified software development and operations through continuous integration and delivery (CI/CD), enabling teams to deploy software faster with fewer errors.

However AI/ML applications are inherently more complex than traditional software. While most traditional software is composed primarily of code, AI/ML systems consist of code + data + trained models. In addition, they require well-defined workflows and pipelines for data processing, model training, evaluation and deployment. **MLOps** has emerged to bridge these gaps, adapting DevOps principles to the unique challenges of AI/ML, and ensuring that machine learning solutions are scalable, reliable, and sustainable in real-world operations.[139, 140, 141, 142]

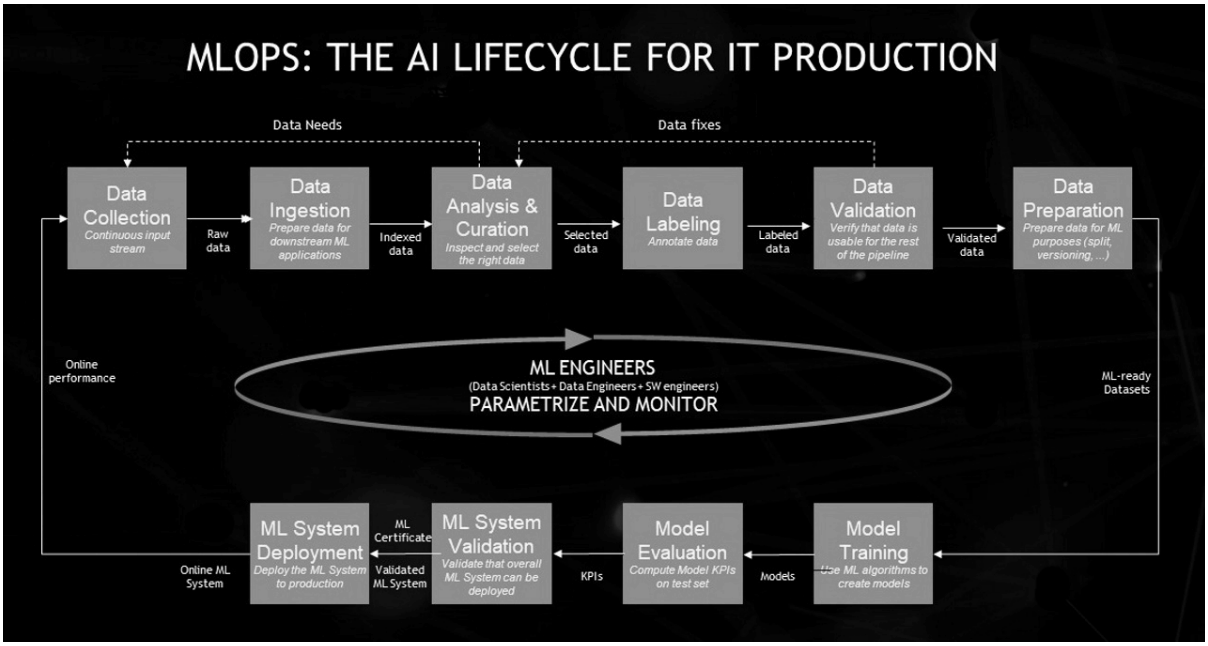


Figure-3.4.2-1 MLOps lifecycle example source: NVIDIA[140]

MLOps is a concept as a workflow, and there is no common standardized definition.
Key Points and relevant remote sensing tasks are shown in Table 3.4.2-1.

Table 3.4.2-1 MLOps stages and tasks

MLOps Stage	Description	Relevant Remote Sensing Tasks
1. Data Collection & Ingestion	Collecting raw data from satellites, aerial sensors, ground truth, etc.	- Data Fusion (multi-sensor)- Time Series Acquisition- Spatial-Temporal Data Gathering
2. Data Processing & Labeling	Preprocessing such as denoising, normalization, labeling, and annotation	- Cloud Masking / Atmospheric Correction- Image Registration- Labeling for Classification, Segmentation, Detection
3. Model Development & Training	Selecting models, training algorithms, tuning hyperparameters	- Land Use Classification- Semantic Segmentation (e.g., flood or crop areas)- Object Detection (e.g., buildings, vehicles)- Change Detection- Anomaly Detection
4. Model Validation & Evaluation	Evaluating model performance and generalizability	- Performance Metrics: Accuracy, F1-score, IoU- Validation using labeled satellite or ground truth data
5. Model Deployment	Integrating trained models into production systems like dashboards, APIs, GIS tools	- Real-time detection for disaster response- Production segmentation pipelines
6. Monitoring & Feedback	Monitoring drift, model performance degradation, triggering retraining	- Distribution/Drift Monitoring- Error analysis (e.g., confusion maps)- Feedback from new imagery or user corrections
7. Continuous Training / CI-CD	Automating retraining, model versioning, and deployment pipelines	- Continuous integration of updated time series- Online learning for dynamic environmental monitoring

3.5. AI/ML Tasks and use cases

The table introduces common AI/ML tasks and the representative models used for them.

Table 3.5-1 AI/ML tasks and use cases

Task	Abstract	Use case	Methods, models
Classification	Assigns each pixel or object to a specific class (e.g., forest, water, urban)	Land use/land cover classification (LULC), crop type mapping	Random Forest, SVM, CNN, ResNet, Transformer
Segmentation	Pixel-level labeling to divide an image into semantic regions	Building extraction, road mapping, flood extent detection	U-Net, DeepLab, SegNet, Mask R-CNN
Object Detection	Identifies specific objects (e.g., buildings, vehicles) using bounding boxes	Urban monitoring, infrastructure analysis, disaster damage mapping	YOLO, Faster R-CNN, RetinaNet
Change Detection	Detects changes between images taken at different times	Deforestation monitoring, urban growth, disaster impact assessment	Siamese Network, FC-EF, CVAE, STANet
Anormaly Detection	Identifies unusual or unexpected patterns in imagery	Early warning of wildfires, oil spills, glacier melting	AutoEncoder, Isolation Forest, GAN
Super-resolution	Enhances low-resolution images to higher resolution	Precision monitoring, SAR image enhancement	SRGAN, ESRGAN, SwinIR
Time Series Analysis	Analyzes temporal patterns of a location over time	Crop monitoring, drought detection, surface temperature trends	LSTM, TCN, Tfansformer, EarthNet
Spatial Modeling	Predicts or interpolates spatial distributions	Soil moisture, PM2.5 estimation, rainfall mapping	Kriging+ML, GCN, GeoAI
Data Fusion	Integrates data from different sensors or	Multi-sensor analysis (e.g.,	CNN+LSTM, Transformer Fusion,

	resolutions	optical + SAR)	DANN

4. Programs and Initiatives

The global space agencies that make up CEOS have launched several AI initiatives and programs. This section provides an overview of those efforts.

4.1. CEOS SEO

Overview

The CEOS Systems Engineering Office provide leadership and support to CEOS through management and technical services, as well as by developing tools and methods that deliver societal benefit. The SEO also drives innovation and thought leadership in the area of AI/ML applied to the use of Earth Observation (EO) data.

AI4EO Examples

The CEOS Systems Engineering Office is pursuing two early-stage research projects which serve as frameworks for experimenting with modern Large Language Model (LLM/AI) research and tooling: EO-GPT and CEOS-GPT.

1. EO-GPT is a Natural language processing (NLP) interface for processing EO data and answering Earth Observation questions. EO-GPT provides a chat interface for the Earth sciences and remote sensing applications domain. It is an LLM augmented interactive analysis framework. Earth observation analysis is modular by nature. The goal of EOGPT is to create a framework that orchestrates custom analysis flexibly using large language models as the orchestration mechanism. EO-GPT features:
    - A module-based system whereby earth-observation algorithms run as microservices. Modules have natural language outputs (to aid in live execution/parameterization).
    - A large language model orchestrates the execution of these modules.
    - An LLM parameterizes the use of modules based on initial conditions/queries, but also utilizes information given from modules for live parameterization of processing steps.
    - Offers a chat visualization of geospatial assets and content.
2. CEOS-GPT is an interface to all the information available on the CEOS website (http://www.ceos.org/). CEOS GPT provides a question and answering chatbot that operates on the large volume of CEOS data, with the vision of addressing a wide

range of topics including training and meeting information, organizational questions, policy questions, and data availability. CEOS-GPT features:

- CEOS website and private documents are indexed in a retrieval augmented generative (RAG) system.
- Mixture of agents architecture with each agent responsible for retrieving some type of information from an index.
- Private models exist for generating document embeddings and a GPT system exists for synthesizing text.
- Can ask questions about CEOS through an interactive chat-interface.
- Improvements are regularly benchmarked and evaluated. Improvements are either heuristic improvements to RAG, or improvements of the core large language models (i.e., fine-tuning embedders or the GPT language model).

The following two approaches are explored for constructing generative systems: (a) AI heuristic-driven, and (b) machine learning-driven. Both approaches improve the quality of the generative system and take a substantial amount of research and experimentation. In the heuristic-driven approach, LLMs are treated as abstracted black boxes. Heuristic structures index and organize the data leveraging the LLMs as tools to aid in search index building, information retrieval and response synthesis. Systems that utilize heuristics would use algorithmic structures built on a large language model. These systems do not aim to modify or optimize an underlying machine learning model, they just utilize them as building blocks for a larger system. The machine learning approach on the other hand, focuses on innovations in the underlying architectures of the models themselves rather than the generative system that's built on them. The machine learning approach would also encompass setting up the feedback mechanism whereby a model can be fine-tuned to user queries.

The CEOS SEO plans to further develop these early-stage research applications and ultimately release them as tools for the CEOS community.

4.2. GEO

Overview

The Group on Earth Observations (GEO) is an intergovernmental partnership that connects governments, academia, organizations, civil society, and the private sector to tackle global challenges through innovative solutions that harness the power of Earth Intelligence. Among its founding Participating Organizations is CEOS, whose member space agencies provide critical EO satellite data that drive GEO’s activities worldwide.

One of the five goals of the GEO Post-2025 Strategy is to integrate EO, models, and innovative new technologies, including artificial intelligence and machine learning, into the design of services that provide Earth intelligence. In line with this goal, GEO is advancing the use of AI and ML across its Work Programme to address complex global challenges. Many of these activities demonstrate how combining AI/ML techniques with EO data from CEOS agencies can deliver practical, high-impact solutions.

AI4EO Examples

To accelerate these developments, GEO Work Programme includes a dedicated Enabling Mechanism—AI for Earth Observations (AI4EO). This builds a network of AI experts across the GEO community, with scope that includes: advancing AI applications within the GEO Work Programme, fostering cross-disciplinary collaboration and addressing ethical considerations associated with AI in EO.

The following examples illustrate GEO Work Programme activities that apply AI/ML in combination with EO satellite data provided by CEOS agencies.

1. GEO Global Agricultural Monitoring (GEOGLAM) Flagship:
GEOGLAM applies AI based methods to integrate EO with in-situ data for near-real-time monitoring of global croplands. Its consensus-based Crop Monitors combine optical and radar time series with ground observations to assess crop condition and drought stress, and to forecast yields. These approaches are implemented both at global and national scales. Examples include the cases in the least developing countries, such as Togo, Uganda and Tanzania as highlighted in boxes J (p.32), H (p. 28) and D (p.22) in GEO Supplement to the UNFCCC NAP Technical Guidelines. GEOGLAM activities are supported by major space agencies, including NASA, JAXA, ESA and the European Commission, which contribute to the development of AI based crop classification, yield modelling, and EO-based agricultural indicators.

2. GEO Global Water Sustainability (GEOGLOWS) Flagship:
GEOGLOWS offers a worldwide open-sourced web-based tool that provides daily 15-day forecasts and an 85-year historical simulation for every river of the world. The GEOGLOWS v2 river “hydrofabric” is based on the 12-m TanDEM-X DEM from the German Aerospace Center (DLR), used by the U.S. NGA to create TDX-Hydro, a global streams and catchments dataset delineated with TauDEM and refined through conditioning. From this, GEOGLOWS derived a network of about 7 million river segments across 125 watershed clusters. Since the quality and availability of in-situ data are not the same across the globe, GEOGLOWS uses AI/ML to capture similarities in hydrological behaviors in different regions around the world to develop bias correction for global forecasts. Methodologies for bias correction of discharge developed with in-situ data are being investigated to extend to satellite altimetry (water elevation) data. A complete list of publications on GEOGLOWS methodologies, including the bias correction efforts, can be found at the GEOGLOWS training and information site. GEOGLOWS work using AI/ML for developing countries such as Malawi has been presented at major conferences, including COP27 and 28 and the AI for Good Global Summit.

3. Data Integration and Analysis System (DIAS) Enabling Mechanism:
DIAS is a data platform which integrates a variety of different data such as satellite and in-situ observations and models, to be analyzed for different application purposes such as forecasting/early warning, real-time monitoring and hindcast for health, biodiversity, flood and drought. In particular, EO satellite observation data includes JAXA's GSMaP. On the DIAS platform, AI/ML/Deep learning has been used to execute models. For example, applying climate prediction data, DIAS uses deep learning for malaria infection prediction and early warning in the Limpopo province in South Africa. AI/ML-based Malaria Transmission Prediction model integrates the climate forecast data with the weather forecast data and malaria patient count data from local municipalities and medical institutions. It enables the local health authority to predict malaria transmission for 3-4 months ahead. The resulting information has been distributed to the medical institutions and the public via a Malaria Forecast App for early warning since 2016. Separately, DIAS implemented a UNESCO project called WADiRe-Africa on flood early warning in 11 West African countries: Benin, Burkina Faso, Cameroon, Chad, Côte d'Ivoire, Ghana, Guinea, Mali, Niger, Nigeria and Togo. This was listed by UNESCO as its example on the use of AI for DRR in Africa and was presented at ITU&WMO/UNEP workshop on AI for Natural Disaster Management (see p.11). DIAS integrates data that are available, including those provided by CEOS agencies.

4. GEO Human Planet Initiative (HPI) :
GEO Work Programme activity, HPI, generates global data on populations (growth) and settlements (including urban extent, critical infrastructure) to assess human exposure (people and infrastructure in hazard-prone areas) to the disasters but also increasingly vulnerability (economic values/relative deprivation). AI is used to extract info on built environment from satellite imagery. More specifically, multi-decadal satellite archived imagery collections are processed by algorithms using the latest AI techniques, making sure that the results are consistent across time and space globally. As a second step, multiple data sources are combined together using AI/ML methods to estimate population characteristics across time and space. Examples of such products are the Global Human Settlement Layer (GHSL) (with relevant papers such as this) and the High Resolution Settlement Layer (HRSL) (in collaboration with facebook/Meta and its Data for Good). HPI provides these global products, which can be downscaled for national/local use.

5. Euro GEO (Regional GEO acitivity):
Euro GEO's Group for Health, coordinated by BEYOND Centre of Earth Observation Research & Satellite Remote Sensing NOA is harnessing AI technology to prevent vector borne disease in Europe. The success story of system EYWA (Early Warning for Epidemics) (1st HE EIC prize on Epidemics) uses EO data to generate analysis-ready products and indicators that inform the dynamic environmental, ecosystem, meteorological, climatological, and geomorphological conditions at the time and place mosquito collections and human cases of Mosquito-Borne Diseases (MBDs) have been recorded over the years. The

computer representations of the Earth are used as input to AI and mathematical models that associate climate and environmental data with the corresponding MBDs cases. The models perform continuous operational predictions for generating entomological and epidemiological risks, which are then used to guide vector control actions, such as larviciding/adulticiding and trap placement, as well as door-to-door awareness raising campaigns deployed by the relevant health authorities. Starting in 2020, the EYWA system provided the first operational predictions in four regions in Greece and one region in Italy. In 2021 the system expanded to include 11 regions in five countries (France, Germany, Greece, Italy, and Serbia), addressing the West Nile Virus and other Mosquito Diseases infection in humans and three genera of mosquitoes, supporting a total of 10,909 municipalities and over 34 million residents. With the support of the e-shape. EuroGEO action and third party Institutions as Bill and Melinda Gates Foundation, and Pharmaceutical Industry – TAKEDA, the EYWA system has expanded its operations in Sub-Sahara countries including Cote d' Ivoire and Cameroun, as well as in Americas (Argentina). This story is included in the WMO 2023 State of Climate Services Report Health.

6. Global Heat Resilience Service (GHRS) :
The Global Heat Resilience Service (GHRS) is a collaborative initiative led by the GEO and C40 Cities, with support from the World Meteorological Organization and other partners, that responds to the UN's call for action on extreme heat by providing city leaders with neighborhood-level heat risk insights through high-resolution heat maps and climate projections for 2030 and 2050. A decision-support tool is currently being developed by IBM-C40 with support from GEO and the Gobal Covernant of Mayors and tested in cities including São Paulo, Rio de Janeiro, Salvador, Belo Horizonte, Caceres, Coxim in Brazil, Bangalore, and Freetown, the digital decision-support tool leverages AI in three key ways:
The tool will leverage AI in three ways:

1. **downscaling** global climate data to neighborhood level using foundation models to produce 100-meter resolution heat maps.
2. **data integration** from satellites, censuses, building specs, and socioeconomic indicators to update vulnerability hotspots.
3. with **scenario planning** to model different intervention strategies - identifying the most effective combinations of policy, physical and nature-based solutions to address heat risks city-wide.

The testing phase utilizes Harmonized Landsat and Sentinel-2 satellite data, with AI models performing the downscaling and temporal interpolation necessary to generate long-term time series of high-resolution land surface temperature data.

7. Digital Earth Pacific:
Digital Earth Pacific (DE Pacific) is a collaborative programme of the Pacific Community (SPC) and Pacific Island countries and territories focused on ensuring accessible use of Earth observations in the Pacific region by leveraging Analysis Ready Data (ARD) and datacube plus over 30 years of open satellite data (Landsat, Sentinel). DE Pacific supports

climate resilience, food security, ecosystems monitoring, disaster risk reduction (DRR) and early warning activities through its products, i.e. coastline change, mangrove, inland wetness, satellite derived bathymetry. Many of DE Pacific's products are built using AI/ML including for cloud masking in coastline change, near shore satellite derived bathymetry, vegetation height and canopy and land cover land use change products. The programme is now investigating the use of foundational models.

8. Digital Earth Africa

Digital Earth Africa (DE Africa) is an African program that provides access to and capacity development in EO technology for the African continent, with the aim of enhancing the application and uptake of EO in African countries. DE Africa supports climate action in particular through data and analytics addressing food and water security, nature based solutions, ecosystem management, land degradation and coastline change. ARD, such as annual surface reflectance geomedian images derived from Landsat and Sentinel missions, are provided to users alongside examples and guidance on how to incorporate them into ML workflows, such as land use classification, while a selection of DE Africa's Continental Services (continental scale thematic products) are derived from ML applied to ARD. For example, the DE Africa Cropland Extent map was produced with ML applied to Sentinel-2 GeoMADs as input data. In this way, ARD provided by DE Africa can also be considered as ML-ready. Digital Earth Africa therefore produces and supports user creation of end-to-end ML workflows based on satellite-derived EO data.

4.3. NASA

Overview

National Aeronautics and Space Administration's Earth Science Division has multiple organisations advancing AI/ML, each contributing to five overarching goals described in Figure 4.3-1. Division-level strategies guide investments to maximise impact and avoid duplication of effort.

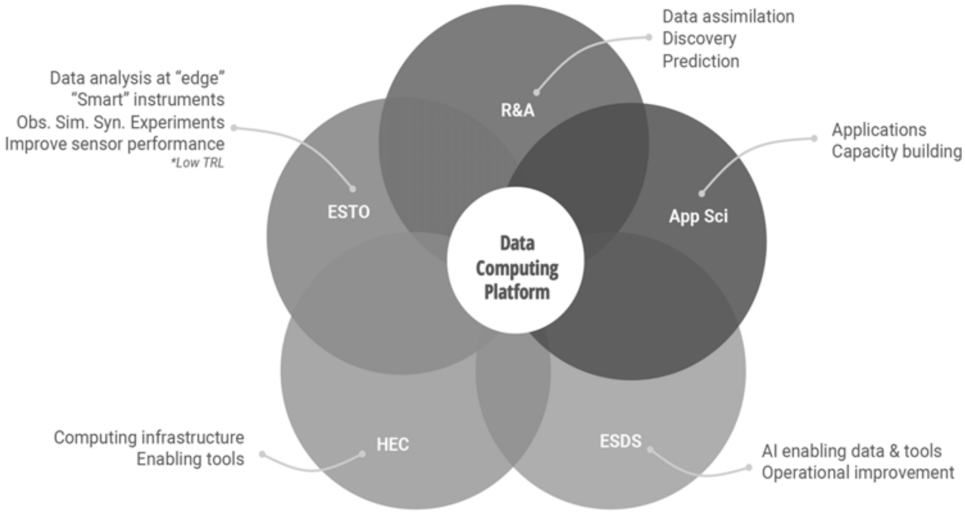


Figure 4.3-1. NASA Earth Science Division AI focus areas

NASA's High-End Computing (HEC) program has made investments in AI-specific platforms. These platforms include HPC and cloud assets with the latest hardware accelerators and AI specific processors and libraries. The Research & Analysis program supports targeted AI activities, some of which have been realized through competitive solicitations. Currently, most of their focus has been around modeling and assimilation.

EOSDIS houses over 100 Petabytes of earth science data in the cloud and is working on ways to make that data easily available to ML practitioners in an Analysis-Ready, Cloud-optimized (ARCO) manner. Improving cloud-based earth science data's interoperability with ML managed services from major cloud providers is also a high priority for EOSDIS.

These goals address the entire data lifecycle process, including collaborations and building AI capacity and expertise within the program. The data systems program has a number of activities related to AI aligning with NASA's strategic goals – that includes;

- competitive program and partnership activities
- augmenting data stewardship tasks such as search and discovery
- maximizing the use of data.

ESDS also fosters AI/ML research through NASA's Advancing Collaborative Connections for Earth System Science (ACCESS) program. This competitive program develops and implements technologies to effectively manage, discover, and utilize NASA's archive of Earth observations for scientific research and applications in support of NASA Earth science research goals. The following are the most recent ACCESS projects utilizing AI:

4.3.1. Advancing an Open-Access Repository for Earth Observation Training Data and Machine Learning Models

Name	Landcovernet
Problem Statement	• Provide a multi-mission global land cover training dataset • Develop an Open API for registering and retrieving ML models
Project Scope	Global spatial coverage Cloud-optimized Geotiff
Data Governance and Compliance	
Version Control	• https://mlhub.earth/data/ref_landcovernet_af_v1 • Current version 1.0
Input data provenance	• Sentinel-1 ground range distance (GRD) with radiometric calibration and orthorectification at 10m spatial resolution • Sentinel-2 surface reflectance product (L2A) at 10m spatial resolution • Landsat-8 surface reflectance product from Collection 2 Level-2
Required infrastructure	
Dependencies	
Key performance metrics	
Security and Privacy	
Documentation	https://mlhub.earth/docs

AI4EO Examples

Recent ACCESS projects highlight how NASA is applying AI/ML to Earth observation data systems:

- Developing Passive Satellite Cloud Remote Sensing Algorithms Using Collocated Observations, Numerical Simulation and Deep Learning
- GeoWeaver: Building An Open-Source Platform for Enabling Ad Hoc Management, Open Sharing, and Robust Reuse of NASA Earth Data-Driven Hybrid AI Workflows
- Machine Learning Datasets for the Earth's Natural Microwave Emission
- Machine Learning Planet High Resolution Training Data for Medium Resolution Land Cover and Disturbance Mapping
- Pangeo ML: Open Source Tools and Pipelines for Scalable Machine Learning Using NASA Earth Observation Data
- Spatio-Temporal Machine Learning and Cloud Computing for Predicting Dynamics of Global Vegetation Structure from Active Satellite Sensors
- Training Data for Streamflow Estimation

4.4. NOAA

Overview

National Oceanic and Atmospheric Administration has a long history using AI/ML to support its mission areas, such as deep-sea exploration, habitat characterization, fishery species assessments, environmental modeling, and interpretation of Earth observation data. In 2021, NOAA released its first AI Strategy with five goals:

1. Establish an efficient organizational structure and processes to advance AI across NOAA.
2. Advance AI research and innovation in support of NOAA's mission.
3. Accelerate the transition of AI research to applications.
4. Strengthen and expand AI partnerships.
5. Promote AI proficiency in the workforce.

