Introducing the AI/ML white paper

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Agenda Item 6.1

WGISS-61

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CEOS
Committee on Earth Observation Satellites

ML/DL/AI White Paper

CEOS ML/DL/AI White Paper
CEOS.WGISS.TEIG Issue 1.0 Dec. 2025

CEOS

Working Group on Information Systems and Services
Technology Exploration Interest Group

CEOS ML/DL/AI White Paper

CEOS Document

[CEOS-MLDLAI-WP-V1.0]

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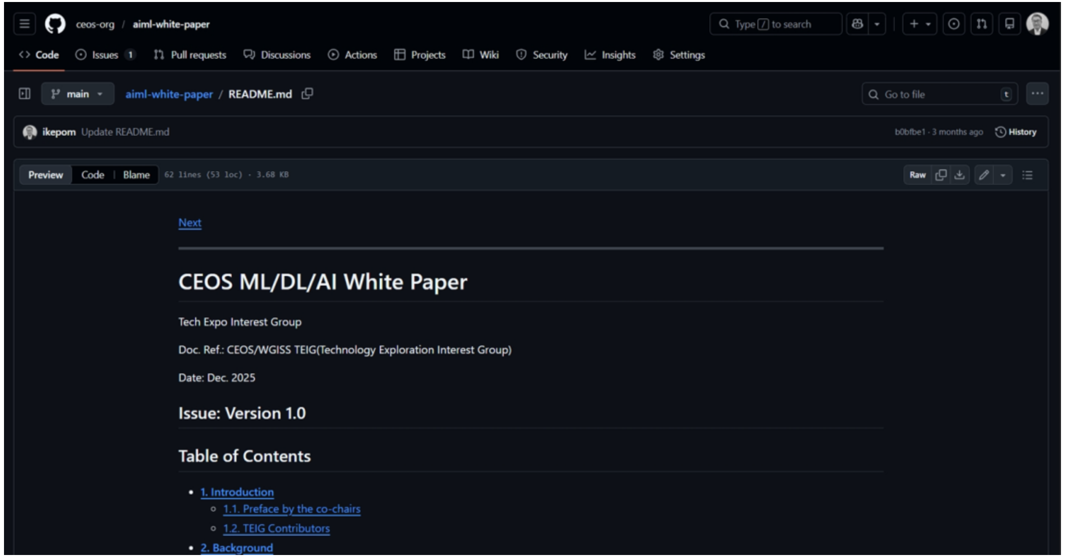
Github site

We use github to keep our documentation up to date.
Please post the “issue”, if you have any comments.

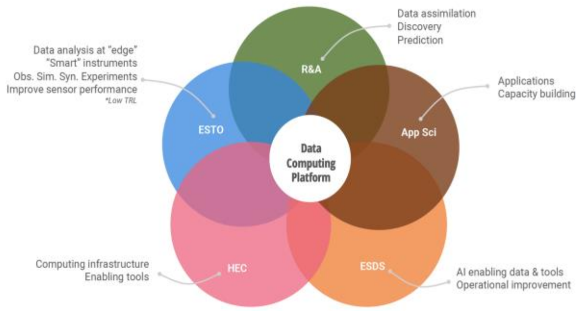


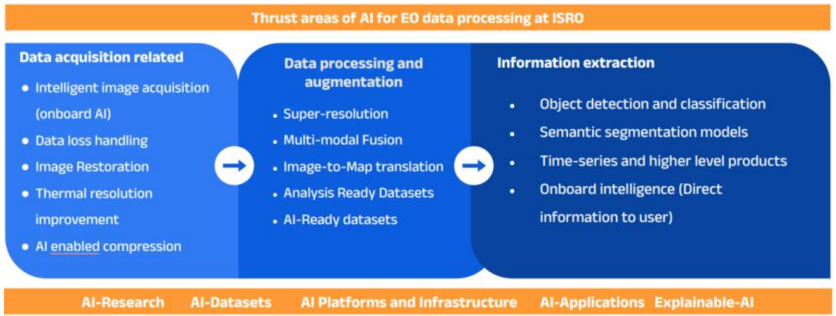
https://github.com/ceos-org/aiml-white-paper/blob/main/README.md

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]						

