







by

Thomas Brunschwiller (IBM Research Europe), Hamed Alemohammad (Clark University)

1. Session Summary:

This two-part session showcased cutting-edge advances in AI foundation models for Earth observation (EO), emphasizing the development of scalable, multimodal, and sensor-agnostic architectures. The session highlighted both methodological innovations and practical applications, demonstrating how foundation models are transforming geospatial analysis across a wide range of EO use cases.



2. Highlights - Model Architectures

Mixed-Modality Models: Several presentations introduced new masked autoencoding strategies (AuxMAE and MixMAE) for integrating multi-sensor data (such as S-1 and S-2), AnySat & OmniSat, and TerraMind to cover additional modalities.

Vision Language Model for EO: Release of GeoLangBind, a vision-language model trained on 2M image-text pairs, and GeoViT for Temporal-Spatial Progressive Learning



3. Highlights – Sensor Adaptation

Sensor and Acquisition Awareness: Several talks emphasized architectures that explicitly encode or adapt to sensor characteristics and metadata.

Sensor-Agnostic Approaches: SA-MAE and SenPaMAE & SARFormer injected sensor parameters or projected spectra into model design to allow transferability across sensors.



4. Highlights - Scalability

Scalability and Efficiency: Efforts ranged from massive model pretraining (e.g., FAST-EO, Copernicus-FM) to lightweight fine-tuning or pruning approaches. Introduction of Modality-Aware Pruning of Experts for adaptable input data configuration (MAPEX), resulting in model size efficiency.

Understanding Redundancy: One presentation explored redundancy in EO imagery and its implications for model design using redundancy-aware ViTs.



5. Future Directions

- Truly Multi-Dimensional Models (Multi-Modality, Multi-Temporal, Multi-Resolution)
- Fusion of EO and Weather / Climate to Model Processes (Biological, Phenological, Atmospheric, etc)
- Edge Deployment of Foundation Models
- Operationalize Models for Decision-Making





by

Gustau Camps-Valls (Universitat de València)

Sujit Roy (UAH/NASA)



• Session Summary:

This session showcased the growing application of foundation models (FMs) in Earth observation (EO) and weather/climate science. The presentations highlighted how self-supervised learning, multi-modal data integration, and large-scale training are enabling new capabilities in areas like precipitation forecasting, climate monitoring, and disaster response. Speakers emphasized advances in accuracy, scalability, and the physical interpretability of FM-based models. The work reflects a broader trend toward operational, real-time, and high-resolution EO applications driven by foundation model architectures.

2. Key Presentations & Highlights:

- Foundation Models for EO and Climate Are Maturing: Multiple studies demonstrated operational applications of FMs (e.g., FM4CS, Prithvi WxC, ORBIT, 3D-ABC) for snow mapping, flood prediction, permafrost monitoring, and weather forecasting.
- Multi-Modal Learning Is Key: Integrating EO data across sensors (Sentinel-1/2/3, LiDAR, hyperspectral, GNSS-R, etc.) enhances spatial and temporal resolution, improves feature representation, and enables holistic environmental monitoring.
- Self-Supervised and Efficient Learning: Use of masked autoencoders, contrastive learning, and models like SatMAE enables learning from unlabeled data, reducing dependence on costly ground truth and improving model transferability.
- Validation Through Physics and Real-World Impact: Efforts to benchmark FMs against physical constraints (e.g., conservation laws, convective processes) and societal relevance (e.g., air quality, disaster mitigation, hydrology) are increasing.



3. Common Themes / Emerging Trends

- Scalable, General-Purpose AI for EO and Weather: There is a clear movement toward universal FMs capable of generalizing across tasks, regions, and time scales, supporting climate adaptation, early warning, and environmental forecasting.
- Fusion of Physics and Data-Driven Models: Many approaches aim to combine machine learning with physical knowledge, either through hybrid modeling or enforcing physical constraints (e.g., radiative transfer, hydrology).
- 4. Notable Audience Engagement / Discussion Points
- Around FM models (ViT, diffusion, SWIN backbone) methods and how to validate them scientifically.
- Change detection, encoder design and specific loss functions.



5. Key Takeaways / Recommendations

Invest in Multi-Sensor, Multi-Resolution Training Pipelines: Broader and more diverse data integration (optical, SAR, gravimetry, LiDAR, etc.) will improve model robustness, especially in under-observed regions.