To achieve these goals, NOAA created a five-year strategic plan with a more coordinated approach across NOAA to embrace AI in support of NOAA's mission areas through effectively developing the AI-ready data and tools for reliable and efficient processing, interpretation, and utilization of Earth observations.

AI4EO examples

Working with scientific fields and offices, NOAA has established the NOAA Center for Artificial Intelligence (NCAI) to support new and ongoing projects and to propel innovative uses of responsible AI technology to support environmental equity, knowledge, and study.

Since its inception, NCAI has been focused on developing a focal point for NOAA to facilitate the advancement of AI-ready data and workforce development. NCAI is leading the development of community-driven data standards for AI-ready open environmental data through the collaboration with Earth Science Information Partners. The collaboration produced the first AI-readiness checklist for open environmental data (https://github.com/esipfed/data-readiness) that are currently being used or plan to be used by NOAA, UK Met Office, World Data Systems, and other geoscience data repositories to conduct assessments of the readiness of environmental data including earth observations for AI development.

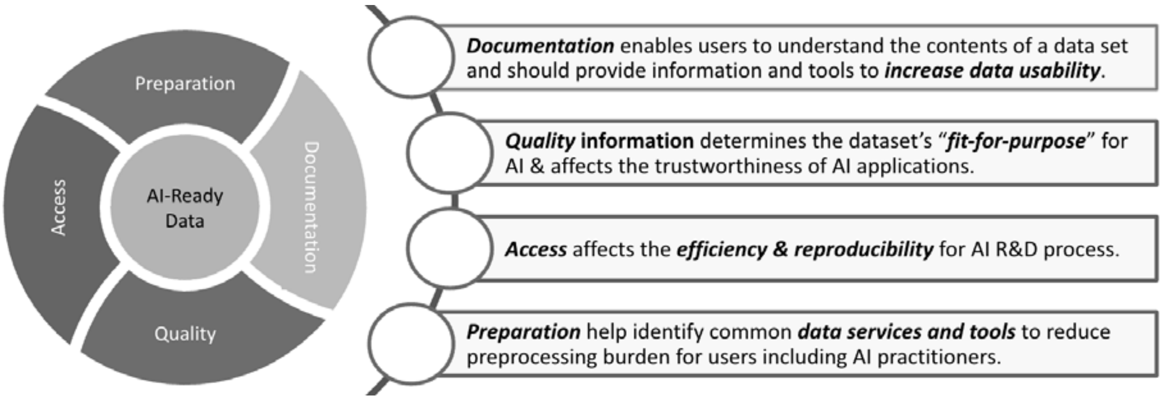


Figure 4.4-1. Four groups of characteristics of AI-ready data defined by the Earth Science Information Partners (https://github.com/esipfed/data-readiness).

At its current stage, the AI-readiness assessment requires data experts to go through the published checklist manually which is difficult to be scaled to more than 60 PBs of environmental datasets at NOAA. Thus, NOAA is investing in a prototype tool using a natural language processing method to automate the AI-readiness assessment process and recommend improvements to existing NOAA datasets for AI development.

NOAA has invested in the improvement of selected datasets for AI applications, such as, Tropical Cyclone PRecipitation, Infrared, Microwave, and Environmental Dataset (TC PRIMED), NOAA Climate Data Records, and water column sonar data.

Additionally, NOAA is actively seeking public-private partnership to enhance the usability of earth observation data for high-impact AI applications including AI for numerical weather prediction. One specific example is the collaboration between the NOAA Physical Sciences Laboratory and Brigntband to transform the archive of a diverse set of quality-controlled satellite observations to cloud-native data format to support data assimilation (https://techpartnerships.noaa.gov/tpo_partnership/making-observation-data-ai-ready/). The resulting dataset – NOAA-NASA Joint Archive AI-ready data (NNJA-AI) – is made publicly available via the NOAA Open Data Dissemination program on Google Cloud.

4.5. ISRO

Overview

The Indian Space Research Organisation (ISRO) has increasingly incorporated AI/ML in various facets of Earth observation data processing, marking a transformative shift in data processing technology. AI is playing a pivotal role in automating and enhancing the efficiency of data analysis, enabling ISRO to glean valuable insights from the vast amounts of information gathered by Earth observation satellites.

AI4EO Examples

ISRO's work in the field of AI can be categorized in three broad domains - data acquisition related processing, data processing/fusion/augmentation and information extraction. Some key representative tasks in each category, that are being addressed through the use of AI, are shown in Figure 4.5-1. Machine learning algorithms, particularly deep learning models, are being utilized to surpass the classical approaches in each of these domains to improve the overall impact of the Earth observation data collected and processed at ISRO.

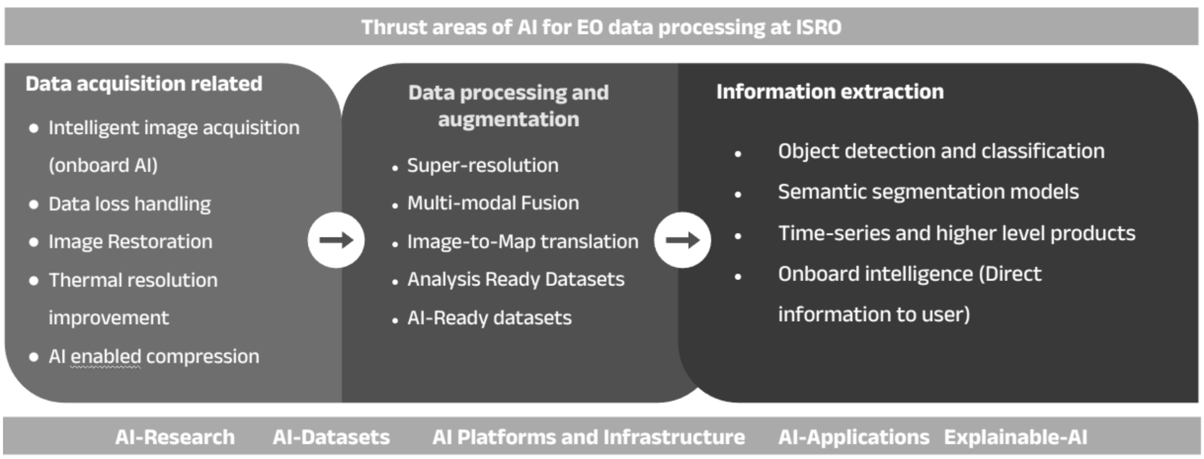


Figure 4.5-1. Broad categorisation of AI/ML related projects at ISRO.

In the data acquisition related AI processing, the emphasis is on improving the quality of the data which is obtained from various spaceborne/airborne sensors. Various models developed in this area include data reconstruction, image restoration, thermal resolution improvement as well as models related to compression/decompression of the high-resolution data.

The second category is for the data processing and augmentation research projects that are focusing on using data from multiple-sources (multimodal, multi-temporal or multi-sensor) to generate enhanced value products through the use of AI. This includes tasks such as spatial or spectral super-resolution, data fusion, image-to-image translation and generation of various types of AI-ready data for downstream tasks.

The final category of AI related tasks is the information extraction category. The primary objective here is to derive information such as resource maps, land-use land cover classification, specific object detection, content aware image search, as well as onboard intelligence applications. Some of the methods are targeting the time-series and change detection applications. Many models have been built in this category, e.g. cloud-detection, forest-fire detection, solar rooftop potential estimation, building footprint extraction, etc.

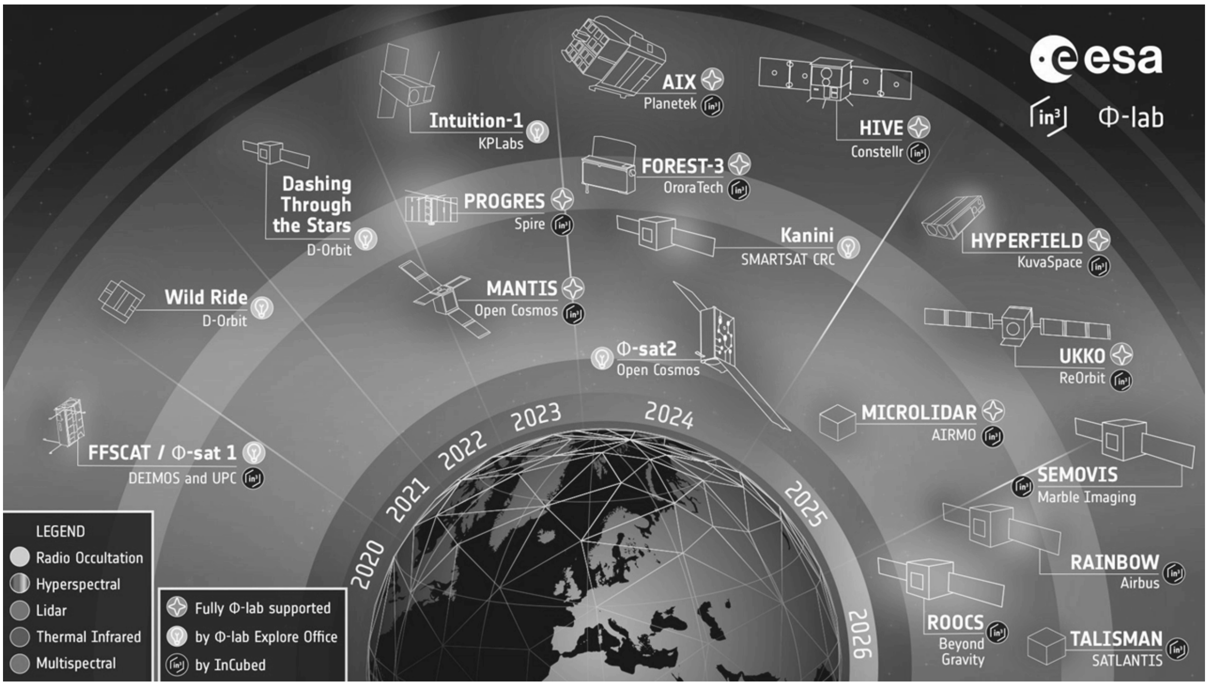
The work related to this aspect is integrated via research and development related to core topics in AI such as development of new models for specific applications, adaptation of cutting edge research for specific use cases, implementation of infrastructure for supporting development and deployment of AI applications, and core AI research such as explainable AI. Work is also being done to integrate and harness the potential of vast amounts of data available from ISRO's fleet of remote sensing sensors.

ISRO is also working towards a common framework, where the work related to AI that is taking place across different teams and projects can be synergized. In this direction, some standards have been studied and are planned to be implemented in near future. Some of these models are now being integrated into publicly available web-platforms.

4.6. European Space Agency φ-lab

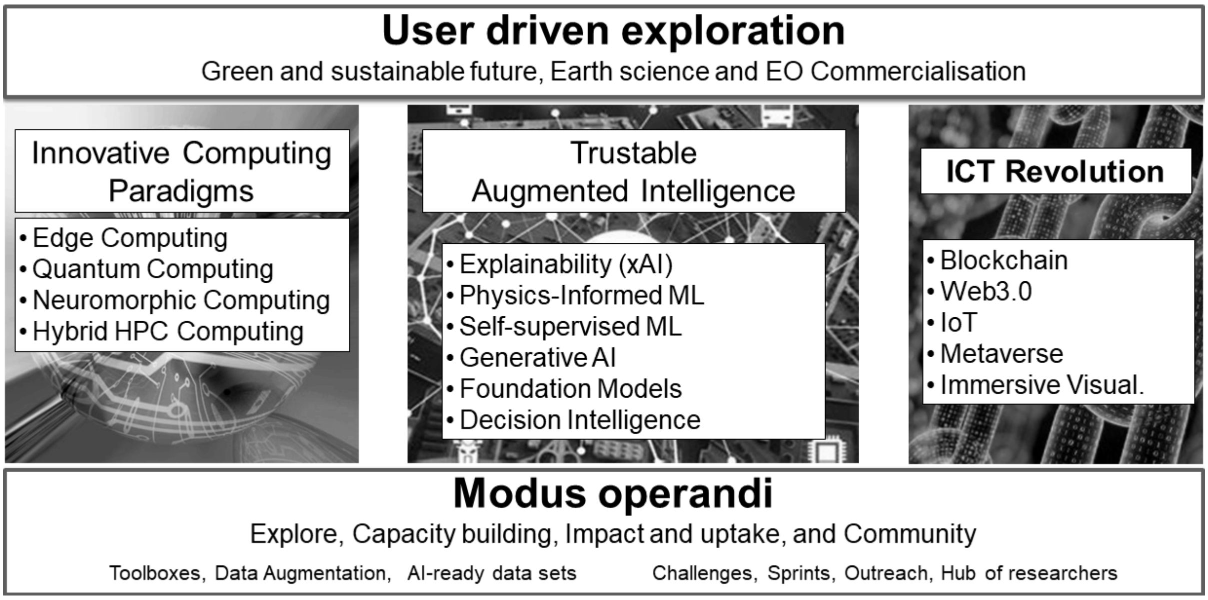
Overview

The ESA Φ-lab is the ESA Earth Observation innovation laboratory that aims to accelerate the future of Earth Observation (EO) via transformative innovation and commercialisation actions, thereby strengthening Europe's global competitiveness. Artificial Intelligence (AI) is a core focus areas for the ESA Φ-lab, as it offers unprecedented capabilities to extract actionable insights from vast amounts of EO data, enabling novel applications and business models. The ESA Φ-lab covers the whole spectrum of AI development, from ideation to generating tangible impacts in science, technology, or commercial field through its two offices: the **Explore Office** and the **Invest Office**. Additionally, the ESA Φ-lab also engages at different levels with the development of about 20 satellites, ranging from technology demonstrators to operational or commercial missions, the vast majority of which are AI-powered as shown in the image below.



The Explore Office conducts R&D activities on AI for EO by using a *user-driven* approach in exploring the technology from ideation to proof of concept. The office explore technologies and transformative ideas, prove their benefits, builds capacities from validated ideas and finally prepare the impact and uptake by end user. The office also spend a significant effort in growing a large community around Φ-lab. In doing this, the Explore Office mainly works on 3 technological pillars:

1. Innovative computing paradigms
2. Trustable Augmented Intelligence
3. ICT revolution



The Invest Office promotes commercial initiatives through the InCubed (Investing in Industrial Innovation) program. InCubed is a Public Private Partnership co-funding program run by the ESA Φ-lab Invest Office, focusing on developing innovative and commercially viable products and services that exploit the value of EO imagery and datasets. The program's broad scope supports everything from building satellites to developing new EO business models. Today, the majority of proposals for downstream activities are AI-related and focus on agriculture, forestry, emergency response, insurance, maritime, carbon monitoring, and asset management and identification. Instead, for upstream activities, it is trendy to bring AI-processing capabilities at-the-edge to address the data downlink bottleneck and reduce data latency for value maximisation. The InCubed programme size is about 225m€ and has 140 activities in the pipeline with about 10 satellite constellations under development.

AI4EO Examples

R&D activities conducted by the Φ-lab Explore focus on key AI-related technologies and explore their potential for various EO use cases. In particular, the main topics of interest involve:

- *Innovative computing paradigms:* the Φ-lab Explore Office combines AI-related research to the investigation of alternative computing paradigms that could further enhance benefits introduced by AI for specific use cases. Alternative computing paradigms involve:
    - **Edge Computing:** when moved on board EO satellites, AI could enable the detection of actionable information that could significantly reduce the latency for EO use cases having near-real-time requirements (e.g., civil security

applications, operational services for natural disasters management). In addition, it could enable novel acquisition systems. [143, 144]. Onboard AI is a central element in the scope of Φ-Sat-1, Φsat-2 missions, to which the Φ-lab Explore Office has provided a pivotal contribution.
    - **Neuromorphic computing:** neuromorphic computing is a brain-inspired asynchronous, event-based, and massively parallel computing paradigm. Among various neuromorphic computing techniques, spiking neural networks have attracted the interest of researchers for their potential energy efficiency, which makes it promising for onboard satellite implementations.
    - **Quantum Machine Learning:** when combined with quantum computing algorithms, ML could further enhance its capability to process intricate data structures and very large volumes of data. The Φ-lab Explore Office is investigating the potential of quantum and hybrid implementations of ML algorithms for EO use cases[145]
- *Trustable Augmented Intelligence:* this topic investigates numerous AI branches to augment the capabilities to extract actionable and trusthworthy insights from EO data and take informed decisions. The main AI branches under investigation include:
    - **Explainable AI:** the goal of explainable AI is to provide transparent and/or interpreatable models for various EO use cases.
    - **Physics-informed Machine Learning:** physics-informed ML incorporates physics principles into the training process with potential advantages in terms of data efficiency, computational intensity, and robustness to noisy data.
    - **Foundation models:** Given the scarcity of labeled EO data, foundation models—large-scale models trained on extensive datasets—have the potential to surpass specialized application models while requiring significantly fewer labeled examples. A key contribution from the Φ-lab Explore Office is the creation of the PhilEO Bench, a benchmark designed for rigourous evaluation of foundation models for EO applications. Research on foundation models is often coupled with the investigation of *self-supervised learning*, which aims to train Machine Learning (ML) models in an unsupervised manner.
    - **Generative AI:** generative AI has various applications in Earth Observation, including spatial resolution of EO data and automatic generation of synthetic images to augment datasets.
    - **Digital assistant for EO:** Large Language Models could be used to create an assistant to facilitate the processing and the interaction with EO data by using natural language[146].
- *User-driven* approach: plethora of R&D activities in AI for EO characterized by an application-centric methodology, which scrutinizes AI's potential for specific, socially impactful use cases, for example:
    -

- **AI for health:** by using ensemble of ML models to process satellite data, it is possible to predict dengue fever outbreaks.
- **AI for Earth Science:** AI is providing a significant contribution to numerous fields of Earth Science. The Φ-lab Explore Office has investigated the potential of AI for weather modelling, solar forecasting, and other related applications.
- **AI for Green and sustainable future:** in the face of escalating climate changes, the urgency for efficient forecasting and response systems for natural disasters has never been greater. AI can play a critical role in processing and fusing in-situ with satellite data for high spatial and temporal resolution forecasting of global storm surges.
- **AI for Destination Earth:** Destination Earth (DestinE) is a European Commission initiative to develop an ambitious AI-driven decision-support system based on a very high accurate digital model of the Earth. This system aims to monitor and simulate natural and human activity, along with developing and validating policy scenarios. ESA participates in the initiative by leading the overall effort in collaboration with EUMETSAT and ECMWF. ESA Member States have initiated a companion programme, the ESA Digital Twin Earth (DTE), to foster the exploitation of DestinE data for Earth observation and innovation. Φ-lab actively supports the activities of DestinE and ESA DTE to bring the demonstrated analysis and reasoning capabilities of AI technologies to the heart of the operations, along with stimulating further exploitation by various user communities. DestinE will use unprecedented observation and simulation products, powered by Europe's HPC computers and AI power, to push the limits of computing, forecasting, planning, and acting.

In pursuit of these goals, Φ-lab Explore Office extensively on activities aiming at community engagement, dissemination and partnership creation with academic and industrial partners, international organizations, and other ESA divisions. To foster research and use of AI for EO use cases, the Φ-lab Explore Office has contributed to the release of: numerous *datasets* (e.g., WorldStrat, Seeing Beyond the Visible, Major TOM, THRawS, VSD2Raw, and DENETHOR) and toolboxes (please consult ESA-PhiLab GitHub).

4.7. UKSA Initiative in AI and ML for Earth Observation

Overview

The UKSA supports thef collaboration and synergy among various organizations and initiatives within the UK's Earth Observation ecosystem. In this regard, the UKSA has established strong partnerships with the UK National Center for Earth Observation (NCEO) and the NERC Earth Observation Data Analysis and AI Service (NEODAAS).

Artificial Intelligence (AI) is central to the UK Government's plan to kickstart an era of economic growth, transform public service delivery and boost living standards. The government aims to harness AI to advance its missions and priorities across healthcare, the economy and society. Through the AI Opportunities Action Plan, the UK seeks to build scalable AI sector with global impact, outlining a framework to maximise AI's benefits across the system. AI also forms a part of the UK government's development Industrial Strategy, guiding the country's strategic direction in criticalindustries.

NCEO is a world-leading center of excellence in Earth Observation science and technology, bringing together a network of leading universities and research institutions. The UKSA actively engages with the NCEO to leverage its expertise and capabilities in areas such as satellite data processing, scientific algorithm development, and the application of advanced analytical techniques, including AI and ML. Through joint research projects and technology development initiatives, the UKSA and the NCEO work together to address critical challenges in Earth Observation. This collaboration aims to accelerate the translation of scientific advancements into practical applications and operational services that can benefit society, the economy, and the environment. The UKSA work with NCEO and NEODAAS to develop the UK's AI and Earth Observation Capacities. NEODAAS hosts the Massive GPU Cluster for Earth Observation (MAGEO) and provides EO Data, AI support and development to UK based researchers working on a range of EO focused domains. This has resulted in numerous successful projects applying advanced ML techniques to EO data.

AI4EO Examples

Key Contributions of UKSA and NCEO

- Data Processing and Analysis: One of the primary focuses of the UKSA initiative is to improve the processing of EO data. By leveraging AI and ML, NCEO has developed advanced algorithms that can analyze large datasets more quickly and accurately than traditional methods. This is particularly important for time-sensitive applications, such as monitoring natural disasters or tracking climate change impacts.
- Harmonization and Fusion of Data: The integration of AI and ML has also facilitated the harmonization and fusion of different types of EO data. This means that data from various sources, such as multispectral and hyperspectral sensors, can be combined to provide a more comprehensive view of the Earth's surface. The NCEO has been

instrumental in demonstrating how AI can enhance the understanding of land use and land cover (LULC) changes, which is crucial for effective environmental management.
- Development of Analysis Ready Data (ARD): The initiative has focused on creating Analysis Ready Data (ARD) products that are pre-processed and ready for analysis. For instance, the Sentinel-2 satellite data undergoes atmospheric correction using the Sen2Cor algorithm, which is a proprietary method that ensures the data is suitable for further analysis. This preprocessing step is vital for ensuring the accuracy of AI and ML applications in Earth observation.
- Applications in Agriculture: AI and ML applications in agriculture have been a significant area of focus. The NCEO has worked on projects that utilize satellite data to monitor crop health, predict yields, and assess the impact of climate variability on agricultural practices. By employing AI techniques, the NCEO can provide farmers and policymakers with actionable insights that can lead to better decision-making and resource management.
- Super-resolution Techniques: Another innovative approach being explored is the use of super-resolution techniques to enhance the spatial resolution of satellite images. This is particularly beneficial for applications that require detailed imagery, such as urban planning and environmental monitoring. The NCEO is investigating how AI can be used to improve the quality of satellite images, making them more useful for various applications.

JASMIN support for AI: ORCHID

The JASMIN platform, managed by the STFC Centre for Environmental Data Analysis (CEDA), has traditionally supported a diverse range of environmental science users, including EO and climate archives alongside large-scale batch computing clusters, a JupyterHub service and private cloud infrastructure. JASMIN now includes a GPU cluster, known as ORCHID, which is tailored towards the needs of AI and ML workflows. A range of different scientific use cases are managed on ORCHID, and additional resources are being tapped to expand the AI-on-JASMIN community.

NEODAAS AI Service

The NERC Earth Observation Data Analysis and AI service is funded by NERC, through NCEO to support national EO and AI services. They provide a range of support services, and work with JASMIN to develop their GPU and JupyterHub fasciitis to best support users, and individually support users through AI expertise, training and support, and method implementations. This facility has enabled the acceleration of uptake of AI within the EO community within the UK, by combining EO domain experts and AI domain experts, within the NCEO structure.There are a range of scientific use cases which demonstrate the benefits of this approach through interdisciplinary collaboration.