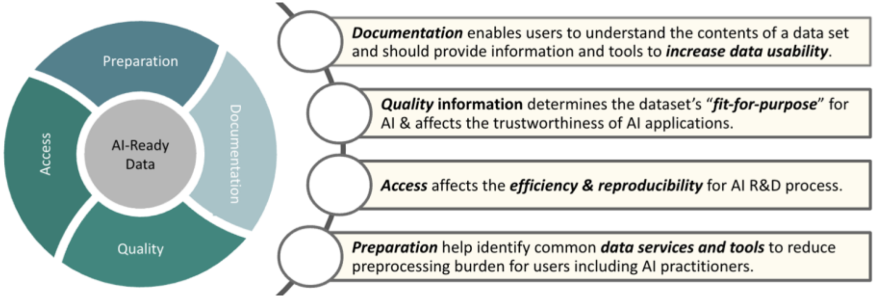
Content modified and adapted with permission from the Satellite Applications Catapult Whitepaper by Kalaitzis et al. (2022) : State of AI for Earth Observation.

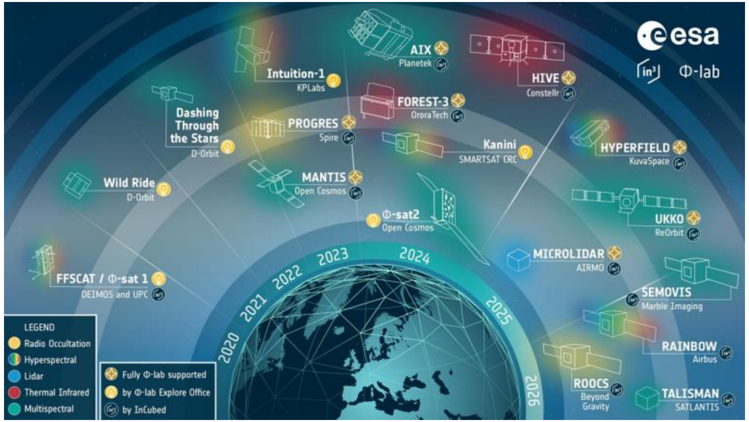
Contents: Programs and Initiatives





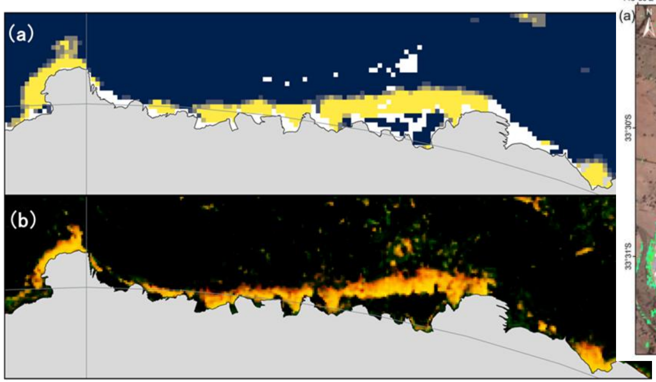
4.1. CEOS SEO
4.2. GEO
4.3. NASA/ESDIS
4.4. NOAA/NCAI
4.5. ISRO
4.6. ESA/φ-lab
4.7. UKSA