Advance Real-Time and Adaptive Systems: Self-updating, geospatially aware FMs should be prioritized for applications in dynamic and high-risk contexts like urban planning, disaster response, and air quality.

Bridge Research and Operational Use: FMs should be designed with deployment in mind—emphasizing interpretability, efficiency, and ease of integration with downstream systems (e.g., digital twins, public dashboards).





Computational challenges in training / running large-scale Foundation Models

by

Gabriele Cavallaro (Forschungszentrum Jülich GmbH),

Muthukumaran Ramasubramanian (UAH/NASA)



Computational challenges in training / running largescale Foundation Models

• Session Summary:

This session focused on the computational complexities and challenges that come with the use of Foundation Models for Earth Observation in operational setups. We discussed strategies for efficient task adaptation (efficient fine-tuning strategies, knowledge distillation, etc.) and the design of models, techniques, and frameworks suitable for on-board satellite processing (edge computing for FMs).

- 2. Key Presentations & Highlights:
- Focus on scaling down than scaling up and out
- Edge computing more than HPC Novel techniques (or transfer of techniques) for EO towards efficient adaptation of FMs to circumvent computational challenges



Computational challenges in training / running largescale Foundation Models

- 3. Common Themes / Emerging Trends
- Novel Fine-tuning strategies
 - Head only fine tuning
 - Knowledge Distillation as an efficient alternative
- Frameworks for Edge / On-board Computing
- Model augmentations as alternate operations for memory and compute hungry FM operations
- 4. Notable Audience Engagement / Discussion Points
- Effects and generalizability of learned weights and embeddings
- Data and compute efficiency questions
- Questions on capabilities and extensibility of Edge computing frameworks that leverage less common hardware



Computational challenges in training / running largescale Foundation Models

- 5. Key Takeaways / Recommendations
- Future directions
 - Highlight general availability of HPC resources
 - Focus on Reproducibility in EO FMs to lessen burden on computational resources
 - A more informed, regimented approach to Edge computing for EO and inherent challenges latency, connectivity, redundancy, security, etc, and generally efficient in the session, the focus was on making models compatible with specific hardware and making the footprint smaller.

6. Additional Comments

Session that received a low number of contributions, together with the sessions 'Agent AI, Digital Assistant, LLM' and 'Ethical considerations and responsible AI use in EO'.





by

Paolo Fraccaro (IBM Research Europe),

Nikolaos Dionelis (ESA, Φ-lab)



- 1. Session Summary:
- Established framework for benchmarking described (eg GEO-Bench, PANGEA, PhilEO-Bench)
- More innovative approaches around interpreting models embeddings (GFM-Bench), confidence/uncertainty quantification (PhilEO, National Technical University of Athens), and predicting model ranking based on model and dataset characteristics (meta-analysis style)
 - NTUA, e.g.: "Pretrained Visual Uncertainties", <u>http://arxiv.org/pdf/2402.16569</u>
- Datasets for pretraining multi-sensory/multi-modal models MMEarth and GAIA for VLMs and benchmarking for trees related mapping (Forty)
- Real world applications require careful consideration around trade off between performance and resources used (computation/memory/latency)
- 2. Key Presentations & Highlights:
- Prithvi 2 seems to have a very well defined embedding space for common LULC classes and change detection (eg burn scars) (GFM-Bench)
- Unet still better of most GFM with frozen backbone finetuning (PANGEA) (not true for TerraMind)
- Real world applications require smaller/faster models, how do we account for that in benchmarks? (Ororatech)
- No cross-sensor generalization if finetuning on a specific sensor (especially from S1 to S2) (CNES)



- 3. Common Themes / Emerging Trends
- How accessible benchmarking frameworks are?
- How are they different between each other?
- How can we better interpret what models learn and how confident are they?
- How can we quantify uncertainty?
- 4. Notable Audience Engagement / Discussion Points
- What is the point of FMs if performance very similar to a custom Unet?
- Can we trust ranking and prediction of performance based on a meta-analysis of published finetuning results on different datasets?



- 5. Key Takeaways / Recommendations
- Benchmarks have to be accessible, reproducible and give researchers and practitioners actionable insights
- Explainability of models predictions
- Pretraining/benchmarking datasets require high quality multisensory/modal high-quality data

6. Additional Comments

Really good quality contributions and interesting discussions!!!