Future Directions
The collaboration between UKSA and NCEO is set to expand further, with ongoing research into new AI and ML methodologies that can enhance Earth observation capabilities. The focus will likely include:

- Increased Accessibility of Data: Efforts to make Earth observation data more accessible to researchers, policymakers, and the public will continue. This includes developing user-friendly platforms that allow for easy access and analysis of satellite data.
- Interdisciplinary Research: The initiative will promote interdisciplinary research that combines Earth observation with other fields, such as social sciences and economics, to address complex global challenges like climate change and food security.
- Capacity Building: Training and capacity building will be essential to ensure that stakeholders can effectively utilize AI and ML tools in their work. This includes workshops, online courses, and collaborative projects that foster knowledge sharing.
- Interoperability and Platform Integration: With the new Isambard-AI supercomputer coming online soon, NEODASS and CEDA will reach out to the University of Bristol to optimize the integration between their AI analysis platforms.

In conclusion, the UKSA initiative, in collaboration with NCEO, is making significant strides in utilizing AI and ML for Earth observation. Through innovative data processing, harmonization, and application development, they are enhancing our understanding of the Earth and its systems, ultimately contributing to better environmental management and policy-making.

4.8. GISTDA

The Geo-Informatics and Space Technology Development Agency (GISTDA) is utilizing AI/ML across various fields in Thailand's Earth observation ecosystem and geospatial intelligence missions. GISTDA's long-term vision is to leverage AI/ML for space data analysis through the evidence-based Geointelligence LLM platform, in order to support effective decision-making, promote sustainable development, and provide insights to inform national policymaking. Recognizing the importance of AI/ML technology, a five-year AI/ML development roadmap has currently been drafted for GISTDA's key missions, emphasizing resilience, innovation, and responsiveness to societal needs, as shown in the image below.

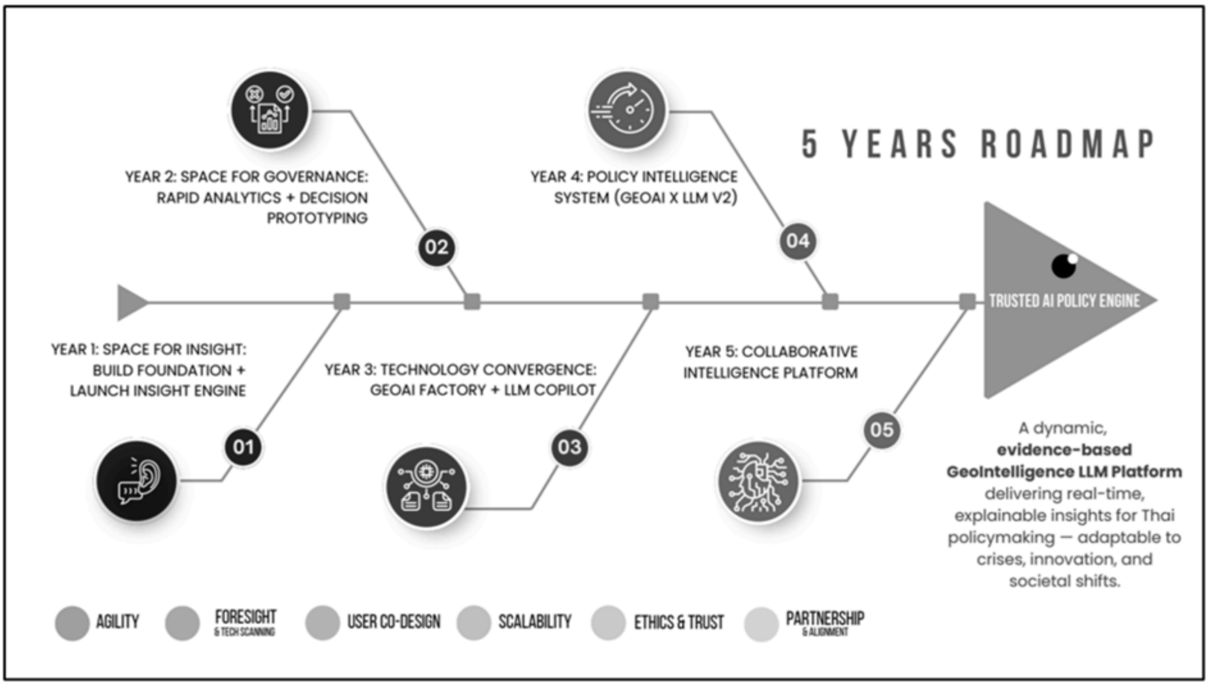


Figure 4.8-1. A five-year AI/ML development roadmap established by GISTDA.

AI4EO Examples

AI for Air Quality and Well-being

To support public health awareness and helps citizens make informed decisions to prepare for or respond to pollution, GISTDA developed Check Phoon, a mobile and web-based application for monitoring PM2.5 at sub-district level resolution. The system integrates in-situ measurements from Thailand’s Pollution Control Department (PCD) with meteorological and satellite data, and applying ML for forecasting 3-hour air quality predictions and accuracy reports.

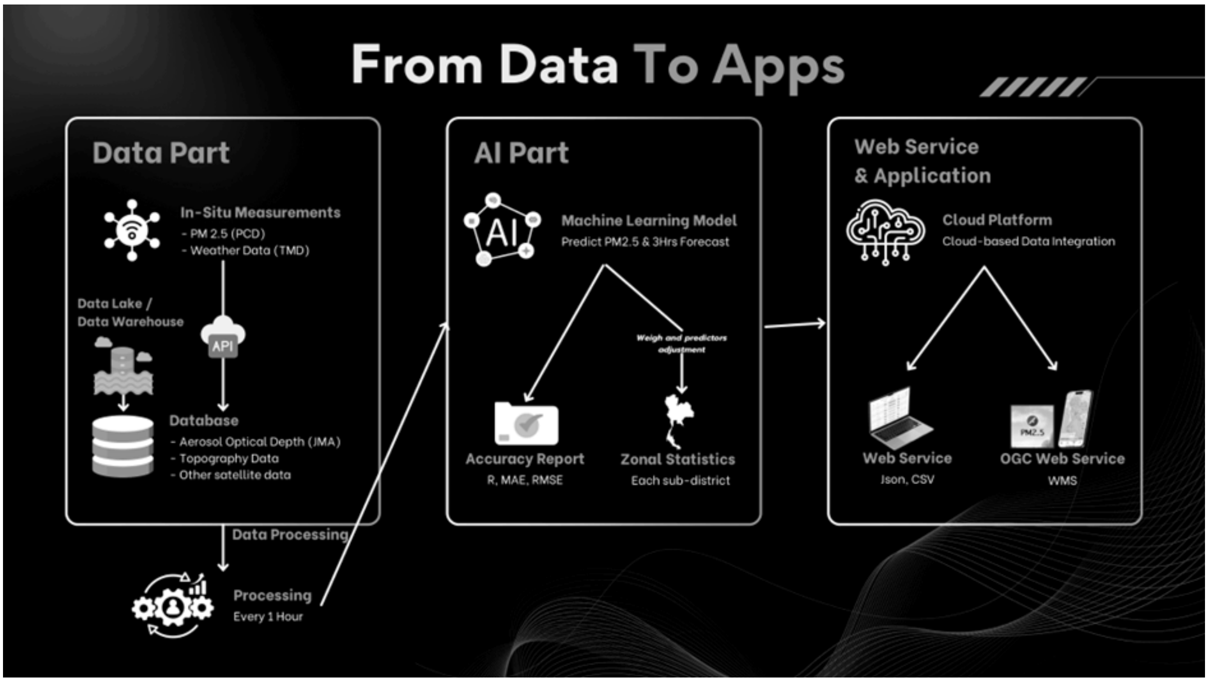


Figure 4.8-2. Example workflow for the development of GISTDA's PM2.5 monitoring application.

AI for Disaster Risk Reduction
Thailand is one of the countries that experience a lot of disaster due to the signature of South East Asia's climate. To support both local authorities and regional cooperation, GISTDA operates the Disaster Monitoring and Decision Support Platform, This platform integrating flood, wildfire, and drought models at sub-district level resolution. The three models are under development to incorporate AI-driven flood risk forecasting, wildfire spreading prediction, and drought risk analysis.

Figure 4.8-3. Example workflow for the development of GISTDA's flood monitoring and decision-support application.

AI for Image Quality and Enhancement
Collaborating with Nara Space, GISTDA applies AI-based Super-Resolution technique to THEOS-2 imagery to enhances spatial resolution from 0.5 m to 0.25 m. This processing addresses information gaps by training unpaired datasets across different satellites. This work expands the usability of very-high-resolution imagery for applications such as urban planning, agriculture, national security, and also

escalate the chances to combining other AI/ML technique to the analysis such as image detection.

GeoAgentic AI-LLM Prototype for Urban Governance
GISTDA and National Electronics and Computer Technology Center (NECTEC)plan to developing a prototype Digital Twin platform that combines AI/LLM with geospatial data to address urban challenges such as the Urban Heat Island effect then provide actionable policy recommendations. This project aims to contribute to Thailand's preparedness for climate change and sustainable urban development.

Impact and Future Directions
Through these initiatives, GISTDA is strengthening its foundation in AI and ML for Earth observation and geospatial applications. The continued integration of these technologies will enhance Thailand's capacity in environmental monitoring, disaster resilience, and space technology development. Looking forward, GISTDA aims to expand its AI/ML capabilities through international collaboration and knowledge exchange under CEOS and GEO frameworks. These efforts reflect GISTDA's commitment to advancing responsible, explainable, and impactful AI applications that contribute to global sustainability and equitable access to Earth observation benefits.

5. Demonstrative use-cases

There are numerous AI/ML approaches commonly applied to domains such as computer vision and Satellite Image Processing. In this section, examples of these approaches and how they can be applied to Earth Observation data are presented. This overview highlights example EO applications for various themes and is intended as a guide rather than a comprehensive or exclusive list.

5.1. Climate

5.1.1. Mapping glacier grounding lines

GOAL: AI/ML are becoming integral to climate science, offering new methods to analyze the vast and complex datasets produced by satellites, in-situ measurements, and climate models. For example, artificial intelligence can improve monitoring of ice-sheet dynamics by automatically mapping grounding lines, which are the boundary where glaciers transition from grounded ice to floating ice shelves (Mohajerani et al. (2021)). Accurate delineation of these lines is crucial for understanding ice-sheet stability and sea level rise.

AI4EO example: Mohajerani et al. (2021) applied a deep learning model to Differential Interferometric Synthetic Aperture Radar (DInSAR) data from the Sentinel-1 A/B satellites, training it to recognize grounding line signatures in complex interferometric phase patterns. Unlike traditional manual delineation or threshold-based techniques, the AI approach processes large datasets quickly and consistently, reducing human error and improving efficiency.

The figure below compares grounding lines derived by the deep learning model against those mapped manually. The AI-generated line (black) closely overlaps with the expert-drawn reference (white line), illustrating the accuracy and reliability of the automated approach. This example highlights the potential of AI/ML to scale up glacier and ice-sheet monitoring for climate studies and sea level rise projections.

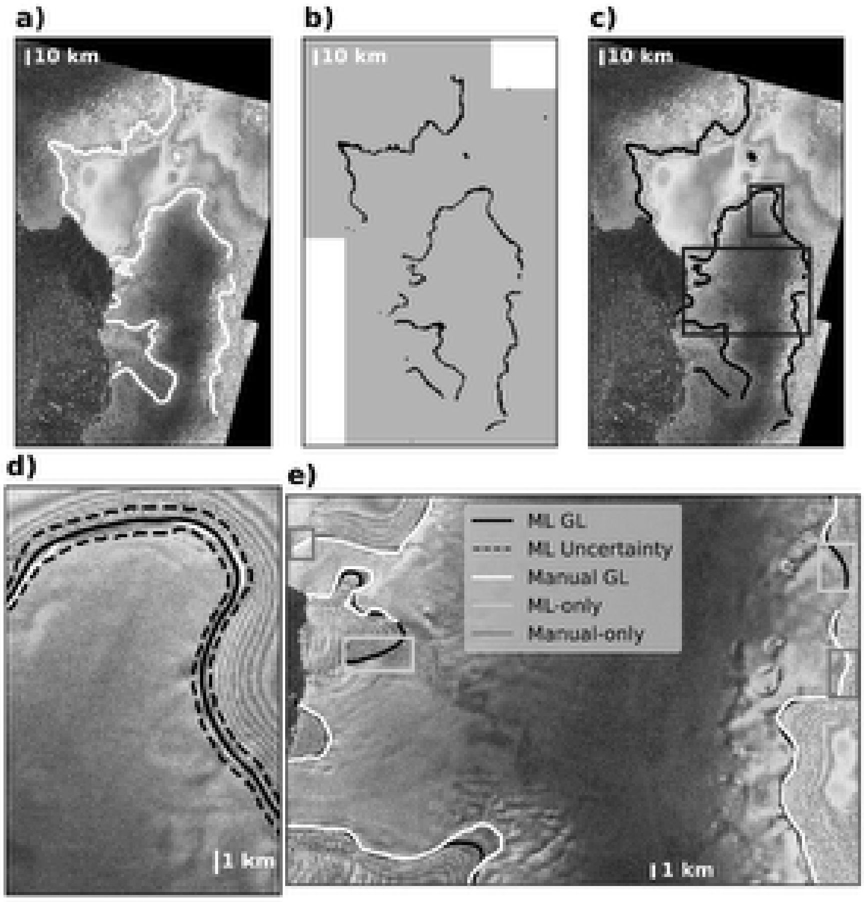


Figure 5.1.1-1 Different steps of the pipeline for (a) a sample interferogram with hand-drawn grounding line in white; (b) output of the neural network in raster format with a variable width that is a measure of uncertainty of the output. The gray mask in the background represents training (white) and testing (gray) sites; (c) Vectorized output and uncertainty contours; (d) zoomed-in region highlighted by the maroon box in panel (c) showing both manual and ML results and uncertainty bars; (e)

Comparison of the manual and ML performances in the area outlined in blue in panel (c).

5.1.2. Thin ice thickness

GOAL: The application of AI/ML in sea ice research has expanded into a wide range of tasks, including the estimation of sea ice concentration, thickness, and drift, classification of ice types, detection of ice edges, leads, and melt ponds, and seasonal forecasting of sea ice distributions. In particular, most studies have focused on these tasks using SAR and optical sensors with high spatial resolution. On the other hand, passive microwave radiometers such as AMSR2 and SSM/I, which can globally observe Earth's surface regardless of day/night conditions or cloud cover and have long been utilized for climate monitoring, have also seen progress in AI/ML-based applications. One example is the retrieval of thin ice thickness. In winter, coastal polynyas, thin ice regions surrounded by pack ice and coasts, experience substantial heat loss to the atmosphere, resulting in the formation of large amounts of sea ice. The dense water formed in association with this sea ice production partly intrudes into the subsurface, intermediate, and deep oceans and drives the overturning circulation and material cycles such as CO_2. Information on thin ice thickness is therefore indispensable for estimating sea ice production, and many studies have developed thin ice thickness retrieval algorithms. Most of these algorithms rely on deriving simple empirical equations by comparing ice thickness obtained from thermal infrared sensors with microwave radiometer data. Such empirical formulations can be replaced by AI/ML methods with greater representational power, offering the potential for improved accuracy.

AI4EO example:Nakata et al. (in prep.) employed a NN model to estimate thin ice thickness below 20 cm across the entire Antarctic sea ice region. To construct a highly generalizable retrieval model, a large volume of high-quality training data was required. They used a total of ~200,000 training samples, consisting of accurate thin ice thickness and thin/thick ice types derived from MODIS data. As input, instead of directly using AMSR2 L1B brightness temperature data (18, 36, and 89 GHz; spatial resolutions of 20 km, 10 km, and 5 km, respectively), they used corrected brightness temperatures obtained through the following preprocessing steps. First, the radiometer version of the Scatterometer Image Reconstruction (rSIR) method was applied to downscale the data to grid spacings of 10 km, 5 km, and 2.5 km. Second, a unidirectional variation model was used to remove stripe noise. Furthermore, the influence of atmospheric water vapor was corrected using a simplified radiative transfer model. To address thin ice retrieval, they employed a simple three-layer neural network that outputs both thin ice thickness and thin ice probability, trained with a loss function combining mean squared error for regression and binary cross-entropy for thin ice classification. As a result, the retrieved thin ice thickness dataset demonstrated remarkable improvements compared to previous algorithms. As shown in Figure 1, the comparison between a previous algorithm and the AI/ML approach demonstrates that, with appropriate preprocessing and the use of a neural network, thin ice distribution can be represented with higher accuracy and greater detail.

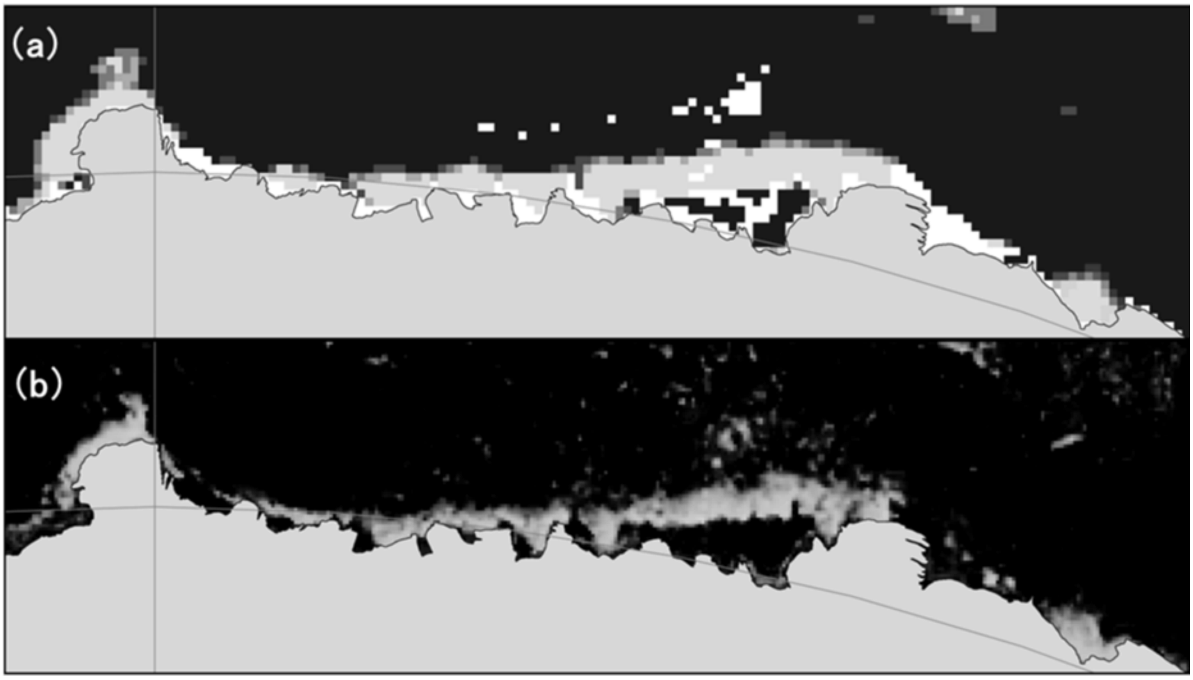


Figure 1. (a) Thin ice area (yellow regions) derived from the previous algorithm. (b) Pseudo-color composite image derived from the AI/ML approach (Red: thin ice probability, 50–100%; Green: thin ice thickness, 20–0 cm).

5.2. Disaster

5.2.1. SAR Flood Mapping

GOAL: Generative AI shows promising capability in reconstructing flood disaster, as shown by Lowe et al. (2021). Without domain and weather diversified ground truth, Lazin et al. (2024) concluded that no generative model currently shows generalizability, transferability, or explainability. Shen et al. (2019, 2021, 2024) demonstrate that the high resolution FIMs over vast spatiotemporal domains from SAR satellites, including Sentinel-1, RadarSat, ALOS-1, and RCM can fill this gap.

AI4EO example: The researchers created a 1-dimensional (1D) statistic signature (PDF similarity), to delineate water areas. By intercomparison with operational 0D method in the Figure below, The 1-D method performs consistently outperforms the 0D method over most types of land cover, and commits significantly lower error in discerning real water and water-alike areas on radar images.

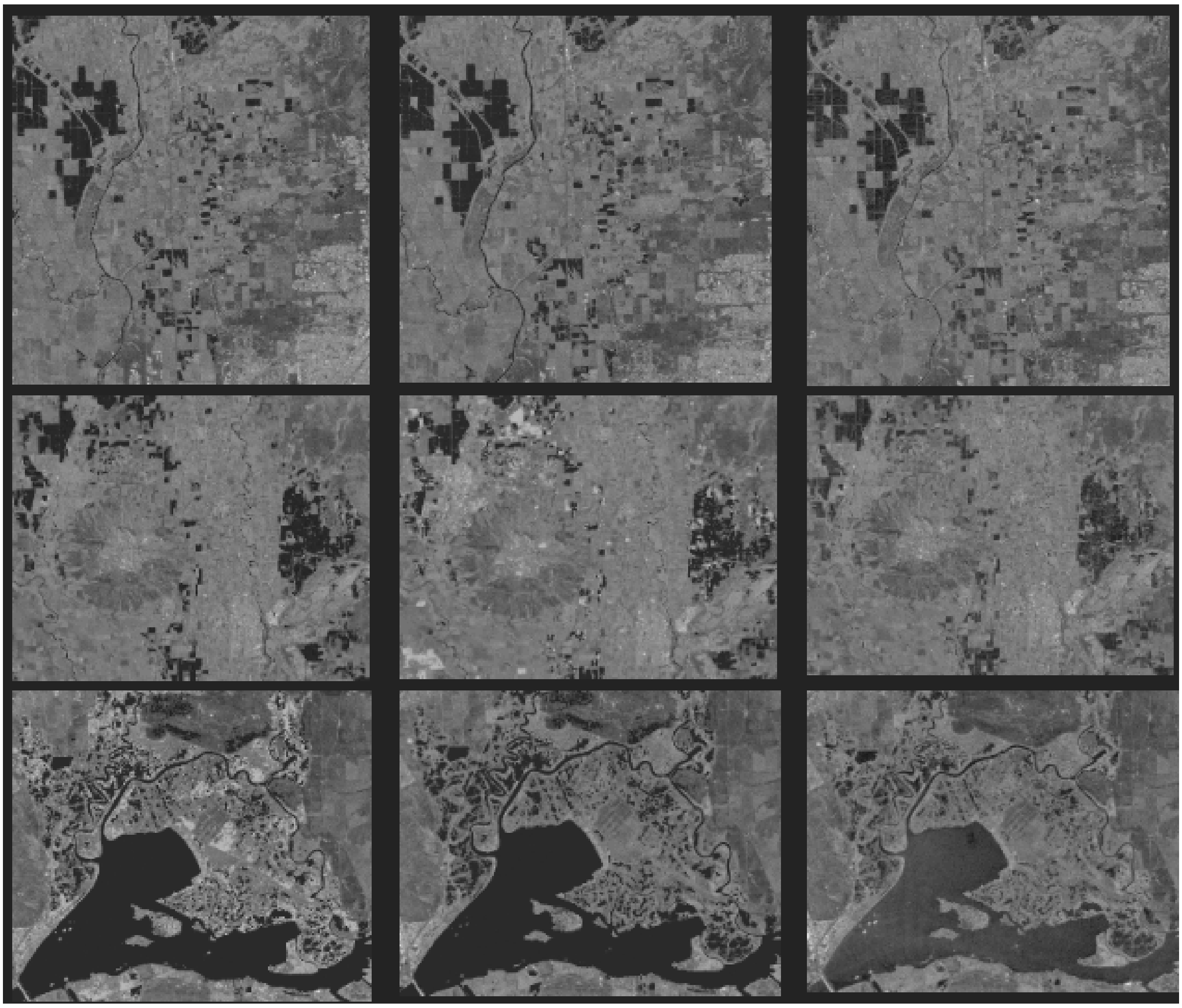


Figure.5.2.1-1 Intercomparison of RAPID v2.0 (1D method in dark blue) with GFM (0D method in red) and OPERA (0 D method in light blue). Row 1 shows RAPID v2.0 against GFM). Row 2 shows RAPID v2.0 against OPERA. And row 3 shows RAPID v2.0 against OPERA and GFM. The last column is the SAR image at VV polarization.

