



Activities and Insights from the GGOS Joint Study Group 3 (AI4EOP)

S. Modiri¹, J. Śliwińska-Bronowicz², S. Belda³, D. Ampatzidis⁴, A. A. Ardalan⁵, E. Azcue⁶, J. Becker¹, L. Biskupek⁷, S. Dhar⁸, R. Dill⁹, S. Guessoum³, D. Halilovic¹, I. N. Huda⁹, J. Gou¹⁰, M. Kiani Shahvandi¹¹, Q. Kong¹², T. Kur¹³, A. Laha¹⁴, Z. Li¹⁵, M. Ligas¹⁶, W. Miao¹⁷, M. Michalczak¹⁸, M. S. Moreira¹⁹, O. Oguntuase¹⁹, X. Papanikolaou²⁰, A. Partyka², V. Puenté⁶, H. Que²¹, S. Raut¹, O. Roggenbuck¹, M. A. Sharifi⁶, S. Shirafkan³, R. G. Suya²², D. Schunck²³, H. Schuh^{8,24}, Y. Shen²⁵, X. Xu¹⁷, K. Yu¹⁶, D. S. Williams²⁶, Y. Wu²⁷, J. Park²⁸, N. Wei¹⁶, Q. Wang²⁹, L. Wang², K. Yan²¹, Z. Zhang³⁰, D. Yao²⁷

1

AI for Earth Orientation Parameter Prediction, Joint Study Group 3 of GGOS (together with IAG Comm. 3)

General Information

This Joint Study Group explores artificial intelligence (AI) to enhance the accuracy, robustness, and interpretability of EOP predictions.

Building on the IERS Second EOP Prediction Comparison Campaign, we integrate machine learning with space-geodetic observations and geophysical drivers such as atmospheric and oceanic angular momentum.

Objectives

- Investigate 2nd EOP PCC results and propose improvements.
- Quantify geophysical/meteorological impacts on EOP prediction.
- Improve Effective Angular Momentum (EAM) prediction with ML.
- Learn dependency structures between EOP and drivers using ML.
- Develop hybrid models (physics + AI) and ensemble strategies.
- Refine EOP theory with AI-derived insights and diagnostics.
- Run sensitivity/robustness studies across horizons and inputs.
- Explore operational/commercial uses (real-time orbit det., navigation).
- Identify the best model per EOP with transparent benchmarks.
- Foster knowledge sharing via datasets, code, and joint campaigns.

Terms of Reference

Purpose: Deliver accurate, timely, and interpretable predictions of EOP, which link the terrestrial and celestial reference frames. Many operational activities, such as deep-space navigation, astronomical pointing, and satellite-based positioning, depend on precise EOP.

AI Opportunity: Machine learning and deep learning (ML/DL) approaches can analyse large, complex datasets, uncover hidden dependencies, and continually improve models, opening new avenues, such as refining EOP theory and forecasts.

Scope: Integrate space-geodetic observations with geophysical drivers. Combine classical baselines with ML/DL and physics-informed hybrids.

Method: Establish an iterative, reproducible workflow for training, validation, and sensitivity analysis.

Community: Foster innovation and knowledge sharing across AI and geodesy through shared datasets/developments, workshops, and joint publications.

Impact: More accurate and robust EOP predictions for navigation, positioning, and astronomy; deeper insight into Earth-rotation dynamics.