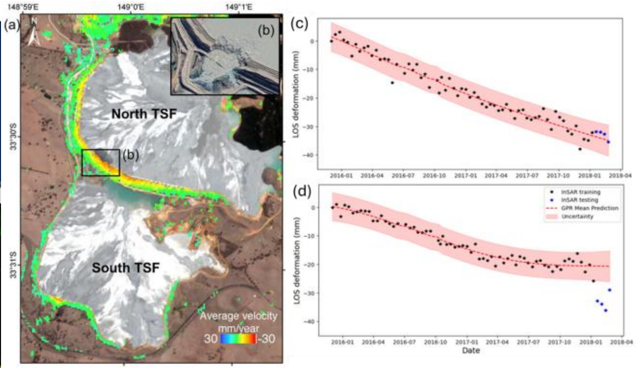


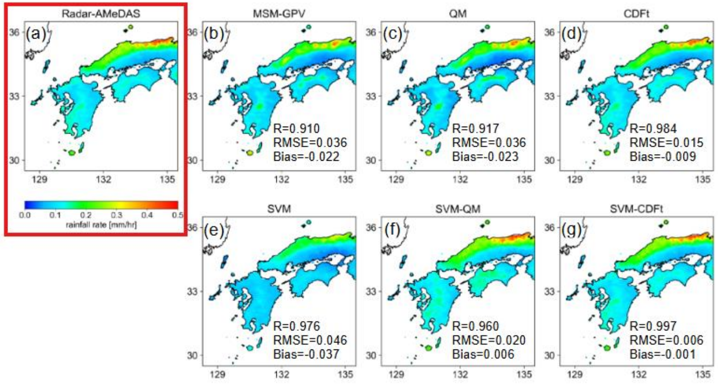


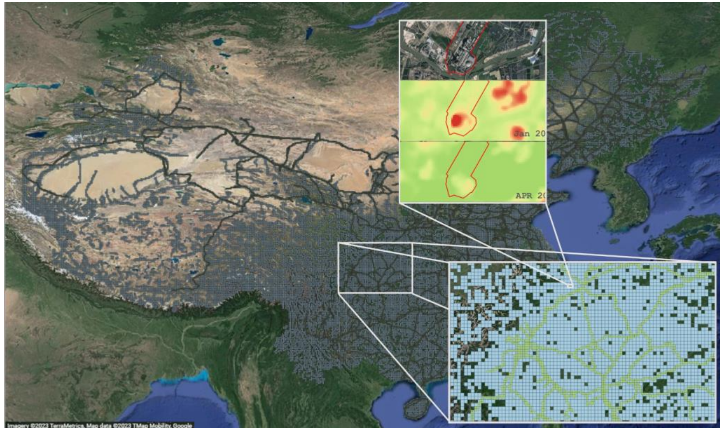
Contents : Demonstrative use-cases

5.1. Climate
5.2. Disaster
5.3. Infrastructure Monitoring
5.4. Precipitation
5.5. Sustainable Finance









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6. Hot topics/New topics

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7.2. Geospatial AI Platforms

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8.1. Data scarcity & labelling challenges

8.2. Computational demands for large-scale analysis

8.3. Model interoperability & trustworthiness

Demonstrative use-cases (1/6)

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.

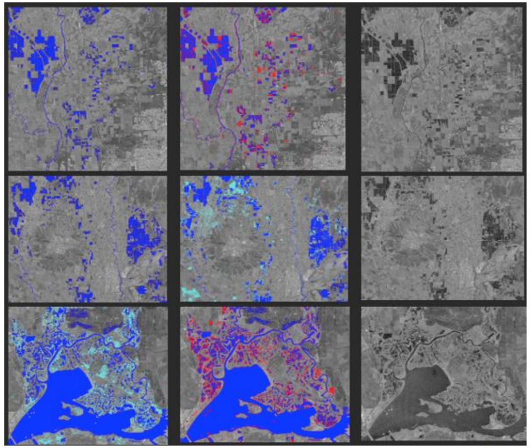


Figure.5.2.1-1 Intercomparison of RAPID v2.0 (1D method in dark blue) with GFM (0D method in red) and OPERA (0 D method in light blue). Row 1 shows RAPID v2.0 against GFM). Row 2 shows RAPID v2.0 against OPERA. And row 3 shows RAPID v2.0 against OPERA and GFM. The last column is the SAR image at VV polarization.

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#521-sar-flood-mapping

Demonstrative use-cases (2/6)

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.

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#5221-machine-learning-in-optical-flood-mapping

Demonstrative use-cases (3/6)

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).

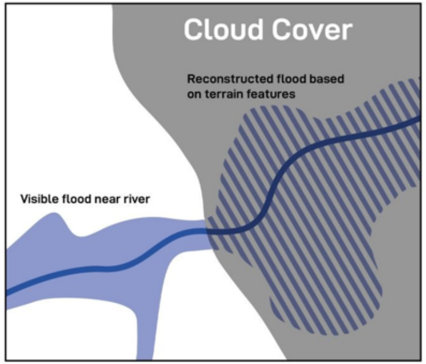


Figure 5.2.2.2-1: In essence, the machine learning algorithm learns to recognise visible floods and extrapolates their extent below clouds based on terrain features such as slope and land use.

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#522-flood-mapping-with-optical-satellite-sensors1

Demonstrative use-cases (4/6)

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).