5.2.2. Flood Mapping with Optical Satellite Sensors[7]

5.2.2.1. Machine Learning in Optical Flood Mapping

Floods are among the most devastating natural disasters, yet traditional methods for mapping them often fall short. Machine learning (ML) has introduced a transformative approach, moving beyond manual analysis and simple algorithmic methods to a more dynamic and intelligent system for flood detection and mapping. This is particularly valuable for disaster resilience, as it allows for rapid and automated processing of vast amounts of Earth Observation (EO) data from satellites.

The core innovation lies in the ability of ML models, especially deep learning networks, to "learn" from historical data. By analyzing past flood events and their corresponding satellite imagery, these models can identify subtle patterns and relationships that are difficult for humans or simpler algorithms to detect. This leads to high-accuracy flood detection that is more adaptable to diverse environments and challenging conditions. Instead of relying on a single data type, ML models can fuse information from multiple sources—such as optical images, digital elevation models, and water flow grids—to create a more comprehensive and robust flood map. This fusion of data allows for a more complete picture of a flood's extent, including areas that might be obscured from direct view.

5.2.2.2. The FloodSENS Method: One Possible Method Among Many

FloodSENS, a project developed by RSS-Hydro (Gaffinet et al., 2023), exemplifies the power of this ML-driven innovation. It is a machine-learning-powered flood mapping tool that uses a U-Net model, a type of convolutional neural network well-suited for image segmentation tasks. The method's primary focus is on optical satellite imagery, specifically from the Sentinel-2 (S-2) mission.

The central challenge with using optical images for flood mapping is that they are rendered useless by cloud cover, which often accompanies major weather events and floods. The groundbreaking aspect of FloodSENS is its ability to overcome this limitation. The U-Net model is trained on expertly labeled flood images and, crucially, integrates auxiliary datasets. By incorporating digital elevation models (DEMs), which describe the terrain's height and slope, the algorithm learns the correlation between water bodies and low-lying areas. This allows FloodSENS to effectively reconstruct the flood extent beneath cloud cover. The model can identify visible flooded areas in cloud-free parts of an image and, using the topographical data, extrapolate the likely flood extent into the cloud-obscured regions (see abstract representation in Figure 5.2.2.2-1 below).

[7] This section was provided by Guy Schumann and is based on FloodSENS ML using Sentinel-2. Main paper is here: https://ieeexplore.ieee.org/document/10282274 for reference.

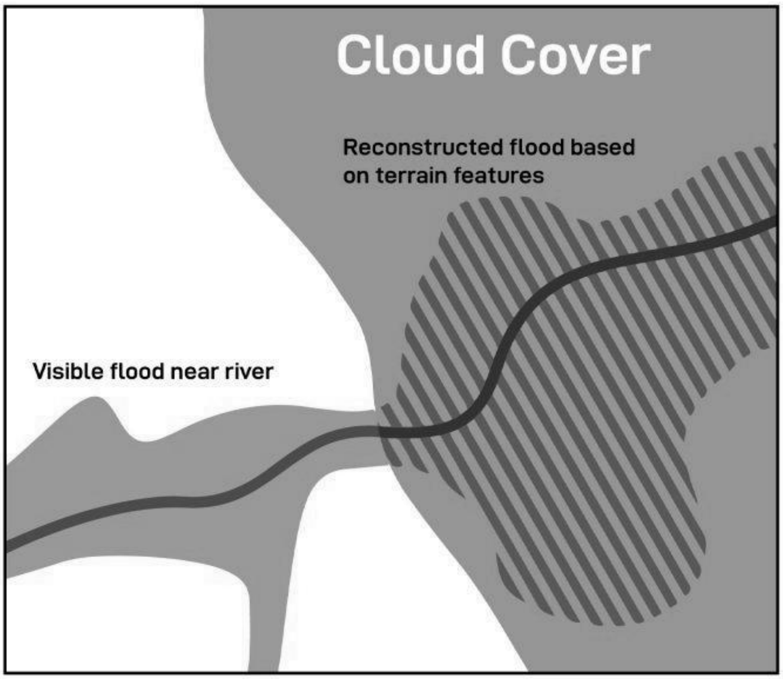


Figure 5.2.2.2-1: In essence, the machine learning algorithm learns to recognise visible floods and extrapolates their extent below clouds based on terrain features such as slope and land use.

5.2.2.3. Benefits of Using ML for Flood Mapping on Optical Images

The application of ML to optical imagery for flood mapping provides significant benefits for various stakeholders, from humanitarian agencies to insurance companies.

- Improved Accuracy and Global Transferability: By training the model on a large number of diverse flood events across different biomes, FloodSENS achieves a high degree of accuracy and global transferability (Figure 5.2.2.3-1 below). It can outperform traditional methods and correctly identify complex flood boundaries, such as those defined by debris lines. This ensures consistent and reliable mapping across different geographical locations without needing extensive manual calibration for each new site. When testing locally-trained versus globally transferable models on several individual events against standard index-based mapping approaches, such as the NDWI, a locally trained model achieves excellent performance of an IoU over 90% (Intersection over Union) while the best transferable model achieves an IoU of 80% (Gaffinet et al., 2023).

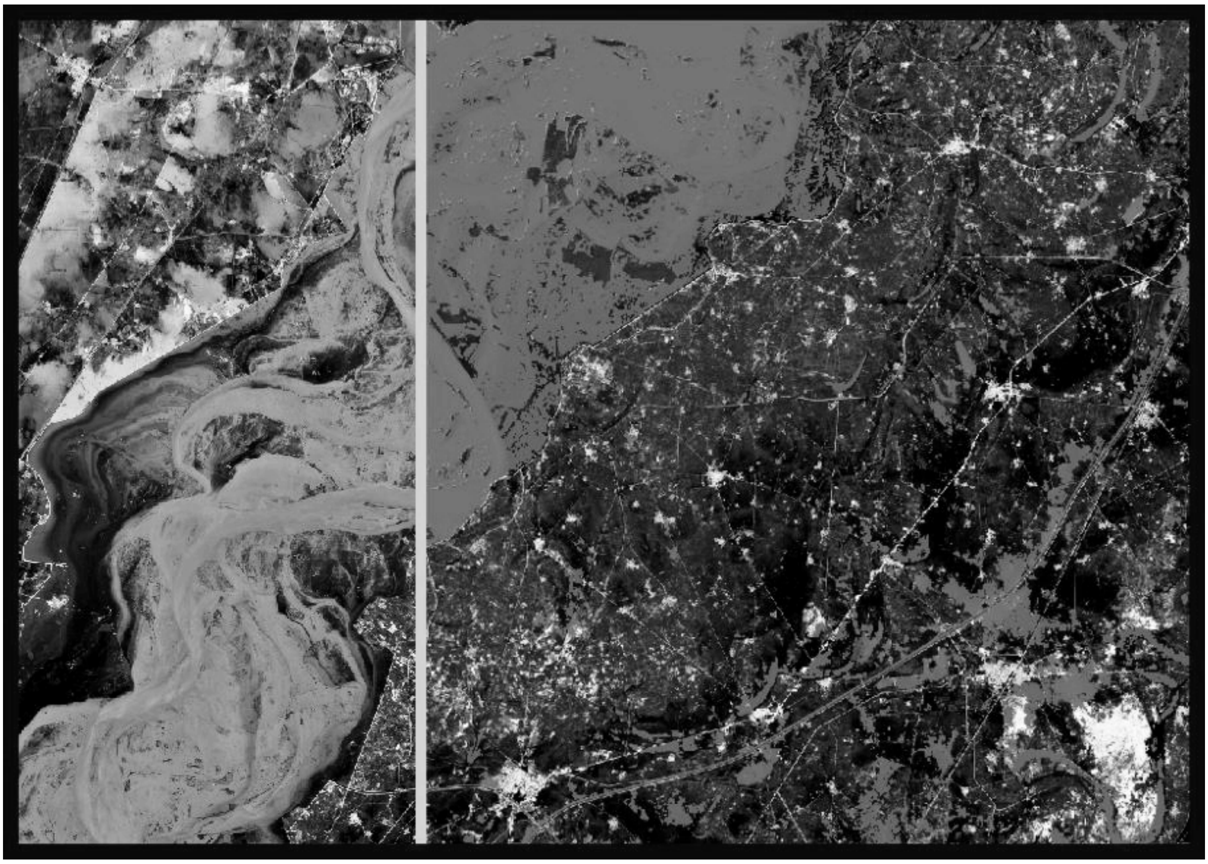


Figure 5.2.2.3-1: FloodSENS is a living ML-based algorithm that generates accurate flood maps from optical imagery consistently across diverse biomes, providing invaluable up-to-date information at regional, national, and global scales.

- Timely and Actionable Information: ML-based models can process satellite data much faster than manual methods, providing timely information crucial for emergency response. The outputs of FloodSENS are not just static maps but are designed to provide actionable intelligence. This includes feeding into 3D visualizations created with free tools like Blender or NVIDIA Omniverse, which allow decision-makers to immerse themselves in a simulated flood scenario. This provides a deeper understanding of flood patterns and potential impacts (illustrated in Figure 5.2.2.3-2 below), supporting better preparedness and resource allocation.

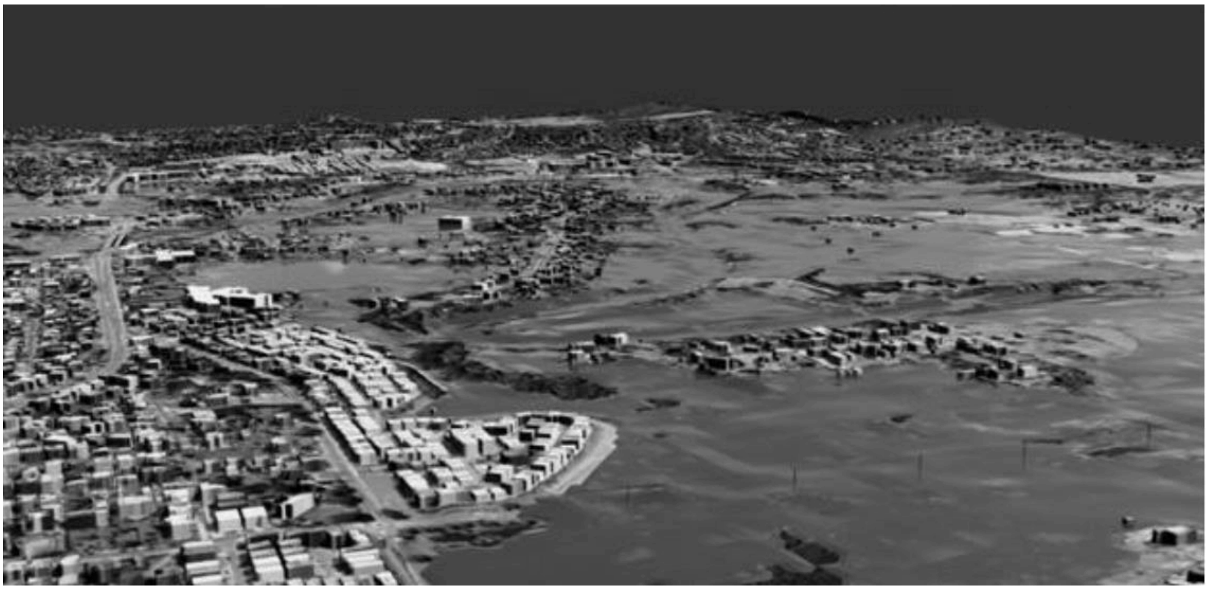


Figure 5.2.2.3-2: A sample 3D scene generation of a FloodSENS S-2 map simulation within NVIDIA's Omniverse platform. Significant flooding in the urban areas of Brisbane is shown for the 2022 event, with flooded above-ground electricity lines, depicted in the lower right area of the scene.

- Enhanced Data Utility: The ability to generate flood maps from cloud-covered optical images significantly increases the amount of usable data. Previously, many valuable images from major flood events were discarded due to cloud obscuration. FloodSENS renders these images usable, building a more accurate and reliable historical record of floods. This long-term data collection is vital for climate change analysis, risk assessment, and urban planning.

5.2.3. FloodML : Flood Extent rapid mapping from EO satellite data[8]

Written by Raquel Rodríguez Suquet - CNES, provided to WGDisaster Flood pilot for inclusion.

The SCO FloodDAM Digital Twin project is a demonstrator which provides an automated service to reliably detect, monitor, assess and predict floods at local and global scale within digital twin Franco-American collaboration. The main blocks of the processing chain are (I) flood detection and alert, (II) rapid flood extent mapping, and monitoring of on-going flood events, (III) representation and short-term forecasting of flood surfaces and free-surface elevation maps using high-fidelity hydrodynamic models over local areas, and (IV) real-time and post-event estimation and assessment of flood-related risks and economic impacts.

FloodDAM-DT produces a near-real time (NRT) flood monitoring product by generating flood extent maps after detecting water level anomalies in the time series of in-situ stations. The

[8] This section was written by Raquel Rodriguez Suquet, and it is based on FloodML algorithm[147]

goal of the second processing block is the generation of rapid flood extent maps at global scale within less than 11 minutes, once satellite acquisition is realised and provided. This product is produced using the open-source FloodML algorithm based on a Random Forest algorithm to detect flood extent from EO satellite data (Sentinel 2, Sentinel-1 VV-VH images, Landsat 8&9, Terrasar-X) along with MERIT or COPDEM GLO-30 DEM for SAR data, but also ESA World Cover. FloodML algorithm is trained on Copernicus EMSR cases, using samples for training and validation defined as areas having >90% water occurrence. This way, the algorithm can train optical and SAR data to detect water either flooded or not in

Sentinel-1 and Sentinel-2 images. Transfer learning method is then used for application on TerraSAR-X and Landsat products. New EO products might be integrated further on with the future launch of new satellite missions (for instance NISAR or ROSE-L SAR data), improving both time and space cover at a global scale, as well as a better detection of floodwater under vegetated areas.

In order to provide an a priori information of areas where flood might not be directly detected, the ESA World Cover has been integrated into the FloodML algorithm as shown in figure 5.2.3-1 here below with 8 levels of flooded surface classification.

Figure 5.2.3-1 FloodML flood extent map from Sentinel-2 data, ESA World Cover and GSWO over the Ohio River flood event on the 27th February 2018

All data produced within the FloodDAM framework is published on the Hydroweb.Next platform https://hydroweb.next.theia-land.fr/ , developed by CNES.

5.2.4. Wildfire

GOAL: GWSS (Global Wildfire System, OroraTech) is a near-real-time wildfire detection, alerting, and monitoring to support civil protection agencies, utilities, insurers, and asset operators. Provide risk assessment before ignition, early hotspot detection, and continuous situational awareness during incidents.

Expected outcomes, output format etc:
- Burn area classification, active fire detection, cloud/smoke detection & masking
- Alert feeds (API/SMS/Email), confidence/QA layers, incident dashboards (progressive web app), GeoTIFF rasters and vector perimeters (GeoJSON/GPKG).

AI4EO example:
- Image Segmentation & Multi-sensor Fusion

Fuse thermal-infrared WITH optical detections; apply CNN segmentation (burn scars, severity via NBR/dNBR), active-fire classifiers, and object-based post-processing. Visualize and task via GWSS progressive web app.

- Scope

Problem statement and project scope
Deliver global coverage with rapid revisit by combining public satellites and OroraTech's proprietary thermal constellation; provide automated detection/alerts and incident analytics across customer Areas of Interest (AOIs).

- Output
    - 2 raster segmented images (GeoTIFF):
        - Burn area/severity (unburned/low/mod/high)
        - Active fire probability/intensity, with cloud/smoke mask
    - Vector fire perimeters + incident report (area, severity stats, confidence, time).

- Verification Data sets
    - CAL FIRE incident catalogue (US), EFFIS (EU), NASA FIRMS/agency reports for cross-checks and after-action review.
    - Independent mission records for OroraTech satellites (e.g., FOREST-1).

Documentation
Refer the document and doi.
- GWSS project page (ESA Business Applications) and ESA InCubed portfolio entries; mission docs for FOREST satellites;
- ESA Business Applications – GWSS project page. Overview, objectives, system description. business.esa.int
- ESA InCubed – OroraTech Wildfire Solution. Multi-sensor approach, PWA, market context. incubed.esa.int
- OroraTech press & product pages. Wildfire Solution capabilities; dedicated thermal constellation launches (2022–2025). OroraTech

- eoPortal mission pages. FOREST-1 satellite technical background and purpose. eoportal.org

5.3. Infrastructure Monitoring

GOAL: EO for infrastructure management are relatively novel, with emerging applications that integrate satellite-based Synthetic Aperture Radar Interferometry (InSAR) with civil engineering modelling and ground instrumentation for structures such as bridges (e.g. Selvakumaran et al. (2018), Cusson et al. (2020)) and mine tailings (e.g. Bayaraa et al. (2024)).

In parallel, deep learning approaches have been applied to detect ground deformation over critical infrastructure such as tunnels or gas / water extraction (Anantrasirichai et al. (2020)) and airports (Ma et al. (2020)). Of particular importance are mine tailings, where early detection of anomalous deformation may help protect the surrounding communities and the environment from catastrophic failures of toxic mine waste (Bayaraa et al. (2023))).

AI4EO example: A variety of data science approaches, from deep learning to shallow machine (e.g. random forest) models and probabilistic models such as gaussian process regression have shown promise in detecting anomalous deformation signals from InSAR (e.g. Bayaraa et al. (2023)). Example is in Figure 5.3-1.

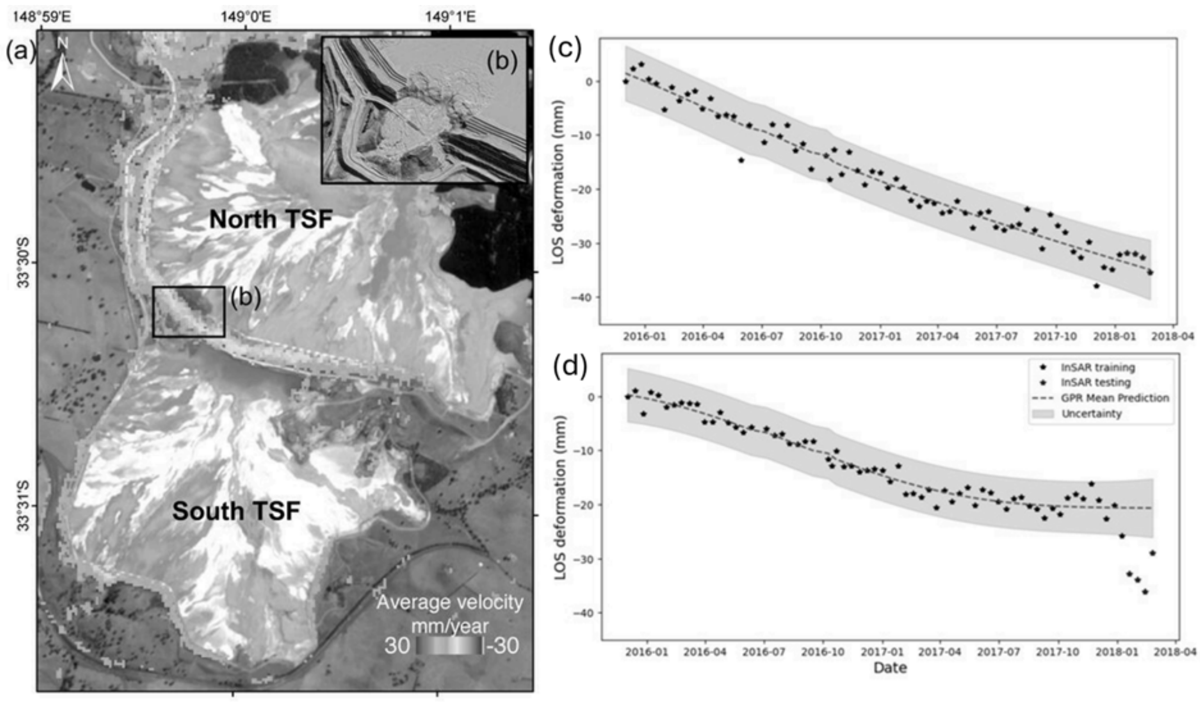


Figure 5.3-1: Use of machine learning approaches for detecting anomalous deformation signals from satellite InSAR data. (a) InSAR data visualised spatially over the Cadia tailings dam. © ESA Sentinel-2data and ISBAS InSAR data © Terra Motion. (b) Zoom in to the failed area of the dam. Basemap image copyright © 2021 Maxar Technologies, © CNES/Airbus, © Google Earth. (c) An example of an InSAR measurement showing a typical linear deformation with all test measurements within uncertainty envelope of Gaussian Process Regression. (d) An example of anomalous deformation behaviour, with the last four measurements (in blue) falling significantly outside the uncertainty envelope. Modified with permission from Bayaraa et al. (2023).

5.5. Precipitation

GOAL : Bias correction of precipitation forecast data from numerical weather prediction (MSM/GPV) by JMA in Japan. Finally aiming at the utilization for hydrological simulation.

METHOD : Assuming a relationship between observed precipitation and the areal precipitation distribution reproduced by numerical weather forecasts, we applied machine learning to correct precipitation bias. Specifically, the target variable was observed precipitation (JMA's in-situ and ground radar–based observations, Radar-AMeDAS), while the predictor variable was precipitation from the JMA mesoscale numerical forecast model (MSM) 39-hour forecasts. The relationship was trained using data from 2007 to 2020. Bias correction was then performed by estimating precipitation at the center of the distribution from forecast precipitation distributions not included in training. After correcting the spatial distribution with a support vector machine (SVM), additional quantitative adjustments for precipitation associated with individual convective clouds and squall lines—phenomena that are difficult to capture with machine learning—were made using a statistical method known as cumulative distribution function transform (CDFt).Support vector machine (SVM) regression with quantile-based bias correction For more detail, please refer to (Yin et al., 2022.)
https://doi.org/10.1016/j.jhydrol.2022.128125.
This method is now operationally used in "Today's Earth - Japan", which is terrestrial hydrological simulation system for Japan, developed by Japan Aerospace Exploration Agency (JAXA) and the University of Tokyo (see the document for more detailes).

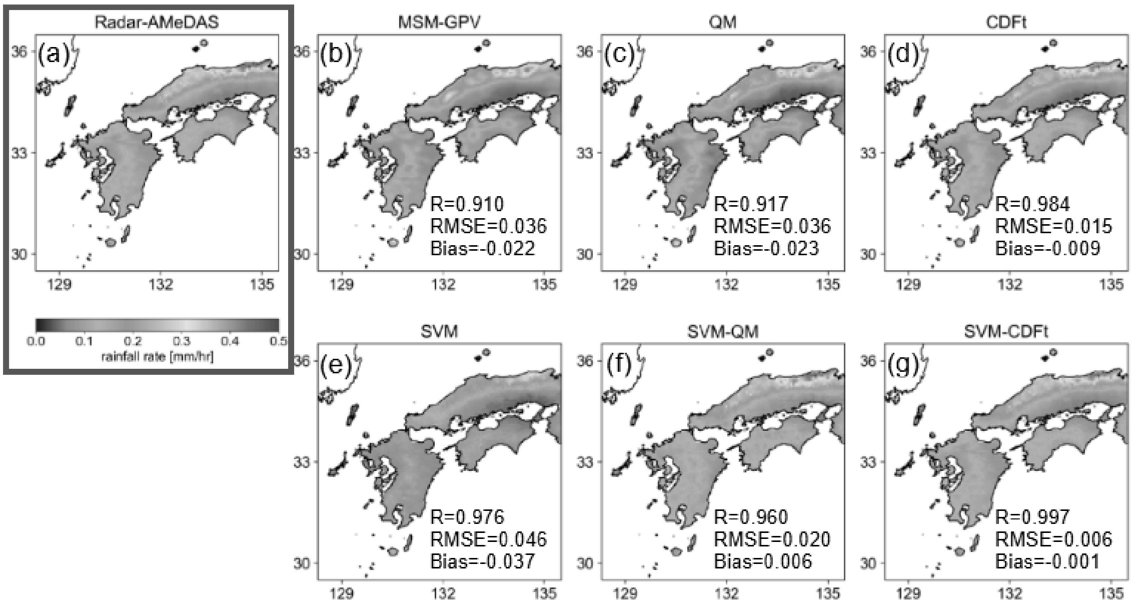


Figure 5.5-1: Averaged hourly precipitation in January from (a) Radar-AMeDAS, (b) MSM-GPV, (c) QM, and (d) CDFt, (e) SVM, (f) SVM-QM, and (g) SVM-CDFt. The statistical metrics evaluated against Radar-AMeDAS were shown in each subplot, and the units for R, RMSE, and bias are unitless, mm/hr, and mm/hr, respectively. Modified with permission from Yin et al., 2022

5.6. Sustainable Finance

GOAL : Leverage the global coverage of satellite data to develop comprehensive datasets that support sustainable finance initiatives. The financial sector often encounter challenges such as incomplete or missing data, particularly when assessing emissions-intensive industries and assets.