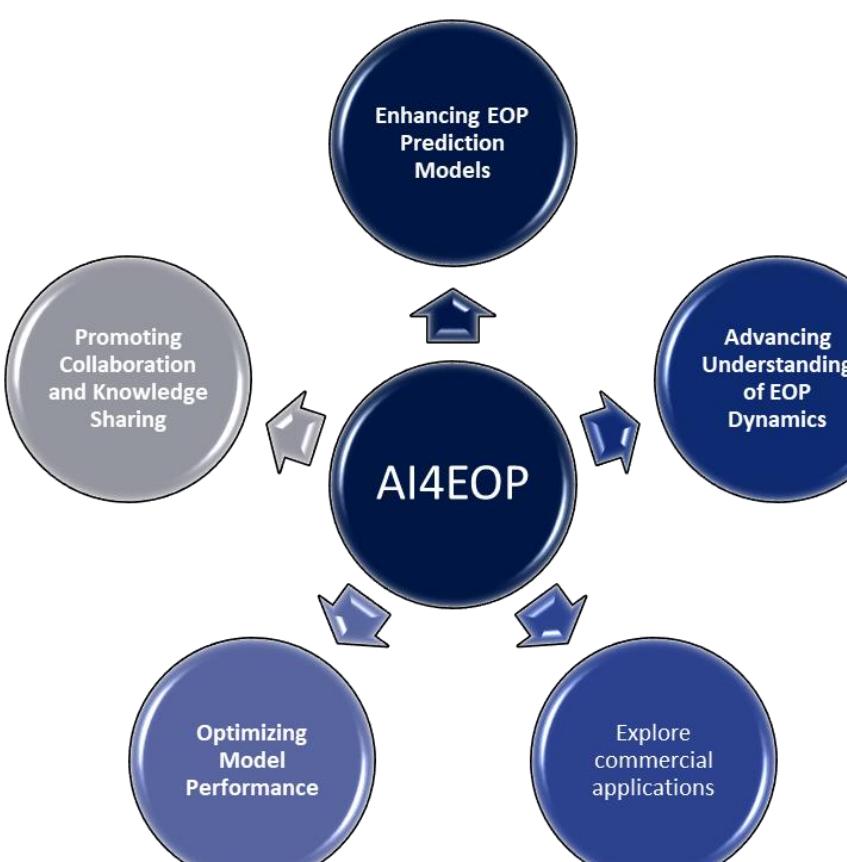


Fig. 1: AI4EOP Objectives: improve EOP predictions, deepen dynamics insight, optimize models, enable applications, and foster collaboration.