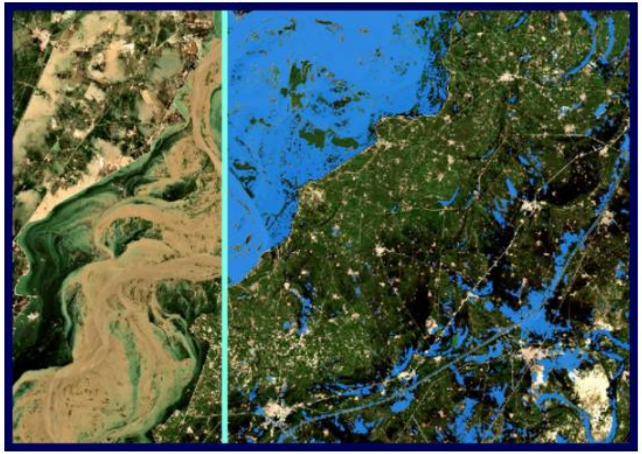


Figure 5.2.2.3-1: FloodSENS is a living ML-based algorithm that generates accurate flood maps from optical imagery consistently across diverse biomes, providing invaluable up-to-date information at regional, national, and global scales.

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#5223-benefits-of-using-ml-for-flood-mapping-on-optical-images

Demonstrative use-cases (5/6)

5.2.3. FloodML : Flood Extent rapid mapping from EO satellite data[2]

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 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.

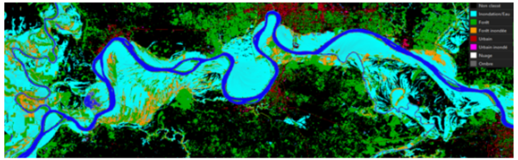


Figure 5.2.3-1 FloodML flood extent map from Sentinel-2 data, ESA World Cover and GSWO over the Ohio River flood event on the 27th February 2018

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

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#523--floodml--flood-extent-rapid-mapping-from-eo-satellite-data2

Demonstrative use-cases (6/6)

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.

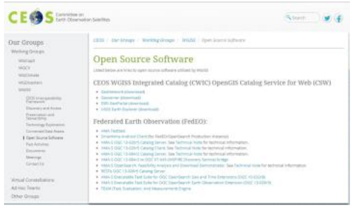
- GWSS project page (ESA Business Applications) and ESA InCubed portfolio entries; mission docs for FOREST satellites;
- ESA Business Applications – GWSS project page. Overview, objectives, system description. business.esa.int
- ESA InCubed – OroraTech Wildfire Solution. Multi-sensor approach, PWA, market 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

https://github.com/ceos-org/aiml-white-paper/blob/main/demonstrative-use-cases/disaster.md#524-wildfire

Routine about AI/ML for WGISS.

Update white paper

Upload homepage



Collaborate with other groups.

WGCapD, WGDisaster, …

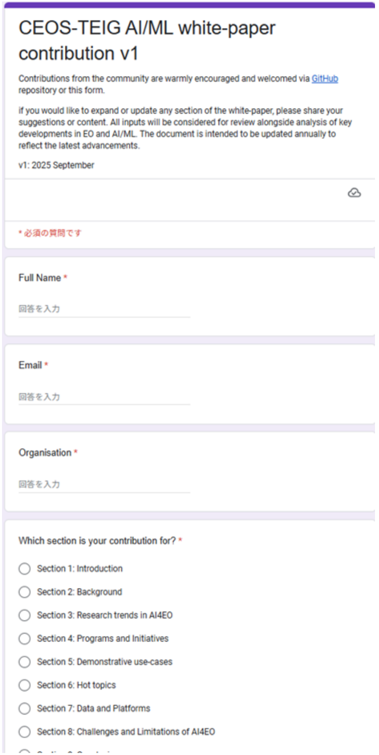
Invite presenters to WGISS.

AI/ML studies, Reports.

Form for collecting contribution

To collect new topics and contribution, we build the form in parallel to the current GitHub site.

https://github.com/ceos-org/aiml-white-paper



CEOS-TEIG AI/ML white-paper contribution v1

Contributions from the community are warmly encouraged and welcomed via GitHub repository or this form.

if you would like to expand or update any section of the white-paper, please share your suggestions or content. 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.

v1: 2025 September

* 必須の質問です

Full Name *

回答を入力

Email *

回答を入力

Organisation *

回答を入力

Which section is your contribution for? *

- Section 1: Introduction
- Section 2: Background
- Section 3: Research trends in AI4EO
- Section 4: Programs and Initiatives
- Section 5: Demonstrative use-cases
- Section 6: Hot topics
- Section 7: Data and Platforms
- Section 8: Challenges and Limitations of AI4EO

CEOS-TEIG AI/ML white paper contribution form (version 1)