AI4EO example: Use of a variety of advanced deep learning approaches with satellite data to find and characterise cement assets (e.g. Rossi et al. (2022) and Tkachenko et al. 2023).

> Example task 1: cement plant assets identified and characterised through CNNs from high resolution multi-spectral satellite data (e.g. Worldview-4).
> Example task 2: cement plant assets identified and classified through thermal infra-red satellite data.
> Example task 3: metadata for cement plant assets are searched through LLMs and webscraping.

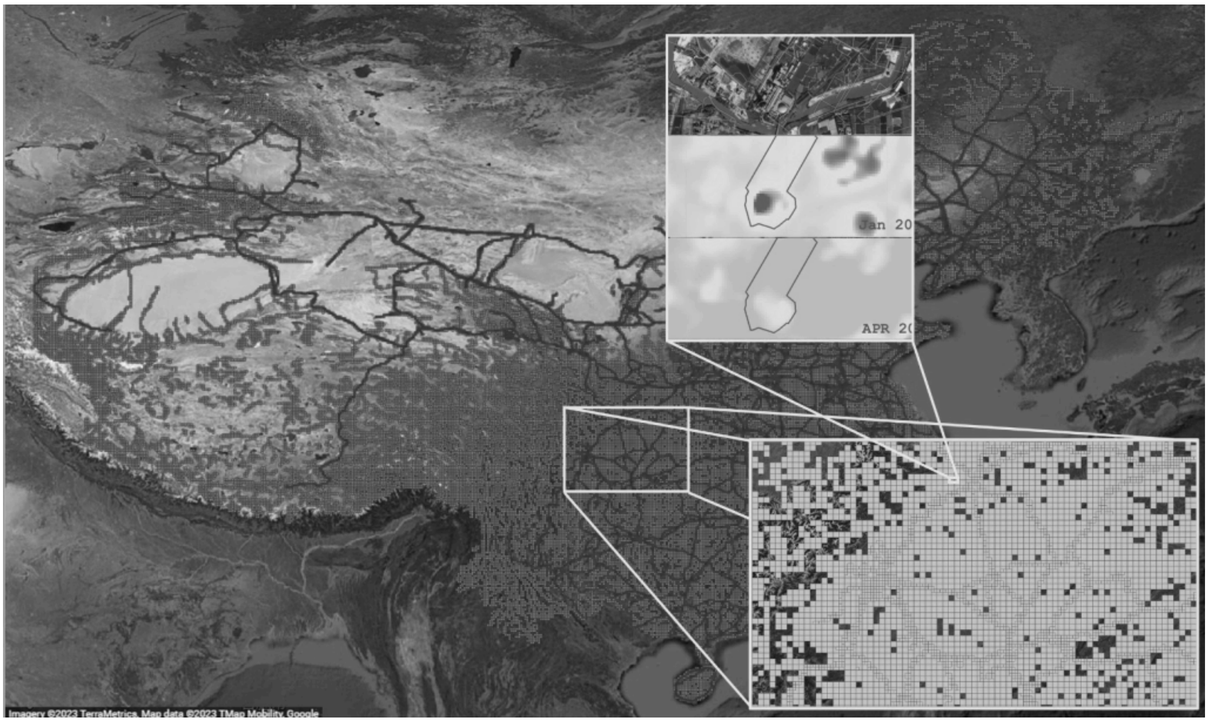


Figure 5.6-1: Use of deep learning and satellite data for characterising global cement assets. Modified with permission from Rossi et al. (2022).

6. Hot topics/New topics

6.1. Foundational Models

The paradigm shift in AI/ML is the idea of being able to train a machine learning model capable of doing many different tasks (object detection, segmentation, image captioning, classification..) based on data from a variety of satellite sensors. This is the promise of ‘foundation models’, as shown in Figure 5.1-1. It represents a shift away from task-specific AI/ML approaches (such as the ones described in Section Y) to versatile models that are trained on multi-modal data from different satellite sensors, resolutions that can be adapted to make predictions across a range of downstream tasks, such as predicting wildfires to mapping land cover and floods to forest monitoring.

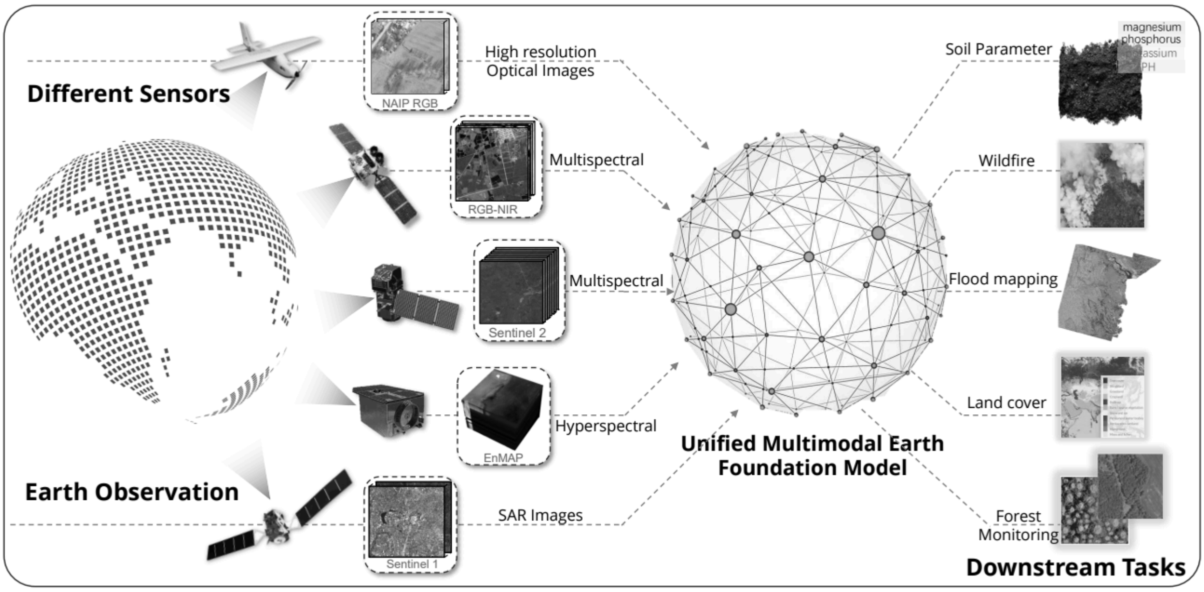


Figure 6.1-1: foundation models aim to be able to take many different types of data, including different EO data modalities for a variety of downstream taks. From Xiong et al. (2024)

Foundation models can be categorized by its functions.

6.1.1. Vision Foundation Model

These models are trained solely on visual (image-based) data from remote sensing platforms such as satellites or drones. They are designed to understand and interpret spatial features and patterns in imagery. Applications include land cover classification, object detection, semantic segmentation, and change detection.

Key characteristic:
Exclusively trained on visual data, these models learn hierarchical, multi-scale representations that capture spatial context, texture, and morphology. This enables consistently strong performance on dense, pixel-wise inference (semantic/instance segmentation, change detection) and object-level reasoning (detection, tracking) across sensors and resolutions. Pretraining objectives such as contrastive learning and masked-image modeling promote invariance to viewpoint, illumination, seasonal, and atmospheric variation, improving robustness, domain transfer, and few-shot fine-tuning in geospatial applications.

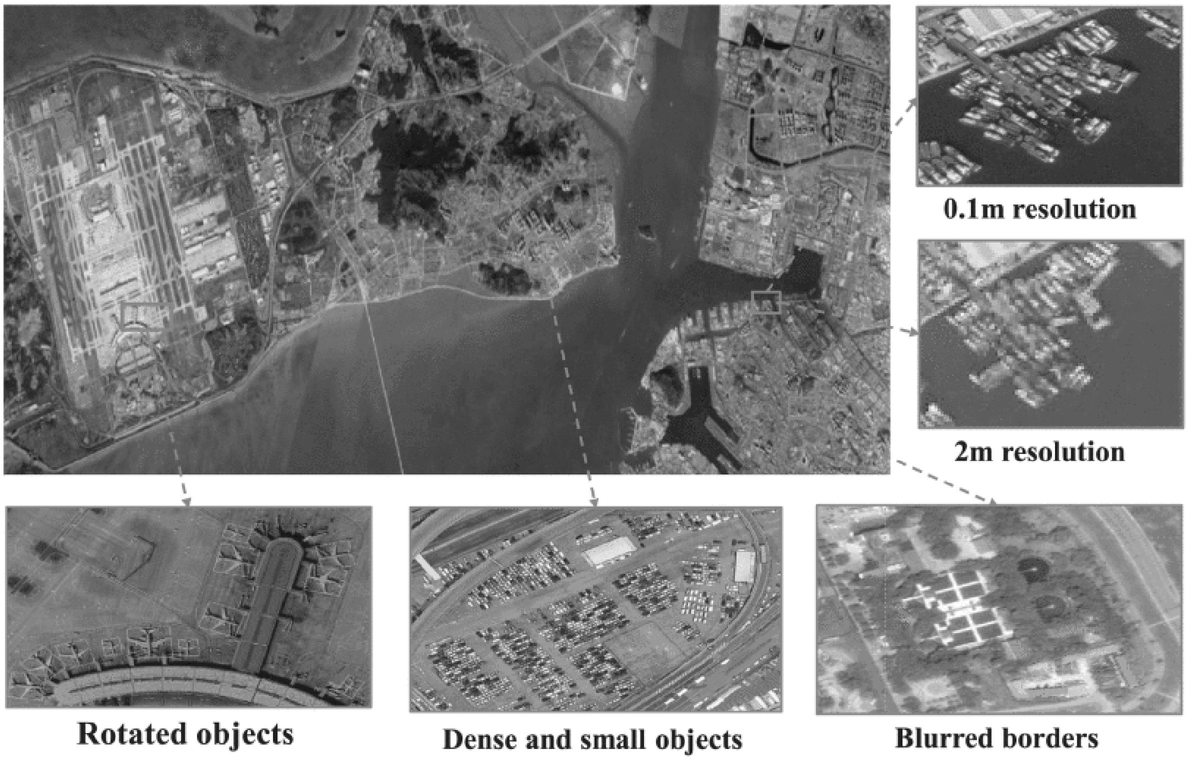


Figure 6.1.1-1: foundation models aim to be able to take many different types of data, including different EO data modalities for a variety of downstream tasks. From XIan Sun et al.

6.1.2. Vision-Language Foundation Model

These models combine visual data with textual data (e.g., labels, descriptions, captions, metadata). They are trained on paired image-text datasets and can understand and generate natural language related to remote sensing imagery. This allows for capabilities like image captioning, visual question answering (VQA), and cross-modal retrieval (e.g., finding images based on text queries or vice versa).

Key characteristic:
Multimodal learning that fuses vision and language by aligning image and text representations (e.g., via contrastive objectives and cross-attention) to enable interactive, interpretable analysis of EO data. This alignment supports open-vocabulary, promptable understanding and zero-/few-shot generalization for tasks such as captioning, VQA, cross-modal retrieval, and classification across sensors and resolutions. Incorporating textual prompts, ontologies, and metadata (e.g., geotags, acquisition time, sensor) provides semantic grounding and controllable inference, while instruction-tuning yields robust

performance under distribution shifts and facilitates natural-language rationales for improved explainability.

Figure 6.1.2-1:EarthGPT as Vision Language Models From *Wei Zhang et al.(2024)*

6.1.3. Generative Foundation Models

These models are capable of generating new data, either visual or multimodal, based on learned representations. They include generative models like GANs, diffusion models, or transformer-based models such as GPT for geospatial data. Applications include synthetic image generation (e.g., simulating satellite images), super-resolution, data augmentation, and future prediction (e.g., predicting land change).

Key characteristic:

Generative models perform enhancement and restoration (super-resolution, pan-sharpening, denoising/cloud removal, gap-filling), spatiotemporal forecasting, and cross-sensor translation/fusion (e.g., optical↔SAR) with geometric and radiometric consistency. Physics- and sensor-aware constraints improve realism and provide uncertainty estimates, while synthetic augmentation and generative priors strengthen downstream segmentation/detection and support provenance and bias auditing.

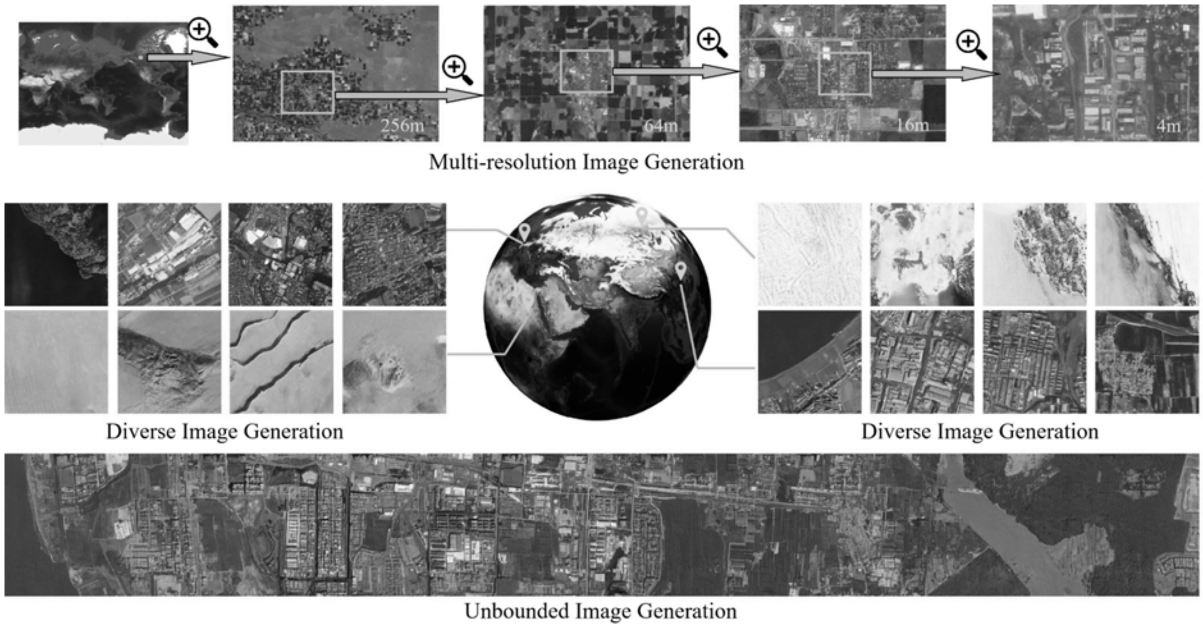


Figure 6.1.3-1. From Zhiping Yu et al. (2024)

6.1.4. Limitation of Foundation Models

There are notable foundation models such as Prithvi, Terramind.

Despite the promise of foundation models, there are critical challenges currently holding back its widespread practical application in remote sensing. The computational resources required for training and fine-tuning foundation models are significantly higher than task-specific AI approaches. Task-specific AI/ML models still perform better and have a much lower computational cost compared to foundation models for a variety of downstream tasks (e.g. Marsocci et al. (2024)). This is illustrated in Figure X2, where task-specific UNet model outperforms most foundation models in a variety of scenarios, except for when there are limited labels available.

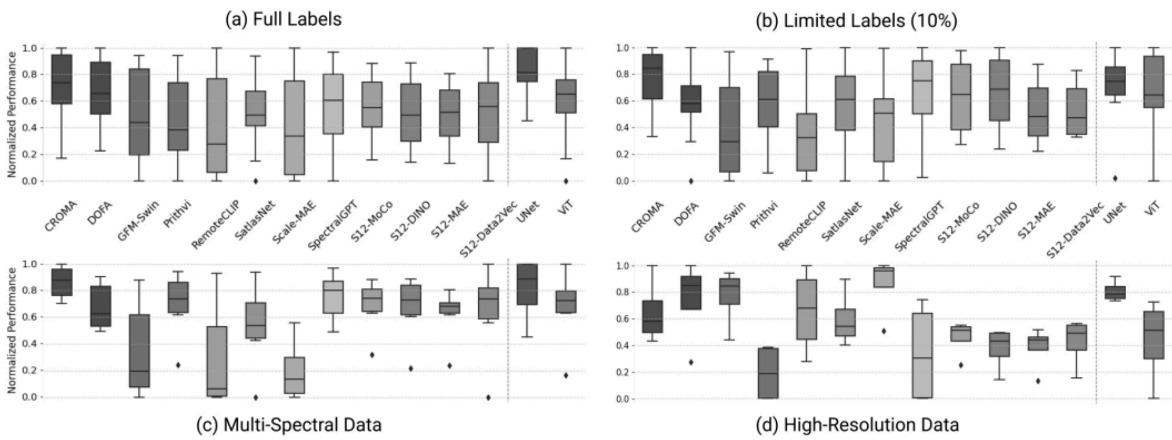


Figure 6.1.4-1: Comparison of the performance of different foundation models and a task-specific UNet model on a variety of dataset. The y-axis represents the normalized performance across the 11 PANGAEA's benchmark datasets, where the best performing model is assigned a value of 1 and the worst performing model, a value of 0. (a) Full Labels: the models are trained on downstream tasks with access to fall the labelled dataset. The task-specific baselines, especially UNet outperforms the foundation models. (b) Limited Labels (10%): models are trained on downstream tasks with access to only 10% of labelled data. In this scenario, the foundation models, especially CROMA, excel and outperform the supervised baselines. (c) Multi-spectral data: UNet excels and outperforms foundation models. Foundation models pre-trained on high resolution data, such as Scale-MAE, underperform. (d) High resolution data: Foundation models pre-trained on high-resolution images and UNet perform well. However, most foundation models pre-trained on lower-resolution imagery, such as Prithvi, underperform. From Marsocci et al. (2024).

6.1.5. Prithvi

Prithvi is a first-of-its-kind temporal Vision Transformer foundation model developed collaboratively by IBM and NASA, pre-trained on contiguous US Harmonized Landsat Sentinel 2 (HLS) data using a self-supervised Masked AutoEncoder (MAE) learning strategy. The model uniquely incorporates both spatial attention across multiple patches and temporal attention for each patch, accepting remote sensing data in video format with a crucial temporal dimension that distinguishes it from other geospatial models. Its accuracy outperforms six other geospatial foundation models when benchmarked on remote sensing tasks across different domains and resolutions (from 0.1m to 15m), demonstrating versatility in both classical earth observation and high-resolution applications. The model has wide-ranging potential applications including tracking land use changes, monitoring natural disasters, and predicting crop yields.

6.1.7. TerraMind

TerraMind is the first multimodal generative foundation model for Earth Observation, developed jointly by IBM, the European Space Agency (ESA) Φ-lab, and the FAST-EO project. The model uses a dual-scale transformer-based encoder-decoder architecture built on Prithvi that simultaneously processes pixel-level and token-level data Geospatial foundation models for image analysis: evaluating and enhancing NASA-IBM Prithvi's domain adaptability, combining insights from nine types of Earth observation data, include optical and radar imagery from Sentinel-1 and -2 satellites, textual representations of the environment, geomorphology, AI generated Land cover classification, vegetation, and historical climate data, to provide an intuitive understanding of our planet. TerraMind introduces the "Thinking-in-Modalities" approach to handle missing modalities and reaches new state-of-the-art results on downstream tasks. The model outperforms comparable models in performance tests while requiring less computing power, and is available as an open-source model on Hugging Face for researchers and practitioners working with geospatial data.

6.2. LLMs

Large Language Models(LLMs) are used on various occasions without earth observation.

Use cases
While LLMs have traditionally been applied in natural language processing tasks, their integration into remote sensing is gaining traction. Key current use cases include:

- Metadata and Report Generation: LLMs are used to generate textual summaries of satellite imagery analysis, automate mission reports, and create descriptions for geospatial datasets.
- Semantic Search & Retrieval: By linking natural language queries to remote sensing data, LLMs enable intuitive search and support interfaces (ref. EO advanced AI Assistant)
- Multimodal Systems: Combined with vision models, LLMs support vision-language tasks such as image captioning, question answering, and cross-modal analysis in remote sensing contexts.(ref. Vision-Language Models)

6.2.1. EO Advanced AI Assistant

The EO AI Advanced Assistant is a research demonstrator which aims to provide quick and unrestricted access to ESA Earth Explorers and Third Party Mission data, information and services made available by the European Space Agency.

This project which is currently at the pre-operational beta version stage leverages Large Language Models and Natural Language Processing techniques for intent understanding, query interpretation and name entity recognition. The LLM has been enhanced with features which allow it to extract queries and parameters via the EO MAAP Catalogue API, ESA TellUs API and EO Identity Access Management API. This allows integration with systems for data discovery, data request and personal user profile retrieval. Furthermore the system queries a vector database of regularly updated web information furnished by ESA via the Earth Online (earth.esa.int) and eoPortal (eoportal.org) websites allowing it to provide the latest updates to its users.
To address the limitations of LLM hallucinations the mechanism is validated through transformed based pipelines fine tuned on EO specific entities.
This multi function solution provides users with a single interface to simplify access for both entry-level and experienced users.
The EO AI Advanced Assistant is being developed with operational principles in mind ensuring compliance with security and hosting requirements for future upscaling and operational release as well as integration with a wider range of tools and services.
The strength of the assistant lies in its versatile orchestration of AI tools and pipelines delivering a personalized experience for data product discovery, visualisation, technical and code based support and data access bridging the gap between research and operations.
The assistant uses Retrieval Augmented Generation (RAG) to provide answers from a regularly updated vector database of contents which uses sources such as the Earth Online website (earth.esa.int) and the eoPortal website (eoportal.org). The eoPortal website is a compendium of global Earth Observation missions built on top of the CEOS Missions, Instruments and Measurements Database (https://database.eohandbook.com/).

https://ceos.org/document_management/Working_Groups/WGISS/Meetings/WGISS-59/8.1_An%20AI%20Initiative%20from%20Research%20to%20Operations%20EOP-GE.pptx

7. Data and platforms

This section introduces data and platforms used with machine learning and AI by CEOS/WGISS agencies indicated in the section 5.

7.1. Data for AI/ML data interoperability

7.1.1. ESIP's checklist

ESIP Data Readiness Cluster developed the checklist to promote AI-readiness and Open Environmental Datasets. Data providers can evaluate their dataset for AI by this checklist and the results support understanding by AI application developers.
The checklist consists 5 sections;

Part 1 - General Info
Part 2 - Data Quality
Part 3 - Data Documentation
Part 4 - Data Access
Part 5 - Data Preparation

Are Your Data Ready? Take Stock With ESIP's New AI-Ready Checklist - ESIP
https://doi.org/10.6084/m9.figshare.19983722.v1

7.1.2. CEOS-ARD

CEOS and the member organizations provide their data as Analysis Ready Data(ARD). CEOS-ARD (CEOS Analysis-Ready Data) is a framework and was developed by the Committee on Earth Observation Satellites (CEOS) to provide satellite observation data. They are pre-processed and standardized for immediate analysis.
Additionally, CEOS-ARD also includes "Product Family Specifications (PFS)" for various data types, such as optical, SAR (Synthetic Aperture Radar), surface reflectance over water, and nighttime lights, ensuring data quality and compatibility.
They are used for disaster management and coastal monitoring including DE Africa.
To use the data asAI/ML, they almost cover ESIP's checklist without Part 4 and 5. However CEOS ARDs provides Landing pages and there is related information about Part 4 and 5.