Adapting Foundation Models to geospatial data (multi-modal, multi-resolution, etc.) and specific EO tasks, from adaptation to adoption of FM for EO

by

Hamed Alemohammad (Clark University),

Anna Jungbluth (ESA)



Adapting Foundation Models to geospatial data (multi-modal, multi-resolution, etc.) and specific EO tasks, from adaptation to adoption of FM for EO

1. Session Summary:

The session focused on advanced AI foundation models for remote sensing applications, with emphasis on multimodal, multi-temporal, and multi-spectral approaches. Presentations included methodological advances, better ways to use/interface with existing (off-the-shelf) pre-trained models, reviews/opportunities/shortcomings of current approaches, and application-focussed examples.

2. Key Presentations & Highlights:

- Denoising and gap-filling of EO data
- Comparison of early vs. late fusion strategies for masked autoencoders across EO modalities
- Benefits of a FMs trained on daily temporal data compared to S-2 temporal frequency
- Emphasis on building models to adapt to the properties of EO data (e.g. custom models for SAR)
- Introduction new vision-language datasets and models for EO-specific data
- Detection of rare events (e.g. subtle forest change) is challenging with current foundation models



Adapting Foundation Models to geospatial data (multi-modal, multi-resolution, etc.) and specific EO tasks, from adaptation to adoption of FM for EO

3. Common Themes / Emerging Trends

- **Modality-specific adaptation:** There is a growing consensus that EO data's unique properties (e.g., SAR, hyperspectral, temporal resolution) require custom pretraining and architecture designs.
- Model Architectures: Diffusion models and MAEs are increasingly used for pretraining.
- **Fusion and generalization:** Effective multi-modal and multi-resolution fusion is key to building adaptable and generalizable EO foundation models.
- Benchmarking and reproducibility: The field is moving toward more standardized benchmarks (e.g., REO-Instruct, DOFA4Trees) and open datasets to support evaluation and model comparison.

4. Notable Audience Engagement / Discussion Points

- Does it matter if e.g. augmentations are physically inconsistent if the model performs better downstream?
 => Yes, if we want to create models that eventually understand more physics.
- Not all applications show clear benefit of pre-training (compared to simpler models or training from scratch)
 => The proof might be in the details, but we also need to understand model limitations.



Adapting Foundation Models to geospatial data (multi-modal, multi-resolution, etc.) and specific EO tasks, from adaptation to adoption of FM for EO

5. Key Takeaways / Recommendations

- Custom EO foundation models outperform off-the-shelf models when adapted for modality and resolution.
- Diffusion and MAE models show promise for self-supervised pretraining and synthetic data augmentation in EO.
- Multi-resolution and multi-modal fusion strategies should be matched to the task and data characteristics.

6. Additional Comments (optional)

The sessions demonstrated that the EO and foundation model research communities are increasingly aligned, with a shared interest in **creating robust**, **open**, **and task-aware tools** that can support both scientific research and operational EO applications.





by

Gencer Sümbül (EPFL), Begum Demir (TU Berlin)



• Session Summary: (2-3 sentences): Provide a brief description of the session's focus and relevance.

This session focused on advanced methodologies for embedding learning, geospatial semantic data mining, and data volume reduction within Earth Observation (EO) workflows. Presentations addressed representation learning frameworks grounded in physical plausibility, parameter-efficient adaptation techniques, neural compression strategies, methodologies for leveraging foundation model embeddings, and the role of synthetic data in training AI models. The discussions highlighted the growing importance of scalable, adaptable, efficient, and physically plausible models to support next-generation EO analytics integrated with foundation models.

- 2. Key Presentations & Highlights:
- Integration of physical models into deep representation learning for EO foundation models.
- Al-driven data compression and embedding pipelines to enable scalable EO analytics.
- Parameter-efficient model adaptation using optimal transport techniques.
- Neural compression methods preserving geospatial features with high compression rates.
- Synthetic EO data generation to augment AI training and address data scarcity.