CEOS Analysis Ready Data

7.1.3. Pre-trained dataset

7.1.3.1. BigEarthNet

BigEarthNet is a large-scale benchmark dataset, supporting deep learning (DL) studies for remote sensing image analysis. The recently released version of BigEarthNet (BigEarthNet v2.0) is made up of 549,488 pairs of Sentinel-1 and Sentinel-2 image patches acquired over 10 European countries [148].
Each pair of patches in BigEarthNet is associated with a pixel-level reference map and scene-level multi-labels provided by the CORINE Land Cover (CLC) map of 2018. To pay more justice to the properties of BigEarthNet image pairs, its developers introduced a new class-nomenclature by modifying the labels extracted from the CLC 2018. To this end, the

CLC Level-3 nomenclature is interpreted and arranged in a new nomenclature of 19 classes [149].
The complete dataset, the code for constructing it in a reproducible manner and also the weights of several pre-trained models (which are: i) ResNet; ii) vision transformer; iii) MLP-Mixer; iv) ConvMixer; v) MobileViT; and vi) ConvNeXt-v2) using BigEarthNet are publicly available at https://bigearth.net.
We would like to note that the public availability of the code developed for its construction allows all its users not only to reproduce the dataset but also to extend it to any geographical area of interest. Moreover, a software tool (called as rico-hdl) that converts the dataset into a DL-optimized data format has been recently released by its developers to minimize the DL model training time. For details, we refer the Reader to the dataset webpage https://bigearth.net.

7.1.4 Benchmark

7.1.4.1. PhilEO Bench

PhilEO Bench is a benchmark framework to evaluate Foundation Models(FMs) and it is considered fair and reproducible.
It provides a testbed and can be used for building density estimation, road segmentation and land cover classification. It provides 400 GB Sentinel-2 data with label.[150]

7.1.4.2. PANGEA

PANGEA is a benchmark to evaluate Foundation Models(FMs) fairly.
It uses various datasets;Opticals(Sentinel-2, Geofen-2, SPOT-6, Maxar, Planet), Radar(Sentinel-1) and Harmonized data(Harmonized Landsat and Sentinel-2).
And it can be used for many tasks; Land cover, Forest monitoring, Disaster response, Wildfire detection, Flood detection, Marine monitoring and Agriculture monitoring.
PANGAEA is also flexible, so it can be used for future research and new applications.[151]

7.2. Geospatial AI Platforms

Geospatial AI platforms are cloud-based computational systems that combine satellite imagery, remote sensing data, and geographic information with artificial intelligence and machine learning capabilities. These platforms provide researchers, government agencies, and private organizations with the tools to process and analyze large volumes of spatial data efficiently. By leveraging cloud computing infrastructure, users can perform complex geospatial analyses such as land cover classification, change detection, and environmental monitoring without requiring extensive local computational resources. The integration of AI

algorithms enables automated pattern recognition, predictive modeling, and time-series analysis across diverse applications including urban planning, agricultural management, climate research, and natural resource monitoring. These platforms have become essential tools for evidence-based decision-making in fields that require spatial and temporal analysis of Earth observation data.
Some of the commonly used platforms (not an exhaustive listing) in this category are listed in this section for reference and further exploration.

Table 6.2-1 Geospatial AI Platforms

Platform	**URL**	**Description & Capabilities**	**Key Features**	**Typical Datasets**
Google Earth Engine (GEE)	**https://earthengine.google.com**	Cloud-based large-scale geospatial analysis platform with petabyte archives.	ML-ready APIs, Python ,scalable image analysis, visualization.	Landsat, Sentinel, MODIS, VIIRS, climate, hydrology, land cover.
Microsoft Planetary Computer	**https://planetarycomputer.microsoft.com**	Combines massive environmental datasets with Azure-scale compute.	STAC API, JupyterHub integration, Python/xarray/ geopandas support.	Sentinel, Landsat, NAIP, ERA5, CMIP6, biodiversity (GBIF).
NASA Earthdata (ESDS)	**https://earthdata.nasa.gov**	Gateway to NASA's ≥60 PB Earth science archive, models, reanalyses.	Cloud-based APIs, DAACs for science domains, Giovanni visualization.	MODIS, VIIRS, SMAP, TRMM, CERES, atmospheric & ocean records.

ESA Climate Change Initiative (CCI)	**https://climate.esa.int**	Long-term harmonized climate datasets, focus on Essential Climate Variables.	Curated ECVs, benchmarks for EO+AI through ESA AI4EO.	Land cover, greenhouse gases, soil moisture, ocean color, fire, glaciers.
Radiant Earth MLHub	**https://radiant.earth/**	Open ML training data hub for geospatial AI benchmarks.	STAC-compliant labeled datasets, benchmarks for competitions.	Sentinel-2, Landsat with ground-truth, agricultural & disaster labels.
Euro Data Cube (EDC)	**https://eurodatacube.com**	EU-based hosted analytics environment for Earth Observation datasets.	Access to Sentinel, Landsat, custom cubes; Notebook environment; service marketplace.	Sentinel-1, Sentinel-2, Sentinel-3, Landsat, Copernicus services.
AI4EO (ESA AI for Earth Observation Initiative)	**ai4eo.eu**	ESA-supported initiative advancing AI/ML for EO with challenges and tools.	Benchmarks, data challenges, ML datasets for research.	Sentinel, Copernicus open datasets, thematic AI challenge datasets.
IBM Environmental Intelligence Suite	**ibm.com/products/environmental-intelligence-suite**	Enterprise solution for climate risk and	Climate/Weather risk dashboards, supply chain	Weather Company data, climate models, EO

		environmental intelligence.	integration, AI forecasting.	data integrations.
AWS Earth on Open Data / Amazon SageMaker Geospatial Capabilities	**registry.opendata.aws & aws.amazon.com/sagemaker/geospatial/**	Petabyte-scale open geospatial datasets and AI/ML integration in cloud.	Registry of open Earth data, scalable analytics, SageMaker ML integration.	Landsat, Sentinel, DEMs, climate reanalysis, aerial imagery, OpenStreetMap
VEDAS by ISRO	**https://vedas.sac.gov.in/**	Large scale resource monitoring and analysis for Indian region	Data visualization, Analytics with API access and prepared Catalogues	Resourcesat, Sentinel, Cartosat datasets

The key advantage of using established geospatial AI platforms over self-developed infrastructures is their ability to drastically reduce technical, computational, and financial barriers to large-scale Earth observation analysis. These platforms provide immediate access to petabyte-scale, analysis-ready datasets—such as satellite constellations, climate reanalysis models, and labeled training archives—eliminating the immense effort required to collect, preprocess, and store such data independently. They offer cloud-based computing environments, integrated AI/ML workflows, and standardized APIs, which allow researchers to focus on scientific inquiry and innovation rather than infrastructure management. Importantly, the low barrier of entry—often through free tiers, open-access datasets, or academic licensing—empowers researchers, NGOs, and governments alike, enabling cutting-edge environmental monitoring and decision-making capabilities even for institutions with limited resources. In essence, these platforms democratize access to planetary-scale intelligence, making impactful geospatial AI research both more efficient and more inclusive. The platforms also aid in reproducible research as the experiments can be exactly explained along with the environment and the data used.

8. Challenges & Limitations of AI4EO

The transformative potential of Artificial Intelligence (AI) is tempered by a set of inherent challenges and limitations that are critical to understand for strategic implementation. AI models are not infallible; their performance is intrinsically linked to the quality of their training data and they can exhibit significant shortcomings when applied outside their original design parameters. Furthermore, the development of sophisticated models necessitates substantial computational resources, creating cost and scalability barriers. Organizations must also navigate a complex landscape of legal and ethical considerations, including data privacy, algorithmic bias, and regulatory compliance. A clear comprehension of these constraints is essential for managing risk, setting realistic expectations, and deploying AI solutions in a sustainable and responsible manner.

8.1. Data scarcity & labelling challenges

The development and deployment of robust Artificial Intelligence and Machine Learning (AI/ML) models for geospatial analysis are fundamentally constrained by the availability and quality of training data. Unlike other domains, the unique characteristics of satellite and aerial imagery present significant hurdles in data acquisition and preparation, which directly impact the feasibility, cost, and timeline of AI initiatives. It is difficult to obtain ground *truth measurements* at a very large scale given the temporal variation due to natural and man made activities.

The primary challenge for geospatial models doesn't lie in a general lack of imagery, but in the scarcity of *relevant, accurately annotated* data required to train these models for specific tasks. This challenge manifests in two core areas: the acquisition of usable data and the subsequent process of labelling it.

The Challenge of Data Scarcity

Data scarcity in the geospatial context is often a problem of relevance and specificity, rather than absolute volume.

- **Class imbalance due to event rarity:** Many critical applications involve detecting events or features that are inherently rare within vast geographical areas. For instance, identifying maritime oil spills, monitoring illegal logging, or detecting specific infrastructure failures requires training models on a significant number of positive examples, which are difficult to acquire due to their low occurrence rate.
- **Lack of Historical Data:** For novel applications or new satellite sensors, sufficient historical data simply may not exist. This absence prevents the training of models that require longitudinal analysis or a deep historical baseline for comparison.

- **Domain-Specific Requirements:** Models are highly sensitive to the conditions under which training data was captured. Variations in atmospheric conditions, seasonal changes, sun illumination angles, and sensor specifications can drastically alter the appearance of a location. Consequently, data that is not representative of the target operational environment has limited utility, effectively creating a scarcity of contextually appropriate imagery.

The Labelling Bottleneck

The process of annotating geospatial imagery, known as labelling, is a critical and resource-intensive bottleneck. The accuracy of the labels directly determines the performance and reliability of the resulting AI model.

- **Requirement for Expert Knowledge:** Accurate labelling of geospatial data is not a trivial task. It requires domain-specific expertise to correctly identify and delineate features. Distinguishing between crop types, classifying geological formations, or identifying specific maritime vessels necessitates skills possessed by geologists, agronomists, and other subject matter experts. This reliance on a scarce and expensive workforce significantly increases the cost and time required for data preparation.
- **Subjectivity and Consistency:** Labelling can involve a degree of interpretation, leading to inconsistencies. Different experts may have differing opinions on the precise boundaries of a feature or its classification. Without rigorous standardized protocols, this subjectivity introduces "label noise," which degrades model performance and erodes trust in the AI's outputs.
- **Scale and Labor Intensity:** Labelling is a manual process that does not scale efficiently. High-resolution imagery covers extensive areas, and annotating features at the pixel level (e.g., for land cover classification) is an immensely time-consuming and tedious endeavour. The cost of creating large, accurately labelled datasets often constitutes one of the largest investments in an AI/ML project.

8.2. Computational demands for large-scale analysis

The application of artificial intelligence and machine learning to large-scale geospatial data analysis entails significant computational requirements, which in turn pose substantial environmental and operational challenges [152]. Training sophisticated deep learning models—particularly those processing high-resolution satellite imagery across extensive geographical areas—demands immense processing power, typically supplied by high-performance computing clusters or cloud-based Graphic Processing Unit (GPU) arrays. This reliance on energy-intensive hardware contributes directly to elevated carbon emissions, particularly in regions where electricity generation remains dependent on fossil fuels. The financial cost of such computational resources can also be prohibitive, limiting access for smaller organizations or public sector entities and potentially widening the gap between well-resourced and emerging players in the field.

Moreover, the environmental footprint of model training and inference is further amplified by the need for repeated experiments, hyperparameter tuning, and continuous model updates to maintain accuracy over time. As geospatial datasets grow in volume and resolution, and as algorithms increase in complexity, the energy consumption required for meaningful analysis will continue to rise. Organizations are therefore encouraged to adopt efficiency-minded strategies such as model optimization, selective processing, and energy-aware computing infrastructure to align technological advancement with sustainability goals. Without deliberate mitigation efforts, the scalability of AI-driven geospatial insights may come at a considerable ecological cost.

8.3. Model interoperability & trustworthiness

Model interoperability refers to the ability of AI systems to seamlessly exchange information and utilize functionality across diverse platforms, software environments, and data formats, which is essential for integrating specialized tools into broader analytical workflows and avoiding vendor lock-in. Trustworthiness, a multifaceted requirement, encompasses not only the technical performance such as accuracy, robustness, and reliability, but also adherence to ethical principles, including fairness, transparency, and accountability. Establishing trust requires that models operate consistently under varying conditions, provide explanations for their outputs, and are developed with rigorous validation and governance frameworks to ensure they perform as intended without causing unintended harm. Therefore, fostering interoperability and embedding trustworthiness are not merely technical challenges but foundational to the responsible adoption, scalability, and long-term success of AI technologies in critical applications.

The current state of model interoperability in geospatial AI remains highly fragmented, with numerous proprietary formats and closed ecosystems limiting seamless integration. While standards like OGC APIs and cloud-optimized formats are emerging, widespread adoption is still evolving. Most models are developed for specific platforms or data structures, creating significant friction in cross-system deployment and collaboration. This lack of cohesion hinders the scalability, reproducibility, and efficient combination of specialized models into unified analytical workflows.

9. Conclusion and Future outlook.

In conclusion, AI/ML in the earth observation domain significantly has enabled the discovery of new insights and the utilization of methods.

The trend of developing applications using AI/ML is expected to continue and expand.
As introduced in section 4, it is clear that each CEOS agency and related organizations are developing AI/ML, and AI technology will also develop, so it is easy to imagine new initiatives emerging.
This document summarizes the snapshot of AI/ML related activities in 2025. We will continue to gather information on the latest AI/ML technologies/activities and introduce them by updating this document.
Finally, we would like to thank the many people who contributed and reviewed this white paper throughout its creation with sincere gratitude.

Appendix A. Glossary

The Glossary is adopted from State of AI for Earth Observation.

Active (sensor)	A sensor—like **lidar**, **SAR**—that emits its own **EM** pulses and perceives the properties of remote objects as alterations in the **backscatter**. See also, **passive.**
Aerial (sensor)	An airborne sensor; on board an aircraft.
Aerosol	Microscopic solid or liquid particles suspended in the atmosphere.
Amplitude	A wave property that signifies the absolute range in which the wave oscillates.
Annotation	Another term for **ground truth** and **labels**. They can be used interchangeably.
Architecture (DL)	The design of a **deep learning** model, specifying how all the **layers** in the neural net connect. Due to their modular nature, rarely do two DL models share the same architecture, but they all fall under one of few types. **Convolution** works well in images; **recurrence** works well in **sequential** data.
Backscatter	An **EM** wave backscatters when its reflection travels back the same direction it came from.
Band (spectral)	An interval in the **EM** wavelength spectrum, within which a sensor measures the intensity of light received at such wavelengths.
Classification	An ML task in which an input is assigned one of many categorical variables, such as detecting the presence of a ship in a satellite image.
Coherence	A measure of alignment between the phases of all waves in a light pulse; useful for measuring the flatness of a surface.
Convolution (layer)	A neural net **layer** found in **CNN architectures**, whose output does not change when the input signal is shifted. For example, a convolutional layer trained on building footprints activating when a building is present anywhere in the input image.
Deep learning	A modular approach to ML with **neural nets** that contain many **layers**. Deep neural nets can learn complex features automatically from data, thus minimising the need for humans to engineer features based on intuition. For this reason **DL** is also known as *representation learning*, in the sense that deep nets form their own internal bank of features that best solve the task at hand. DL works best with at least thousands of datapoints available, and the use of larger models (in terms of **layers** and **parameters**) makes sense when more data is available. However, their modelling power comes at the cost of interpretability.
Diffuse reflection	A reflected EM wave that travels in a direction different to that of **backscatter**.
Earth observation	The combination of remote and in-situ based sensing for the Earth.
Feature (ML)	The part of a ML model that numerically represents a certain pattern in the data. Features can be engineered by a human based on their domain expertise and intuition. A classic example is **NDVI**—a vegetation index commonly used in **optical** imagery. In **neural nets**, features can be learned automatically from data, and can be found in the output of a **layer** or the input of the layer after it.
Frequency	The number of oscillations per second (in Hz units); useful for measuring the energy stored in a light wave and therefore determining the chemical composition of the material from which it was emitted—like water, soil, and vegetation.
Generative (model)	A type of ML model that attempts to characterise how the observed data are generated. If successful, the model can generate novel instances of similar data, like rivers that do not actually exist.
Ground sensor	A sensor installed on the ground.
Ground truth (data)	The part of the dataset that is compared against the predictions of a ML model to assess its predictive ability. Typically such data are provided by human annotators and subject matter experts. Not to be confused with **ground**-based data.
Hyperspectral	Similar to **multispectral** imagery, but each pixel is described by tens or hundreds of **bands**.
Ill-posed / ill-conditioned	A characterization of mathematical problems referring to their difficulty due to not having enough input data to constrain the space of solutions to a useful degree. All ML problems are inherently ill-posed because they involve the inference of unknown quantities (locations, pixel values, etc) from noisy data. Such quantities cannot be verified with complete certainty, otherwise ML would not be required.
Image translation	A type of ML task that changes the properties and look of an image. This can be a low-level change of the signal properties, like a radiometric calibration for harmonising two sensors; or a higher level change of the image semantics, like cloud removal.
In situ (data)	The opposite of remotely sensed data, when a sensor is physically connected to the observed object. In continual monitoring, a sensor might be transmitting measurements in real-time, like the water-level at a perennial (always flowing) part of a river; or the soil moisture in the middle of an agricultural field. Non-real time in-situ data come from occasional or regular ground surveys.

Interferometry	The use of overlapping EM waves and the interference between them, as a way to measure properties of remote objects, like distance or movement.
Labels (data)	Another term for **ground truth** and **annotations**. They can be used interchangeably.
Land cover (data)	Land classification scheme with respect to the surface physical material. Examples: water, wetland, forest, grassland, shrubland, barren land, farmland, tundra, snow / ice.
Land use (data)	Land classification scheme with respect to human use, e.g. agricultural, urban, industrial.
Laser	Light in which all pulses are synced in phase (**coherent**).
Layer (DL)	A module of a neural network which applies many **linear** functions independently to its input, each with a separate output. Also, a nonlinear function is often applied to further constrain the outputs to a desired range of values, like from 0 to 1, or to non-negative values.
Learning (ML)	The fitting of a statistical model's parameters to data, by means of a mathematical *criterion* that a) specifies the learned task, like precipitation forecasting; and b) instruments the progress of learning, like the error between the forecasted and **ground-truth** values. For example: A regressor that forecasts precipitation, and a classifier that indicates flooding, are both fit by minimising a discrepancy between their predictions and the **ground-truth** target values.
Light	Colloquially referring to electromagnetic radiation of all wavelengths. These include (from longer to shorter wavelengths): radio, microwaves, infrared, visible, UV, X rays, gamma rays.
Linear function	A mathematical function of the form $y = w \cdot x + b$ that describes a linear relationship between x and y, with w and b as the slope and vertical offset of the line, respectively. Such functions are fast to compute (even faster on GPUs) and can be easily interpreted by humans. For this reason, linear functions form the basis of most ML models—from **linear regression** to **neural nets**.
Linear regression	A statistical model that **learns** a **linear function** to model the relationship of two quantities. The model **parameters** (w and b) are **learned** from data. However, linear functions are limited in the complexity of **features** that they can learn from data. Therefore, neural **layers** often further apply a nonlinear function to allow for more complex (non-linear) **features** to be learned by the model.
Machine learning	An approach to AI by learning correlations from data, and extrapolating them to new unseen data. Recent breakthroughs in ML are so often discussed as AI breakthroughs that the terms are seemingly synonymous. Strictly speaking, **ML** is a subfield of **AI**, but we use them interchangeably.
Multispectral	A type of **optical** data where each pixel has a reflectance value per **band**, typically for 3-12 bands.
Neural net	A modular composition of simple neural **layers** that together form more complex mathematical functions than that of a single neural layer. Large neural nets contain hundreds of layers, each with hundreds of features. As a result, modern deep learning models contain between several thousand to billions of **parameters**, depending on the application.
Off-nadir angle	The angle between the nadir (direction beneath the satellite) and the direction of view.
Optical (sensor)	A type of light sensor operating on the visible and near-visible part of the spectrum.
Orbital (sensor)	A satellite sensor, flying at an altitude ranging from hundreds (LEO) to thousands of km (MEO, GEO).
Panchromatic (band)	An interval in the **EM** spectrum encompassing all visible light wavelengths. Wider bands capture more light per unit area, so images in the **PAN** band come naturally in higher spatial resolution, usually by an order of magnitude. On the other hand, equally bright objects that look distinct in **RGB**, do not look distinct in PAN. In this sense, some material properties become harder to resolve in a PAN band..
Pansharpening	An enhancement of **optical** products that combines the higher spatial resolution of a **PAN** band, with the higher spectral information of **RGB** bands. This results in pansharpened RGB bands.
Parameter (ML)	A degree of freedom in a statistical model, typically **learned** automatically from data. See also, **linear**.
Passive (sensor)	A sensor, typically **optical**, that detects **EM** pulses from external sources. See also, **active**.
Phase	A wave property that signifies the fraction of a full oscillation. As such, it can describe the relative shift between two waves in the direction of travel.
Point cloud (data)	A dataset of coordinates in 3D space, each recording the origin of a **backscattered** pulse. Knowing the speed of light, a high-precision clock can convert the return time to a distance at the meter scale.
Polarisation	The orientation of the oscillation plane of the wave with respect to an observer facing the direction of travel of the wave. One of many applications with SAR sensors is to infer tree density in a forest.
Polarimetry	The use of the **polarisation** of an EM wave to infer properties of the observed surface, such as structure, orientation and environmental conditions around the surface.
Product (data)	A compilation of digital signals generated by a sensor. The data product makes sense only in the context of its specification: the physical units of measure, pre-processing levels, metadata.
Radar	A type of sensor that uses radio waves to measure distances (ranging), angles, velocities of objects.
Radiance (spectral)	The power (energy per second) per unit area per unit frequency of an EM wave.
Recurrent (layer)	A neural net **layer** found in **RNN architectures**, whose output is fed back to its input for many timesteps, and that allows them to retain a memory of common patterns in the sequential data. For example, a recurrent layer trained on crop yield time-series activating at the end of a harvest cycle.

Remote sensing	The engineering field of **sensors**, their data processing, and the subsequent inference of properties of remote objects. On the Earth, sensors can be **ground-based**, **aerial** or **orbital**. In astronomy, objects of interest include (in order of proximity) the Sun, planets, stars, exoplanets, supernovae, gravitational waves, black holes, galaxies, the Cosmic Microwave Background.
Return time	The time it takes for a light pulse to travel to the receiver (**backscatter**) after being reflected from a surface. Useful for measuring the distance to an object.
Revisit (satellite)	The acquisition of multiple images from the same geolocation during different flybys of the satellite.
Semantic Segmentation	An ML task in which each pixel of an image is **classified** into one of many categorical variables, such as belonging to a building or not (building footprint segmentation).
Sensor	A device designed to measure a physical quantity, like temperature.
Spectrum	The continuum of wavelengths (and reciprocally, frequencies) of **EM** waves. The wavelengths that we can meaningfully observe range from 10^{-12} meters (smaller than an atom) to 100 km.
Specular reflection	A mirror reflection of an **EM** wave (with respect to the surface normal).
Super-resolution	The problem of enhancing the spatial resolution of an image.
Wavelength	The distance of a full oscillation of an EM wave. It equals the speed of light divided by its frequency.

Appendix B Related Standards and Principles

Related standards for AI and ML.

ISO

1) ISO/IEC 23053 Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)

OGC

1) OGC 23-008r3 OGC Training Data Markup Language for Artificial Intelligence (TrainingDML-AI) Part 1: Conceptual Model Standard

ESIP

1) ESIP Data Readiness Cluster(https://github.com/ESIPFed/data-readiness)

Appendix C. Templates for use case

The following is a general template. It should be noted that it might need updates, additions etc., depending on the use case in hand. For example in the case of transfer learning flow might need to be adjusted accordingly.

Note: Following template is summarized from the ITU Data report[153]. This report needs to be included in the references.