- 3. Common Themes / Emerging Trends
- Efficiency at Scale: Focus on data compression, parameter-efficient adaptation, and scalable embeddingbased workflows for managing EO's growing data volumes.
- **Trustworthy AI:** Emphasis on physically plausible models, domain knowledge and synthetic data to enhance robustness, reliability, and coverage.
- Accessibility: Calls for open, systematic access to pre-trained embeddings and scalable AI for broader EO analytics capabilities.
- 4. Notable Audience Engagement / Discussion Points
- How much compression is acceptable before critical semantic information is lost.
- Questions on integrating physical models into deep learning pipelines (e.g., differentiability)
- Concerns about the generalizability and representativeness of synthetic geospatial data for real applications.



- 5. Key Takeaways / Recommendations
- **Prioritize Scalable, Efficient Al Solutions:** Embedding-based workflows, neural compression, and parameter-efficient adaptation are essential to manage future EO data challenges.
- Integrate Domain Knowledge into Al Models: Physically plausible and interpretable models will be critical for operational EO applications.





by

Xiaoxiang Zhu (TU Munich), Jose Manuel Delgado Blasco (ESA), Robert Kennedy (OSU),



- Session Summary:

Very applied session illustrating real-world applications of GeoAI/geospatial foundation models, including both public and commercial examples.

- 2. Key Presentations & Highlights:
- Foundation models already successful in some real world situations, and show emerging promise in others.
- Constraints and challenges drive much of the innovation and also are a substantial component of what has to be dealt with in application of these models



3. Common Themes / Emerging Trends

We saw examples of several non-image based AI in actual use

- Filip Sabo showed an example using tabular data applied spatially for crop prediction in South Africa, and Francesco Asaro gave an example using graph neural networks applied to urban mobility prediction.
- Several examples of testing existing foundation model infrastructures in real-world situations
 - Dr Loredana Spezzi provided examples of successfully using Prithvi as applied to coarse-resolution weather data.
 - Dr Ferdinand Schenk provided tests of Prithvi, Dino, and ViT of various flavors for detecting change across high resolution images, finding that multi-task pretraining was a key component of success.
 - Niccolo Taggio show examples of using models in improving land cover mapping along coastal zone.
- Another theme was an emphasis on the practical constraints or challenges of working in a real world environment
 - Ferdinand Schenk had an example where vision transformers might solve the problem of monitoring ground disturbance near pipelines in the face of expensive high resolution imagery and non-target change.
 - Martinez described efforts to solve a key upstream image co-registration problem on the way to implementing an edge computing solution for CISERES mission to detect landslides
 - Spezzi suggested that pretrained models like Prithvi might be able to address key questions of latency and reliability in near real time cloud masking for EUMETSAT
 - Constraint of training data for land cover labeling. Ideally we would like to be able to augment the data collection phase with foundation models.



- 5. Key Takeaways / Recommendations
- Foundation models appear to have promise in applied settings.
- Non-image based approaches are effective and should be considered depending on the use case.
- Pre-processing, pre-training, and real world constraints still represent an important component of any application to real world scenarios.
- Different models are in fact different in their abilities, and do not necessarily always work better than traditional counterparts everywhere. Should we be really be trying to use one model for every case?
- A fair and comprehensive benchmarking of all existing geospatial foundation models might be helpful for downstream users





by

Muthukumaran Ramasubramanian (UAH/NASA),

Nicolas Longépé (ESA Φ-lab)

• Session Summary:

This session explores the role of Large Language Models (LLMs), generative AI, and multi-agent systems in advancing Earth Observation (EO) and scientific research. It highlights how LLM-based tools are being developed with the overarching objectives to enhance data accessibility, automate complex workflows, and democratize the use of satellite imagery and scientific datasets.

- 2. Key Presentations & Highlights:
 - **Open-source Tools:** Prioritization on open-source tools, APIs, and interfaces for all user levels.
 - Enable Natural Language Interaction: Make EO data and APIs understandable through plain language.
 - Adapt LLMs for EO: Focus on domain-specific LLMs EVE and establish scientific guardrails AD.

• Implement Multi-Agent Architectures: Automate complex EO tasks using Multi-Agentic Frameworks. - SATCHAT, AD,

- LLM Assistants: Use retrieval-based chat for better data discovery and analysis. EO AI,
- Combine EO Data with RAG: Integrate external knowledge to make AI insights clearer and more relevant.
- Open LLM Inference Server Blabador: Leverage privacy oriented, open-source LLM serving by JSC to host open models.

3. Common Themes / Emerging Trends

- Focus on natural language interfaces (e.g., chatbots, assistants) to make complex EO data and tools accessible to non-experts.
 - lower the barrier to entry for scientific data use and analysis.
- several systems used multi-agent frameworks to coordinate tasks like data ingestion, model training, and result interpretation.
- Increased Multimodal RAG Utility Combining text, imagery, metadata, API, and external knowledge into unified AI systems capable of richer analysis and insight generation.
- 4. Notable Audience Engagement / Discussion Points
- Limitations / uncertainties in Licensing around current open source LLM models as backbone (e.g. Llama family Licensing Issues – Fails to provide freedom to use models for any purpose)
- Limited Generalization capabilities of the automated LLM-powered EO workflow systems limited set of restricted use cases.
 - Complex Reasoning / Long-Tail dependency tasks crucial for EO still relatively unexplored.

- 5. Key Takeaways / Recommendations
- Tailored LLMs for Earth Observation. Future efforts should focus on expanding domain-specific pretraining datasets and benchmarks to improve model performance and relevance in EO and earth science contexts.
- multi-agent architectures and natural language interfaces in making EO data more accessible.
 Continued development should prioritize interoperability, modularity, EO-Guided Reasoning and user experience to support broader adoption.
- 6. Additional Comments
- 6 Talks + 2 posters, limited community so far (or present in this workshop)
 - Unexplored areas exist: deeper discussion on AI Alignment, Reinforcement Learning, guardrails, domain evaluation for EO data, AI safety with EO focus, EO API function calling support,





Closing words

nature

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Fostering collaboration

Laying the groundwork for international standards

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Global Initiative for Resilience to Natural Hazards through AI Solutions

Advancing research through proof of concepts

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Register to participate in our next workshop and meeting, 8/9 May

Monique Kuglitsch, Ph.D. Fraunhofer Heinrich Hertz Institute



MedEWSa





Collaboration opportunities at Φ -lab

Funded

Shared mutual interest

Join the Φ-lab to explore disruptive ideas

as a Visiting Researcher (industry, academia), Visiting Professor, Research Fellow, PhD, YGT, etc.

1. Φ-lab's Invitation To Tender on ESA-STARS

- Foundation Models, Generative AI, QC4EO, Edge computing, Web 3.0, etc..
- 2. <u>InCubed</u> : partnership development of commercial products or services
- 3. <u>Open Space Innovation Platform</u>: co-funded research or researchers
- 4. EO Science4Society : no SOW, 100/200K, 6/18 months
- 5. ESA Technology Programmes like <u>GSTP</u> and <u>TDE</u>



→ THE EUROPEAN SPACE AGENCY

This afternoon

13.30 - 14.30	Lunch break							
14.30 – 15.00	Setting Infrastructure for hands-on participants							
15.00 – 18.00	Hands-on 1 <u>Using Geospatial AI FM</u>		Hands-on 2 LLMs in use for EO		Hands-on 3 <u>Benchmark FM4EO</u>			
Plenary Big Hall (main stage), Magellan	Big Hall	Magellan		Room 15111 (main stage), Room 15109	,	James Cook		

For those that registered for the hands-on session: Please get your credentials to get access your personal environment

Other may join, just attending (without hands-on environment...) and pending room capacity

The people behind...

ESA - NASA Organising Committee

Nicolas Longépé - EO Data scientist at Φ-lab Explore Office - ESA

Giuseppe Borghi - Head of Φ-lab Division - ESA

Anca Anghelea - Open Science Platform Engineer at Green Solution Division - ESA

Clement Albergel - Head of Actionable Climate Information section - ESA

Rahul Ramachandran - Senior Data Science Strategist | AI/ML Theme Lead - NASA MSFC

Tsengdar Lee - Program Manager for the R&A Weather Focus Area, the High-End Computing Program, and for NASA's Data for Operation and Assessment - NASA HQ

Kevin Murphy - Chief Science Data Office for NASA SMD - NASA HQ

Francesca Romana Cupellini - Junior Event project Manager - Olly Services Srl for ESA

Sharon Gallo Carpentieri - Communication And Event Coordinator at Φ-lab - Starion Group S.A. for ESA

The people behind...

Programme Committee

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Hands-on

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Thanks ALL !!