Use case Example:

A - General Definitions:

Item	**description**	**example**
Application Area	Subject	wildfires
Goal	Expected outcomes, output format etc	Burn area classification, Active fire detection, Cloud detection
Method	Main point	Image Segmentation
Scope	Problem statement and project scope	
Input	-	-
Input Data Sets		LandSat 8,9
Data Governance and Compliance	Governance of compliance requirements specific to your CEOS Agency	Term of use for input dataset.
Output	-	-
Output		2 raster segmented Images
Data Governance and Compliance	Governance of compliance requirements specific to	Term of use for output.

	your CEOS Agency	
Verification	-	-
Verification Data sets		CAL Fire https://www.fire.ca.gov/incidents
Data Governance and Compliance	Governance of compliance requirements specific to your CEOS Agency	Term of use for output.
Data collection processes		Data is collected from USGS (Method) Automated
Version Control	Track different versions of datasets and ensure that models are trained on specific dataset versions.	
Lineage Information	How data is transformed, aggregated, or derived to identify potential sources of errors or bias in the models.	
Infrastructure	Required infrastructure and cloud platform for running models	AWS, Azure, GCP
Environment Management	Software dependencies and libraries needed for model training and deployment	PyTorch, conda,
Monitoring	Key performance metrics to monitor model performance in production.	
Logging	logging practices to capture relevant information for debugging and analysis.	
Security and Privacy	Measures ensuring the confidentiality, integrity, and availability of data in the ML lifecycle, including data encryption, access control, anonymization, and secure storage.	· Input and output datasets are encrypted in transit and at rest using TLS and AES-256. · Role-based access control (RBAC) enforced for

		sensitive satellite imagery. · Personally identifiable information (PII) is anonymized or excluded. · Compliance with GDPR or other regional data protection regulations.
Documentation	Refer the document and doi.	https://doi.org/xxxxxx

B- MLOps related definitions / sections:

Item	**Description**	**Example**
Data Collection	Define data collection processes and data schema.	LandSat data used from cloud
Data Indexing	Create an index or catalog of the available data, describing each dataset's metadata, schema, and data lineage.	Date and time of data point added for time series analysis
Data Labeling	If there is any labeling describe the labeling methods (strategies for manual or automated data labeling).	Semi automated texture analysis
Data preprocessing	Define and automate data preprocessing steps, such as normalization, scaling, handling missing values, and outlier detection.	On the fly data normalization, band resolution adjustment SW channel 60 meter resolution, NIR 30 meter resolution.
Feature engineering	Describe how relevant features from raw data are retrieved in the automated process. Explain if scalability and reproducibility are considered in the flow.	Different channels used for different purposes. For Example, blue channel used for cloud detection for quality control, NIR, SW1 combination for burned area and fire detection.
Data Verification	Verify if data usable by the rest of the process	Automatic data verification: e.g, 70% cloud detected; stop process
Data Splitting	How data is divided into training, validation, and testing sets. Split ratios?	20/80 percent testing/training, 5 fold

Agriculture

Estimated paddy rice planted area

A - General Definitions:

Item	description
Application Area	Estimated paddy rice planted area
Goal	Rice acreage is estimated from satellite data in July, before the USDA (U.S. Department of Agriculture) releases its rice acreage for the year in October.
Method	Machine Learning(RandomForest)
Scope	Cooperative research with private companies
Input	-
Input Data Sets	ALOS-2 PALSAR-2 HH, HV
Data Governance and Compliance	
Output	-
Output	Estimated image of paddy rice cropping area
Data Governance and Compliance	
Verification	-
Verification Data sets	USDA CDL(Cropland Data Layer) https://www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php
Data Governance and Compliance	
Data collection processes	Data is collected by Python Program
Version Control	N/A
Lineage Information	N/A

Infrastructure	on-premise、Python (Tensorflow, Keras, scikit-learn)
Environment Management	
Monitoring	
Logging	
Security and Privacy	
Documentation	

B- MLOps related definitions / sections:

Item	**Description**
Data Collection	ALOS-2 data used from JAXA AUIG2
Data Indexing	Date and time of data point added for time series analysis
Data Labeling	automated by Python Program
Data preprocessing	Speckle noise reduction by MedianFilter Normalized to 25m => 30m resolution to match resolution with training data
Feature engineering	Creation of training data for drought
Data Verification	N/A
Data Splitting	50/50 percent testing/training,

Climate

Sea ice-covered area

A - General Definitions:

Item	**description**
Application Area	Sea ice-covered area
Goal	Thin ice thickness of <20 cm is estimated from AMSR2 L1B data.
Method	Machine Learning (CNN)
Scope	
Input	
Input Data Sets	AMSR2 Horizontal and vertical polarized brightness temperatures at 19, 23, 36 and 89 GHz
Data Governance and Compliance	
Output	
Output	Estimated thin ice thickness
Data Governance and Compliance	
Verification	
Verification Data sets	Thin ice thickness calculated from MODIS data. (2.5 km)
Data Governance and Compliance	
Data collection processes	Data is collected by Python Program
Version Control	N/A
Lineage Information	N/A
Infrastructure	on-premise、Python (Tensorflow, Keras, scikit-learn)
Environment Management	
Monitoring	
Logging	
Security and Privacy	

Documentation	

B- MLOps related definitions / sections:

Item	Description
Data Collection	AMSR2 data in JAXA G-portal.
Data Indexing	Horizontal and vertical polarized brightness temperatures at 19, 23, 36 and 89 GHz, their polarization and gradient ratios, and thin ice thickness.
Data Labeling	For the MODIS thin ice thickness dataset, cloud-covered pixels are manually excluded by using QGIS.
Data preprocessing	Detected sea-ice area using AMSR-E sea ice concentration data. Applied a resolution enhancement method.
Feature engineering	Calculated polarization and gradient ratios.
Data Verification	
Data Splitting	30/70 percent testing/training

Marine monitoring

Monitoring for oil slick in coastal seas

A - General Definitions:

Item	description
Application Area	Monitoring coastal waters for oil slick occurrence

Goal	Detection of oil slicks within the Exclusive Economic Zone (EEZ) from satellite data, providing either warning of a developing spill event or long-term monitoring to assess trends in smaller spill occurrence.
Method	Machine Learning (Random Forest, multi-layer perceptron)
Scope	Service co-development with national marine pollution monitoring entities
Input	-
Input Data Sets	Sentinel-1, Capella Space VV
Data Governance and Compliance	
Output	-
Output	Estimated oil slick location and area within each scene
Data Governance and Compliance	
Verification	-
Verification Data sets	Publications, SkyTruth, USCG National Response Center
Data Governance and Compliance	
Data collection processes	Data is provided by Copernicus and processed in python
Version Control	N/A
Lineage Information	N/A
Infrastructure	On-premise HPC, python (scikit-learn), java (WEKA)
Environment Management	Singularity, conda

Monitoring	
Logging	
Security and Privacy	
Documentation	

B - MLOps related definitions / sections:

Item	Description
Data Collection	Sentinel-1A/B data, VV channel Capella Space constellation data, VV mode
Data Indexing	Acquisition date and time stamp
Data Labelling	
Data preprocessing	Speckle noise reduction, pixel spatial resolution reduction (Capella) mask land area Produce candidate objects with dark object clustering
Feature engineering	Creation of training data for oil slick detection
Data Verification	N/A
Data Splitting	50/50 percent testing/training

Coastal and transitional water quality

A - General Definitions:

Item	description
Application Area	Nearshore and transitional water quality indicator parameters

Goal	Provide regional high quality monitoring data from satellite on chlorophyll-a (indicator of algal activity) and total suspended matter (indicator of sedimentation in the water)
Method	Machine Learning (fuzzy c-mean clustering)
Scope	Cooperative research with regional transitional water system (deltas, estuaries, lagoons, etc) research experts and monitoring entities
Input	-
Input Data Sets	Sentinel-2, Sentinel-3
Data Governance and Compliance	
Output	-
Output	Improved estimation of chlorophyll-a and total suspended matter for brackish water systems
Data Governance and Compliance	
Verification	-
Verification Data sets	In-situ samples collected by field teams or installed sensors on buoys, bridges, etc.
Data Governance and Compliance	
Data collection processes	Data is provided by Copernicus and processed in python
Version Control	yes
Lineage Information	N/A
Infrastructure	Either on-premise or cloud HPC, python (scikit-learn, xarray)
Environment Management	Singularity, cylc rose-suite, conda

Monitoring	
Logging	
Security and Privacy	
Documentation	

B- MLOps related definitions / sections:

Item	**Description**
Data Collection	Sentinel-2A/B, Sentinel-3A/B
Data Indexing	Acquisition date and time stamp
Data Labeling	
Data preprocessing	Atmospheric correction with POLYMER or blended POLYER/ACOLITE
Feature engineering	Data normalization using log and PCA Pan-regional cluster creation built sequentially from separate regional analyses over six European transitional water systems
Data Verification	Comparison with in-situ field data
Data Splitting	40/60 percent testing/training where water quality indicator candidate algorithms are recalibrated per fuzzy clustering Optical Water Type (OWT) class

Weather

A - General Definitions:

Item	**description**
Application Area	Precipitation data

Goal	Bias correction of precipitation data from numerical weather prediction (MSM/GPV) by JMA in Japan
Method	Support vector machine (SVM) regression with quantile-based bias correction (Yin et al., 2022)
Scope	For the use in hydrological prediction by Today's Earth – Japan
Input	
Input Data Sets	Radar-AMeDAS precipitation data by JMA MSM/GPV precipitation data by JMA
Data Governance and Compliance	
Output	
Output	Bias corrected precipitation data
Data Governance and Compliance	
Verification	
Verification Data sets	Radar-AMeDAS precipitation data by JMA
Data Governance and Compliance	
Data collection processes	
Version Control	Classifier used for bias correction is updated approximately once in a year
Lineage Information	Classifier used for bias correction is updated approximately once in a year
Infrastructure	on-premise, SciKit-Learn, Python
Environment Management	
Monitoring	
Logging	
Security and Privacy	
Documentation	

B- MLOps related definitions / sections:

Item	**Description**
Data Collection	Radar-AMeDAS & MSM/GPV precipitation data from JMA
Data Indexing	Date and time, lat/lon
Data Labeling	Automated by Python Program
Data preprocessing	Divided into 5 regions to process in parallel.
Feature engineering	Bias correction with downscaling
Data Verification	
Data Splitting	2007-2019 data for training, 2020 data for testing

Disasters

A - General Definitions:

Item	**description**
Application Area	Flood extent mapping at global scale
Goal	the goal of FloodML algorithm is to detect flood extent at global scale from EO satellite data (optical and SAR data)
Method	Random Forest algorithm trained on Copernicus EMSR past flood event cases, using samples for training and validation defined as areas having >90% water occurrence.
Scope	For the use on operational flood crisis management
Input	Date of flood event

	ROI preprocessed optical and SAR data
Input Data Sets	EO SAR data : Sentinel-1 and TerraSAR-X EO optical data : Sentinel-2, Landsat 8&9 DEM : MERIT or COPDEM GLO-30 DEM for SAR Data ESA World Cover for land classification
Data Governance and Compliance	Term of use for input dataset.
Output	binary flood extent maps flood flood extent maps with 8 levels of flooded surface classification
Output	2 rasters (.tiff)
Data Governance and Compliance	Term of use for output dataset.
Verification	
Verification Data sets	flood sites and events from Copernicus EMSR datasets (https://mapping.emergency.copernicus.eu/)
Data Governance and Compliance	
Data collection processes	All data produced is accessible in the open hydrological platform https://hydroweb.next.theia-land.fr/
Version Control	v1.1 (cf. open-source FloodML algorithm https://github.com/CNES/floodml developed by CNES and CLS group)
Lineage Information	
Infrastructure	Python, conda
Environment Management	
Monitoring	
Logging	to access product using the open

	hydrological platform https://hydroweb.next.theia-land.fr/
Security and Privacy	
Documentation	open-source FloodML algorithm https://github.com/CNES/floodml developed by CNES and CLS group DOI : 10.5281/zenodo.16565154

B- MLOps related definitions / sections:

Item	**Description**
Data Collection	Sentinel-1&2, Landsat 8&9, TerraSAR-X
Data Indexing	Date and time, lat/lon
Data Labeling	The reference data is sourced from the labeled flood extent provided by the Copernicus Emergency Management Service (EMS) Rapid Mapping
Data preprocessing	Data preprocessing on Sentinel-2 L2A Data preprocessing on Sentinel-1 using S1tiling (https://github.com/CNES/S1Tiling)
Feature engineering	
Data Verification	
Data Splitting	data splitting for training, validation and test datasets

Appendix D. AI Ready data checklist

Legends

Color	Compatibility
White	I can find compatibility with CEOS ARD requirements.
Green	I can’t find a definite requirement, but I think it is compatible with other conditions and backgrounds.
Yellow	I can find compatibility, but it is “desired”(not minimum requirement).
Orange	I can’t find requirements, but I think data providers might show related information to support users' estimates.
Red	I can’t find descriptions from CEOS ARD requirements.

Aquatic Reflectance (Optical)

Data Preparation

Have null values/gaps been filled?	Requirements ->Per-Pixel Metadata 2.2 No Data Pixels that do not correspond to an observation (e.g., ‘empty pixels/invalid observation/below noise floor’) are flagged.
Have outliers been identified?	I couldn't find the description about range for values in CEOS ARD.
Is the data single-source or aggregated from several sources?	Requirements ->General Metadata 1.2 Metadata Machine Readability Metadata is provided in a structure that enables a computer algorithm to be used to consistently and automatically identify and extract each component part for further use.
Has the data been gridded (regularized in space and time) or is it in the originally sampled resolution?	Requirements ->General Metadata 1.3 Data Collection Time 1.6 Map Projection 1.7 Geometric Correction Methods 1.8 Geometric Accuracy of the Data Probably, ARD satisfies the requirements by those requirements

Have targets been identified and labeled (i.e. can this be used as a training dataset for supervised learning techniques)?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.

Data Quality

Have measures been taken to ensure completeness?	Requirements ->Per-Pixel Metadata 2.3 Incomplete Testing The metadata identifies pixels for which the per-pixel tests (below) have not all been successfully completed. Note 1: This may be the result of missing ancillary data for a subset of the pixels.
Are there automated processes to monitor consistency?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, including the versions of software used, giving full transparency to the users.

Have measures been taken to reduce bias?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.
What is the timeliness of the data? (Near real-time,1 week, 1 month, 1 year, more than 1 year)	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Is there a difference between raw near real-time access vs fully quality-controlled data that has an additional delay?	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Are there quantitative measures of uncertainty?	Requirements ->General Metadata 1.17 Overall Data Quality Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land and over water affected by non-target phenomena, e.g., cloud and cloud shadows.

Is there quantitative information about data resolution in space and time?	Requirements ->General Metadata 1.8 Geometric Accuracy of the Data. (desired) The metadata includes metrics describing the assessed geodetic accuracy of the data, expressed units of the coordinate system of the data. Accuracy is assessed by independent verification (as well as internal model-fit where applicable). Uncertainties are expressed quantitatively, for example, as root mean square error (RMSE) or Circular Error Probability (CEP90, CEP95), etc. Note 1: Information on geometric accuracy of the data should be available in the metadata as a single DOI landing page. 1.12 Radiometric Accuracy (desired) The metadata includes metrics describing the assessed absolute radiometric uncertainty of the version of the data or product, expressed as absolute radiometric uncertainty relative to appropriate, known reference sites and standards (for example, pseudo-invariant calibration sites, rigorously collected field spectra, PICS, Rayleigh, DCC, etc.) Note 1: Information on radiometric accuracy should be available in the metadata as a single DOI landing page.

Are there published data quality procedures or reports? (Link to reports)	Requirements ->General Metadata 1.17 Overall Data Quality Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land and over water affected by non-target phenomena, e.g., cloud and cloud shadows.
Is the provenance tracked and documented?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, including the versions of software used, giving full transparency to the users.
Are there checksums / other checks for data integrity?	I can't find this requirement in CEOS ARD.
How big is the dataset? Depending on the resource, this might be total data volume, dimensionality, number of images, data files, table rows, image size, etc.	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Is this essentially raw data or a derived/processed data product?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is this observational data or simulation/model output?	ALL of the CEOS ARD may be the observational data.
Has the data been peer-reviewed?	Requirements ->General Metadata 1.13 Algorithms (desired) As threshold, but only algorithms that have been published in a peer-reviewed journal. Note 1: It is possible that high-quality corrections are applied through non-disclosed processes. CARD4L does not per-se require full and open data and methods. Note 2: Information on algorithms should be available in the metadata as a single DOI landing page.
Has it been down-sampled to reduce resolution, or is it raw? If so, are the raw data available?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Data Documentation

Does the dataset have metadata?	Requirements ->General Metadata Requirements ->Per-Pixel Metadata
Is the dataset metadata standardized?	by CEOS ARD
Is the dataset metadata machine-readable?	Requirements ->General Metadata 1.2 Metadata Machine Readability
Does it include details on the spatial and temporal extent?	Requirements ->General Metadata 1.3 Data Collection Time The data collection time is identified in the metadata, expressed in date/time, to the second, with the time offset from UTC unambiguously identified. 1.4 Geographical Area The surface location to which the data relates is identified, typically as a series of four corner points, expressed in an accepted coordinate reference system (e.g., WGS84).
Is there a comprehensive data dictionary/codebook to describe parameters?	I can't find this requirement in CEOS ARD. But there is the requirement for Traceability and it includes DOI/LP. It will be described information about data.
Is the data dictionary standardized?	I can't find this requirement in CEOS ARD, and I don't know the standard for DOI/LP.

Is the data dictionary machine-readable?	I can't find this requirement in CEOS ARD, and I don't know the machine readable standard.
Do the parameters follow a defined standard?	I can't find this requirement in CEOS ARD.
Are parameters crosswalked in an ontology or common vocabulary (e.g. NIEM)?	I can't find this requirement in CEOS ARD.
Does the dataset have a unique persistent identifier,e.g. DOI?	Requirements ->General Metadata 1.1 Traceability
Is there contact information for subject-matter experts?	I couldn't find this requirement at CEOS ARD, but CEOS ARD defines about Metadata such like ISO-19115 and it includes point of contact.
Is there a mechanism for user feedback and suggestions?	I can't find this requirement in CEOS ARD.
Are there example codes / notebooks / toolkits available showing how the data can be used?	I can't find this requirement in CEOS ARD.
Is there a clear data license?	I can't find this requirement in CEOS ARD.
Is the license standardized and machine-readable (e.g. Creative	I can't find this requirement in CEOS ARD.

Commons)?	
Has this dataset already been used in AI or ML activities? Link to publications / reports.	I can't find this requirement in CEOS ARD.
Are there recommendations on the intended use of the data, and uses that are not recommended?	I can't find this requirement in CEOS ARD.

Data Access

What is the file format?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is it machine-readable?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.

Is it available in at least one open, non-proprietary format?	ALL of the CEOS ARD may be the open, non-proprietary format such like geotiff, hdf5 https://ceos.org/ard/
Is it available in several different file formats?	I can't find this requirement in CEOS ARD.
Data delivery:	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Direct file download or ordering?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Is there an API?	I can't find this requirement in CEOS ARD.
Custom-developed or open, standard protocol?	I can't find this requirement in CEOS ARD.

For restricted data, have measures been taken to provide some access while still applying appropriate protection for privacy and security?	I can't find this requirement in CEOS ARD.
Has the data been aggregated to reduce granularity?	I can't find this requirement in CEOS ARD.
Has the data been anonymized / de-identified?	I can't find this requirement in CEOS ARD.
Is there secure access to the full dataset for authorized users?	I can't find this requirement in CEOS ARD.

Nighttime Lights Surface Radiance (Optical)

Data Preparation

Have null values/gaps been filled?	Requirements ->Per-Pixel Metadata 2.2 No Data Pixels that do not correspond to an observation (‘empty pixels’) are flagged.

Have outliers been identified?	I couldn't find the description about range for values in CEOS ARD.
Is the data single-source or aggregated from several sources?	Requirements ->General Metadata 1.2 Metadata Machine Readability Metadata is provided in a structure that enables a computer algorithm to be used consistently and to automatically identify and extract each component part for further use.
Has the data been gridded (regularized in space and time) or is it in the originally sampled resolution?	Requirements ->General Metadata 1.3 Data Collection Time 1.6 Map Projection 1.7 Geometric Correction Methods 1.8 Geometric Accuracy of the Data Probably, ARD satisfies the requirements by those requirements
Have targets been identified and labeled (i.e. can this be used as a training dataset for supervised learning techniques)?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.

Data Quality

Have measures been taken to ensure completeness?	Requirements ->Per-Pixel Metadata 2.3 Incomplete Testing The metadata identifies pixels for which the per-pixel tests (below) have not all been successfully completed. Note 1: This may be the result of missing ancillary data for a subset of the pixels.
Are there automated processes to monitor consistency?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, the organization that performed the processing, and the versions of software used, giving full transparency to the users.
Have measures been taken to reduce bias?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.
What is the timeliness of the data? (Near real-time,1 week, 1 month, 1 year, more than 1 year)	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Is there a difference between raw near real-time access vs fully quality-controlled data that has an	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.

additional delay?	
Are there quantitative measures of uncertainty?	Requirements ->General Metadata 1.17 Overall Data Quality (desired) Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land (c.f. ocean) affected by non-target phenomena, e.g., cloud and cloud shadows

Is there quantitative information about data resolution in space and time?	Requirements ->General Metadata 1.8 Geometric Accuracy of the Data. (desired) The metadata includes metrics describing the assessed geodetic accuracy of the data, expressed units of the coordinate system of the data. Accuracy is assessed by independent verification (as well as internal model-fit where applicable). Uncertainties are expressed quantitatively, for example, as root mean square error (RMSE) or Circular Error Probability (CEP90, CEP95), etc. Note 1: Information on geometric accuracy of the data should be available in the metadata as a single DOI landing page. 1.12 Radiometric Accuracy (desired) The metadata includes metrics describing the assessed absolute radiometric uncertainty of the version of the data or product, expressed as absolute radiometric uncertainty relative to appropriate, known reference sites and standards (for example, pseudo-invariant calibration sites, rigorously collected field spectra, Rayleigh, DCC, etc.) Note 1: Information on radiometric accuracy should be available in the metadata as a single DOI landing page.

Are there published data quality procedures or reports? (Link to reports)	Requirements ->General Metadata 1.17 Overall Data Quality (desired) Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land (c.f. ocean) affected by non-target phenomena, e.g., cloud and cloud shadows
Is the provenance tracked and documented?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, the organization that performed the processing, and the versions of software used, giving full transparency to the users.
Are there checksums / other checks for data integrity?	I can't find this requirement in CEOS ARD.
How big is the dataset? Depending on the resource, this might be total data volume, dimensionality, number of images, data files, table rows, image size, etc.	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Is this essentially raw data or a derived/processed data product?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is this observational data or simulation/model output?	ALL of the CEOS ARD may be the observational data.
Has the data been peer-reviewed?	Requirements ->General Metadata 1.13 Algorithms (desired) As threshold, but only algorithms that have been published in a peer-reviewed journal. Note 1: It is possible that high quality corrections are applied through non-disclosed processes. CARD4L does not per-se require full and open data and methods. Note 2: Information on algorithms should be available in the metadata as a single DOI landing page.
Has it been down-sampled to reduce resolution, or is it raw? If so, are the raw data available?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Data Documentation

Does the dataset have metadata?	Requirements ->General Metadata Requirements ->Per-Pixel Metadata
Is the dataset metadata standardized?	by CEOS ARD
Is the dataset metadata machine-readable?	Requirements ->General Metadata 1.2 Metadata Machine Readability
Does it include details on the spatial and temporal extent?	Requirements ->General Metadata 1.3 Data Collection Time The data collection time is identified in the metadata, expressed in date/time, to the second, with the time offset from UTC unambiguously identified. 1.4 Geographical Area The surface location to which the data relates is identified, typically as a series of four corner points, expressed in an accepted coordinate reference system (e.g., WGS84).
Is there a comprehensive data dictionary/codebook to describe parameters?	I can't find this requirement in CEOS ARD. But there is the requirement for Traceability and it includes DOI/LP. It will be described information about data.
Is the data dictionary standardized?	I can't find this requirement in CEOS ARD, and I don't know the standard for DOI/LP.

Is the data dictionary machine-readable?	I can't find this requirement in CEOS ARD, and I don't know the machine readable standard.
Do the parameters follow a defined standard?	I can't find this requirement in CEOS ARD.
Are parameters crosswalked in an ontology or common vocabulary (e.g. NIEM)?	I can't find this requirement in CEOS ARD.
Does the dataset have a unique persistent identifier,e.g. DOI?	Requirements ->General Metadata 1.1 Traceability
Is there contact information for subject-matter experts?	I couldn't find this requirement at CEOS ARD, but CEOS ARD defines about Metadata such like ISO-19115 and it includes point of contact.
Is there a mechanism for user feedback and suggestions?	I can't find this requirement in CEOS ARD.
Are there example codes / notebooks / toolkits available showing how the data can be used?	I can't find this requirement in CEOS ARD.
Is there a clear data license?	I can't find this requirement in CEOS ARD.
Is the license standardized and machine-readable (e.g. Creative	I can't find this requirement in CEOS ARD.

Commons)?	
Has this dataset already been used in AI or ML activities? Link to publications / reports.	I can't find this requirement in CEOS ARD.
Are there recommendations on the intended use of the data, and uses that are not recommended?	I can't find this requirement in CEOS ARD.

Data Access

What is the file format?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is it machine-readable?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.

Is it available in at least one open, non-proprietary format?	ALL of the CEOS ARD may be the open, non-proprietary format such like geotiff, hdf5 https://ceos.org/ard/
Is it available in several different file formats?	I can't find this requirement in CEOS ARD.
Data delivery:	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Direct file download or ordering?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Is there an API?	I can't find this requirement in CEOS ARD.
Custom-developed or open, standard protocol?	I can't find this requirement in CEOS ARD.

For restricted data, have measures been taken to provide some access while still applying appropriate protection for privacy and security?	I can't find this requirement in CEOS ARD.
Has the data been aggregated to reduce granularity?	I can't find this requirement in CEOS ARD.
Has the data been anonymized / de-identified?	I can't find this requirement in CEOS ARD.
Is there secure access to the full dataset for authorized users?	I can't find this requirement in CEOS ARD.

Surface Reflectance (Optical)

Data Preparation

Have null values/gaps been filled?	Requirements ->Per-Pixel Metadata 2.2 No Data Pixels that do not correspond to an observation (‘empty pixels’) are flagged.

Have outliers been identified?	I couldn't find the description about range for values in CEOS ARD.
Is the data single-source or aggregated from several sources?	Requirements ->General Metadata 1.2 Metadata Machine Readability Metadata is provided in a structure that enables a computer algorithm to be used consistently and to automatically identify and extract each component part for further use
Has the data been gridded (regularized in space and time) or is it in the originally sampled resolution?	Requirements ->General Metadata 1.3 Data Collection Time 1.6 Map Projection 1.7 Geometric Correction Methods 1.8 Geometric Accuracy of the Data Probably, ARD satisfies the requirements by those requirements
Have targets been identified and labeled (i.e. can this be used as a training dataset for supervised learning techniques)?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.

Data Quality

Have measures been taken to ensure completeness?	Requirements ->Per-Pixel Metadata 2.3 Incomplete Testing The metadata identifies pixels for which the per-pixel tests (below) have not all been successfully completed. Note 1: This may be the result of missing ancillary data for a subset of the pixels.
Are there automated processes to monitor consistency?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, including the versions of software used, giving full transparency to the users.
Have measures been taken to reduce bias?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.
What is the timeliness of the data? (Near real-time,1 week, 1 month, 1 year, more than 1 year)	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Is there a difference between raw near real-time access vs fully quality-controlled data that has an	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.

additional delay?	
Are there quantitative measures of uncertainty?	Requirements ->General Metadata 1.17 Overall Data Quality (desired) Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land (c.f. ocean) affected by non-target phenomena, e.g., cloud and cloud shadows

Is there quantitative information about data resolution in space and time?	Requirements ->General Metadata 1.8 Geometric Accuracy of the Data. (desired) The metadata includes metrics describing the assessed geodetic accuracy of the data, expressed units of the coordinate system of the data. Accuracy is assessed by independent verification (as well as internal model-fit where applicable). Uncertainties are expressed quantitatively, for example, as root mean square error (RMSE) or Circular Error Probability (CEP90, CEP95), etc. Note 1: Information on geometric accuracy of the data should be available in the metadata as a single DOI landing page. 1.12 Radiometric Accuracy (desired) The metadata includes metrics describing the assessed absolute radiometric uncertainty of the version of the data or product, expressed as absolute radiometric uncertainty relative to appropriate, known reference sites and standards (for example, pseudo-invariant calibration sites, rigorously collected field spectra, PICS, Rayleigh, DCC, etc.) Note 1: Information on radiometric accuracy should be available in the metadata as a single DOI landing page.

Are there published data quality procedures or reports? (Link to reports)	Requirements ->General Metadata 1.17 Overall Data Quality (desired) Machine-readable metrics describing the overall quality of the data are included in the metadata, at minimum the cloud cover extent, i.e.: - Proportion of observations over land (c.f. ocean) affected by non-target phenomena, e.g., cloud and cloud shadows
Is the provenance tracked and documented?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing detailed description of the processing steps used to generate the product, including the versions of software used, giving full transparency to the users.
Are there checksums / other checks for data integrity?	I can't find this requirement in CEOS ARD.
How big is the dataset? Depending on the resource, this might be total data volume, dimensionality, number of images, data files, table rows, image size, etc.	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Is this essentially raw data or a derived/processed data product?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is this observational data or simulation/model output?	ALL of the CEOS ARD may be the observational data.
Has the data been peer-reviewed?	Requirements ->General Metadata 1.13 Algorithms (desired) As threshold, but only algorithms that have been published in a peer-reviewed journal. Note 1: It is possible that high quality corrections are applied through non-disclosed processes. CEOS-ARD does not per-se require full and open data and methods. Note 2: Information on algorithms should be available in the metadata as a single DOI landing page.
Has it been down-sampled to reduce resolution, or is it raw? If so, are the raw data available?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Data Documentation

Does the dataset have metadata?	Requirements ->General Metadata Requirements ->Per-Pixel Metadata
Is the dataset metadata standardized?	by CEOS ARD
Is the dataset metadata machine-readable?	Requirements ->General Metadata 1.2 Metadata Machine Readability
Does it include details on the spatial and temporal extent?	Requirements ->General Metadata 1.3 Data Collection Time The data collection time is identified in the metadata, expressed in date/time, to the second, with the time offset from UTC unambiguously identified. 1.4 Geographical Area The surface location to which the data relates is identified, typically as a series of four corner points, expressed in an accepted coordinate reference system (e.g., WGS84).
Is there a comprehensive data dictionary/codebook to describe parameters?	I can't find this requirement in CEOS ARD. But there is the requirement for Traceability and it includes DOI/LP. It will be described information about data.
Is the data dictionary standardized?	I can't find this requirement in CEOS ARD, and I don't know the standard for DOI/LP.

Is the data dictionary machine-readable?	I can't find this requirement in CEOS ARD, and I don't know the machine readable standard.
Do the parameters follow a defined standard?	I can't find this requirement in CEOS ARD.
Are parameters crosswalked in an ontology or common vocabulary (e.g. NIEM)?	I can't find this requirement in CEOS ARD.
Does the dataset have a unique persistent identifier,e.g. DOI?	Requirements ->General Metadata 1.1 Traceability
Is there contact information for subject-matter experts?	I couldn't find this requirement at CEOS ARD, but CEOS ARD defines about Metadata such like ISO-19115 and it includes point of contact.
Is there a mechanism for user feedback and suggestions?	I can't find this requirement in CEOS ARD.
Are there example codes / notebooks / toolkits available showing how the data can be used?	I can't find this requirement in CEOS ARD.
Is there a clear data license?	I can't find this requirement in CEOS ARD.
Is the license standardized and machine-readable (e.g. Creative	I can't find this requirement in CEOS ARD.

Commons)?	
Has this dataset already been used in AI or ML activities? Link to publications / reports.	I can't find this requirement in CEOS ARD.
Are there recommendations on the intended use of the data, and uses that are not recommended?	I can't find this requirement in CEOS ARD.

Data Access

What is the file format?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is it machine-readable?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.

Is it available in at least one open, non-proprietary format?	ALL of the CEOS ARD may be the open, non-proprietary format such like geotiff, hdf5 https://ceos.org/ard/
Is it available in several different file formats?	I can't find this requirement in CEOS ARD.
Data delivery:	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Direct file download or ordering?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Is there an API?	I can't find this requirement in CEOS ARD.
Custom-developed or open, standard protocol?	I can't find this requirement in CEOS ARD.

For restricted data, have measures been taken to provide some access while still applying appropriate protection for privacy and security?	I can't find this requirement in CEOS ARD.
Has the data been aggregated to reduce granularity?	I can't find this requirement in CEOS ARD.
Has the data been anonymized / de-identified?	I can't find this requirement in CEOS ARD.
Is there secure access to the full dataset for authorized users?	I can't find this requirement in CEOS ARD.

Surface Temperature (Optical)

Data Preparation

Have null values/gaps been filled?	Requirements ->Per-Pixel Metadata 2.2 No Data Pixels that do not correspond to an observation (‘empty pixels’) are flagged.

Have outliers been identified?	I couldn't find the description about range for values in CEOS ARD.
Is the data single-source or aggregated from several sources?	Requirements ->General Metadata 1.2 Metadata Machine Readability Metadata is provided in a structure that enables a computer algorithm to be used consistently and to automatically identify and extract each component part for further use.
Has the data been gridded (regularized in space and time) or is it in the originally sampled resolution?	Requirements ->General Metadata 1.3 Data Collection Time 1.6 Map Projection 1.7 Geometric Correction Methods 1.8 Geometric Accuracy of the Data Probably, ARD satisfies the requirements by those requirements
Have targets been identified and labeled (i.e. can this be used as a training dataset for supervised learning techniques)?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.

Data Quality

Have measures been taken to ensure completeness?	Requirements ->Per-Pixel Metadata 2.3 Incomplete Testing The metadata identifies pixels for which the per-pixel tests (below) have not all been successfully completed. Note 1: e.g., due to missing ancillary data for some pixels.
Are there automated processes to monitor consistency?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing description of the processing chain used to generate the product, including the versions of the software used and information on the data collection baseline, giving full transparency to the users.
Have measures been taken to reduce bias?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.
What is the timeliness of the data? (Near real-time,1 week, 1 month, 1 year, more than 1 year)	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Is there a difference between raw near real-time access vs fully quality-controlled data that has an	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.

additional delay?	
Are there quantitative measures of uncertainty?	Requirements ->General Metadata 1.17 Overall Data Quality (desired) The metadata includes details of the quality of the product based on quantitative assessment of the product with respect to high quality reference data with full traceability of the uncertainties. Validation and intercomparison statistics can provide the necessary quantification.

Is there quantitative information about data resolution in space and time?	Requirements ->General Metadata 1.8 Geometric Accuracy of the Data. (desired) As threshold, but information on instrument should be available in the metadata as a single DOI landing page with references to the relevant CEOS Missions, Instruments and Measurements Database record. 1.12 Radiometric Accuracy (desired) Information on radiometric accuracy should be available in the metadata as a single DOI landing page providing information on metrics describing the assessed absolute radiometric accuracy of the data, expressed as absolute radiometric uncertainty relative to a known reference standard. Note 1: For example, this may come from comparison with routine and rigorously collected in situ measurements.

Are there published data quality procedures or reports? (Link to reports)	Requirements ->General Metadata 1.17 Overall Data Quality (desired) The metadata includes details of the quality of the product based on quantitative assessment of the product with respect to high quality reference data with full traceability of the uncertainties. Validation and intercomparison statistics can provide the necessary quantification.
Is the provenance tracked and documented?	Requirements ->General Metadata 1.15 Processing Chain Provenance (desired) Information on processing chain provenance should be available in the metadata as a single DOI landing page containing description of the processing chain used to generate the product, including the versions of the software used and information on the data collection baseline, giving full transparency to the users.
Are there checksums / other checks for data integrity?	I can't find this requirement in CEOS ARD.
How big is the dataset? Depending on the resource, this might be total data volume, dimensionality, number of images, data files, table rows, image size, etc.	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Is this essentially raw data or a derived/processed data product?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is this observational data or simulation/model output?	ALL of the CEOS ARD may be the observational data.
Has the data been peer-reviewed?	Requirements ->General Metadata 1.13 Algorithms (desired) As threshold, but only algorithms that have been published in a peer-reviewed journal. Note 1: It is possible that high-quality corrections are applied through non-disclosed processes. CARD4L does not per-se require full and open data and methods. Note 2: Information on algorithms should be available in the metadata as a single DOI landing page.
Has it been down-sampled to reduce resolution, or is it raw? If so, are the raw data available?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Data Documentation

Does the dataset have metadata?	Requirements ->General Metadata Requirements ->Per-Pixel Metadata
Is the dataset metadata standardized?	by CEOS ARD
Is the dataset metadata machine-readable?	Requirements ->General Metadata 1.2 Metadata Machine Readability
Does it include details on the spatial and temporal extent?	Requirements ->General Metadata 1.3 Data Collection Time The start and stop time of data collection is identified in the metadata, expressed in date/time, to the second, with the time offset from UTC unambiguously identified. 1.4 Geographical Area The surface location to which the data relate is identified, typically as a series of four corner points, expressed in an accepted coordinate reference system (e.g., WGS84 coordinates).
Is there a comprehensive data dictionary/codebook to describe parameters?	I can't find this requirement in CEOS ARD. But there is the requirement for Traceability and it includes DOI/LP. It will be described information about data.
Is the data dictionary standardized?	I can't find this requirement in CEOS ARD, and I don't know the standard for DOI/LP.

Is the data dictionary machine-readable?	I can't find this requirement in CEOS ARD, and I don't know the machine readable standard.
Do the parameters follow a defined standard?	I can't find this requirement in CEOS ARD.
Are parameters crosswalked in an ontology or common vocabulary (e.g. NIEM)?	I can't find this requirement in CEOS ARD.
Does the dataset have a unique persistent identifier,e.g. DOI?	Requirements ->General Metadata 1.1 Traceability
Is there contact information for subject-matter experts?	I couldn't find this requirement at CEOS ARD, but CEOS ARD defines about Metadata such like ISO-19115 and it includes point of contact.
Is there a mechanism for user feedback and suggestions?	I can't find this requirement in CEOS ARD.
Are there example codes / notebooks / toolkits available showing how the data can be used?	I can't find this requirement in CEOS ARD.
Is there a clear data license?	I can't find this requirement in CEOS ARD.
Is the license standardized and machine-readable (e.g. Creative	I can't find this requirement in CEOS ARD.

Commons)?	
Has this dataset already been used in AI or ML activities? Link to publications / reports.	I can't find this requirement in CEOS ARD.
Are there recommendations on the intended use of the data, and uses that are not recommended?	I can't find this requirement in CEOS ARD.

Data Access

What is the file format?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is it machine-readable?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.

Is it available in at least one open, non-proprietary format?	ALL of the CEOS ARD may be the open, non-proprietary format such like geotiff, hdf5 https://ceos.org/ard/
Is it available in several different file formats?	I can't find this requirement in CEOS ARD.
Data delivery:	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Direct file download or ordering?	Requirements ->General Metadata 1.16 Data Access Information on data access should be available in the metadata as a single DOI landing page. Note 1: Manual and offline interaction action (e.g., login) may be required.
Is there an API?	I can't find this requirement in CEOS ARD.
Custom-developed or open, standard protocol?	I can't find this requirement in CEOS ARD.

For restricted data, have measures been taken to provide some access while still applying appropriate protection for privacy and security?	I can't find this requirement in CEOS ARD.
Has the data been aggregated to reduce granularity?	I can't find this requirement in CEOS ARD.
Has the data been anonymized / de-identified?	I can't find this requirement in CEOS ARD.
Is there secure access to the full dataset for authorized users?	I can't find this requirement in CEOS ARD.

Synthetic Aperture Radar

Data Preparation

Have null values/gaps been filled?	Requirements ->Per-Pixel Metadata 2.2 Data Mask Image Threshold (Minimum) Requirements Mask image indicating: - Valid data - Invalid data - No data File format specifications/ contents provided in metadata: - Sample Type [Mask] - Data Format [Raw/GeoTIFF/NetCDF, …] - Data Type [Int, ...] - Bits per Sample - Byte Order - Bit Value Representation

Have outliers been identified?	I couldn't find the description about range for values in CEOS ARD.
Is the data single-source or aggregated from several sources?	Requirements ->General Metadata 1.2 Metadata Machine Readability Threshold (Minimum) Requirements Metadata is provided in a structure that enables a computer algorithm to be used consistently and to automatically identify and extract each component part for further use.
Has the data been gridded (regularized in space and time) or is it in the originally sampled resolution?	Requirements ->General Metadata 1.3 Data Collection Time 1.6 Map Projection 1.7 Geometric Correction Methods 1.8 Geometric Accuracy of the Data Probably, ARD satisfies the requirements by those requirements
Have targets been identified and labeled (i.e. can this be used as a training dataset for supervised learning techniques)?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.

Data Quality

Have measures been taken to ensure completeness?	I couldn't find this requirement at CEOS ARD.
Are there automated processes to monitor consistency?	I couldn't find this requirement at CEOS ARD.
Have measures been taken to reduce bias?	This require comes from AI/ML aspect, so CEOS ARD doesn't include this requirement.
What is the timeliness of the data? (Near real-time,1 week, 1 month, 1 year, more than 1 year)	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.
Is there a difference between raw near real-time access vs fully quality-controlled data that has an	I couldn't find this requirement at CEOS ARD, but data provider might show timeliness with dataset.

additional delay?	
Are there quantitative measures of uncertainty?	Requirements ->PerPixel Metadata 2.14 InSAR Phase Uncertainty Image (desired) Estimate of uncertainty in InSAR phase is provided, such as finite signal to noise ratio, quantization noise, or DEM error. Identification of which error sources are included will be provided as DOI/URL reference or brief description. It represents statistical variation from known noise sources only. File format specifications/ contents provided in metadata: - Sample Type [Angle] - Data Format [Raw/GeoTIFF/NetCDF, …] - Data Type [Float, ...] - Bits per Sample - Byte Order

Is there quantitative information about data resolution in space and time?	Requirements ->General Metadata 4.3 Geometric Accuracy of the Data. (desired) Accurate geolocation is a prerequisite to radar processing to correct for terrain and to enable interoperability between radar sensors. The absolute geolocation error (ALE) for a sensor is typically assessed through analysis of Single Look Complex (SLC) imagery and measured along the slant range and azimuth directions (case A: SLC ALE). The end-to-end “ARD” ALE of the final CEOS-ARD product could be measured directly in the final image product in the chosen map projection, i.e., in the map coordinate directions: e.g., Northing and Easting (case B: ARD ALE). Providing accuracy estimates based on measurements following at least one scheme (A or B or both) meets the threshold requirement. Estimates of the ALE is provided as a bias and a standard deviation, with (Case A) SLC ALE expressed in slant range and azimuth, and (Case B) ARD ALE expressed in map projection dimensions. Note 1: This assessment is often made through comparison of measured corner reflector positions with their projected location in the imagery. In some cases, other mission calibration/validation results may be used. Note 2: The ALE is not typically assessed for every processed image, but through an ALE assessment by the data processing team characterizing all or (usually a subset) of the generated products. 3.5 Radiometric Accuracy (desired) Uncertainty (e.g., bounds on γ^0 or σ^0) information is provided as document referenced as URL or DOI. SI traceability is achieved.

Are there published data quality procedures or reports? (Link to reports)	I couldn't find this requirement at CEOS ARD.
Is the provenance tracked and documented?	I couldn't find this requirement at CEOS ARD.
Are there checksums / other checks for data integrity?	I can't find this requirement in CEOS ARD.
How big is the dataset? Depending on the resource, this might be total data volume, dimensionality, number of images, data files, table rows, image size, etc.	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Is this essentially raw data or a derived/processed data product?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is this observational data or simulation/model output?	ALL of the CEOS ARD may be the observational data.
Has the data been peer-reviewed?	Requirements ->PerPixel Metadata 2.15 Atmospheric Phase Correction Image 2.16 Ionospheric Phase Correction Image Radiometrically Corrected Measurements 3.3 Noise Removal 3.4 Radiometric Terrain Correction Algorithm Geometric Corrections 4.1 Geometric Correction Algorithm
Has it been down-sampled to reduce resolution, or is it raw? If so, are the raw data available?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.

Data Documentation

Does the dataset have metadata?	Requirements ->General Metadata Requirements ->Per-Pixel Metadata
Is the dataset metadata standardized?	by CEOS ARD
Is the dataset metadata machine-readable?	Requirements ->General Metadata 1.2 Metadata Machine Readability
Does it include details on the spatial and temporal extent?	Requirements ->General Metadata 1.5 Data Collection Time Number of source data acquisitions of the data collection is identified. The start and stop UTC time of data collection is identified in the metadata, expressed in date/time. In case of composite products, the dates/times of the first and last data takes and the per-pixel metadata 2.8 (Acquisition ID Image) is provided with the product. 1.7.8 Product Geographical Extent The geometry of the SAR image footprint expressed in WGS84, in a standardised format (e.g., WKT Polygon).
Is there a comprehensive data dictionary/codebook to describe parameters?	I can't find this requirement in CEOS ARD. But there is the requirement for Traceability and it includes DOI/LP. It will be described information about data.
Is the data dictionary standardized?	I can't find this requirement in CEOS ARD, and I don't know the standard for DOI/LP.

Is the data dictionary machine-readable?	I can't find this requirement in CEOS ARD, and I don't know the machine readable standard.
Do the parameters follow a defined standard?	I can't find this requirement in CEOS ARD.
Are parameters crosswalked in an ontology or common vocabulary (e.g. NIEM)?	I can't find this requirement in CEOS ARD.
Does the dataset have a unique persistent identifier,e.g. DOI?	Requirements ->General Metadata 1.1 Traceability
Is there contact information for subject-matter experts?	I couldn't find this requirement at CEOS ARD, but CEOS ARD defines about Metadata such like ISO-19115 and it includes point of contact.
Is there a mechanism for user feedback and suggestions?	I can't find this requirement in CEOS ARD.
Are there example codes / notebooks / toolkits available showing how the data can be used?	I can't find this requirement in CEOS ARD.
Is there a clear data license?	I can't find this requirement in CEOS ARD.
Is the license standardized and machine-readable (e.g. Creative	I can't find this requirement in CEOS ARD.

Commons)?	
Has this dataset already been used in AI or ML activities? Link to publications / reports.	I can't find this requirement in CEOS ARD.
Are there recommendations on the intended use of the data, and uses that are not recommended?	I can't find this requirement in CEOS ARD.

Data Access

What is the file format?	I couldn't find this requirement at CEOS ARD, but data provider might show related information to support users can estimate.
Is it machine-readable?	Requirements ->General Metadata 1.7.1 Product Data Access Processing parameters details of the CEOS-ARD product: - Processing facility - Processing date - Software version - Location from where CEOS-ARD product can be retrieved, expressed as a URL or DOI.

Is it available in at least one open, non-proprietary format?	ALL of the CEOS ARD may be the open, non-proprietary format such like geotiff, hdf5 https://ceos.org/ard/
Is it available in several different file formats?	I can't find this requirement in CEOS ARD.
Data delivery:	Requirements ->General Metadata 1.7.1 Product Data Access Processing parameters details of the CEOS-ARD product: - Processing facility - Processing date - Software version - Location from where CEOS-ARD product can be retrieved, expressed as a URL or DOI.
Direct file download or ordering?	Requirements ->General Metadata 1.7.1 Product Data Access Processing parameters details of the CEOS-ARD product: - Processing facility - Processing date - Software version - Location from where CEOS-ARD product can be retrieved, expressed as a URL or DOI.
Is there an API?	I can't find this requirement in CEOS ARD.
Custom-developed or open, standard protocol?	I can't find this requirement in CEOS ARD.

For restricted data, have measures been taken to provide some access while still applying appropriate protection for privacy and security?	I can't find this requirement in CEOS ARD.
Has the data been aggregated to reduce granularity?	I can't find this requirement in CEOS ARD.
Has the data been anonymized / de-identified?	I can't find this requirement in CEOS ARD.
Is there secure access to the full dataset for authorized users?	I can't find this requirement in CEOS ARD.

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