Members

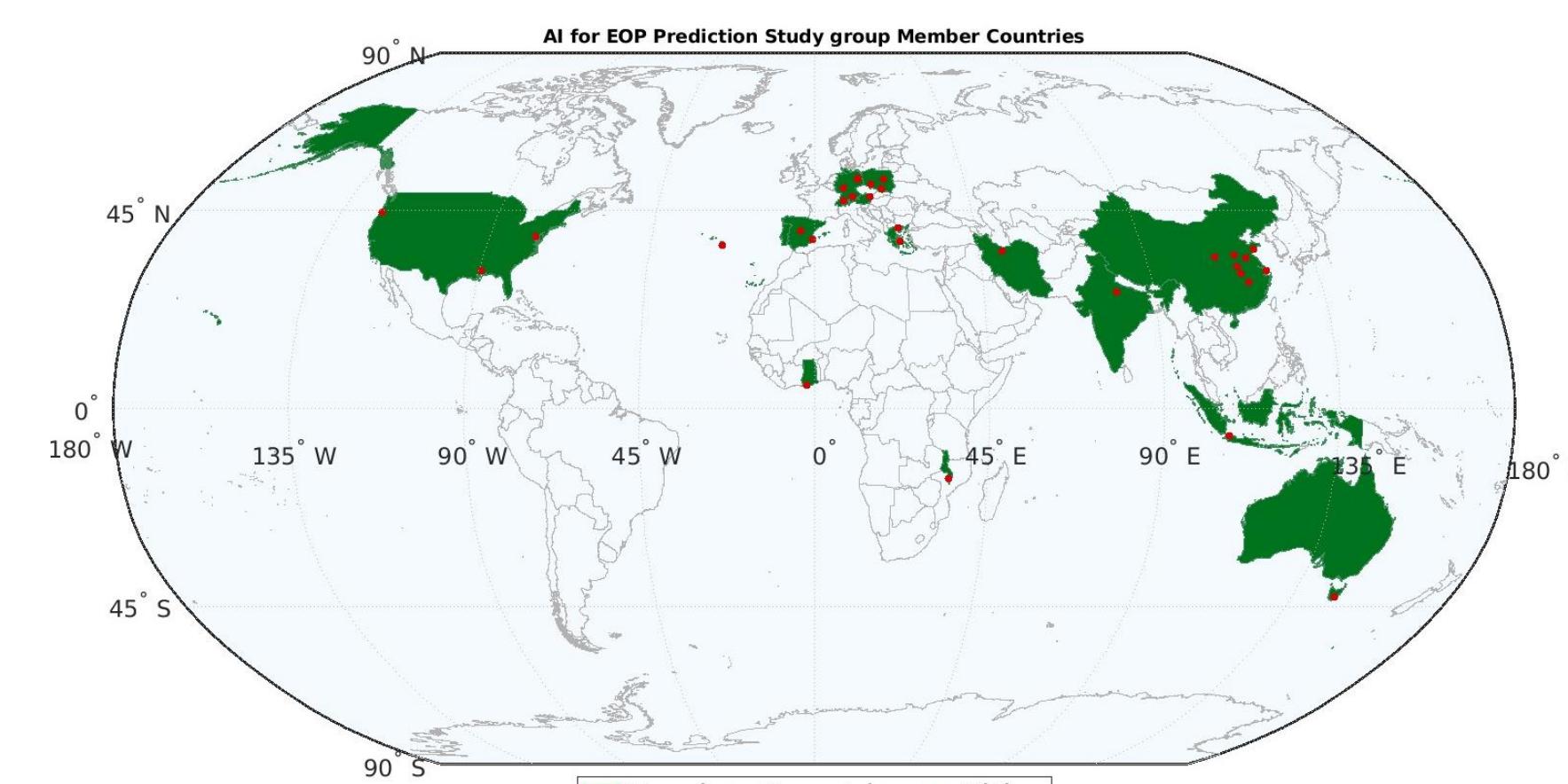


Fig. 2: AI4EOP global footprint: member countries (dark green) and collaborating cities (red). ~50 members from 31 institutions in 15 countries across five continents (Europe, Asia, North America, Africa, Oceania).

2

AI4EOP's Ongoing Activities

EOP I&I (Innovation & Insight)

We are running the EOP I&I scientific series to accelerate knowledge sharing on machine-learning approaches to EOP prediction. From June 2024 to April 2025 we hosted four talks on RNN-based forecasting, physics-informed neural networks for polar motion, and two coordination talks introducing the ML-dedicated EOP PML and CEOPPCC campaigns.

Nr.	Speaker & Affiliation	Title / Focus	Link
1	Junyang Gou, IGP, ETH Zürich, Switzerland	Recurrent neural networks and their applications for EOP prediction – sequence models (RNN/LSTM/GRU) for short- to mid-term EOP forecasts	
2	Mostafa Kiani Shahvandi, IGP ETH Zürich, Switzerland (Currently at University of Vienna, Austria)	Explaining the Causes of Polar Motion by Physics-Informed Neural Networks – embedding physical constraints in NN training to improve interpretability	
3	Justyna Śliwińska-Bronowicz, CBK PAN, Poland	Advancing EOP Prediction Using ML – Insights from the new EOP PML sub-campaign – scope, rules, and first experiences	
4	Yuanwei Wu, NTSC, Chinese Academy of Sciences, China	Report on our activities of the 1st CEOPPCC – organization and progress of the China EOP Prediction Comparison Campaign	

Sub-Campaign on ML-EOP (EOP PML)

Hosted by the EOP PCC Office at CBK PAN (Poland), the EOP PML sub-campaign rigorously assesses machine-learning approaches for EOP forecasting to enable objective, method-focused evaluation. AI4EOP supports participating members by hosting seminars, disseminating calls, and coordinating collaboration; we are not the organizer and do not take part in evaluation or ranking.

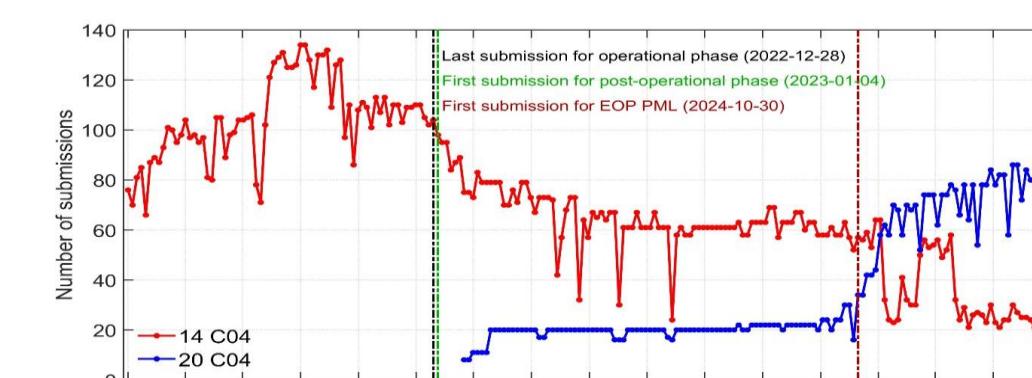


Fig. 3: Number of all submitted forecasts using 14 C04 (red) and 20 C04 (blue) on each submission day (statistics for 2025-08-20)

Tab 1: Number of predictions submitted to the EOP PML (42 weeks). Number of IDs registered in EOP PML: 21. Number of active IDs in EOP PML (at least one submission): 17

Number of predictions	PMx	PMy	UT1-UTC	LOD	dPsi	dEps	dX	dY	Total
Number of predictions	62	62	62	24	0	0	221	221	652

Number of IDs	PMx	PMy	UT1-UTC	LOD	dPsi	dEps	dX	dY	Total
Number of IDs	3	3	3	1	0	0	16	16	17

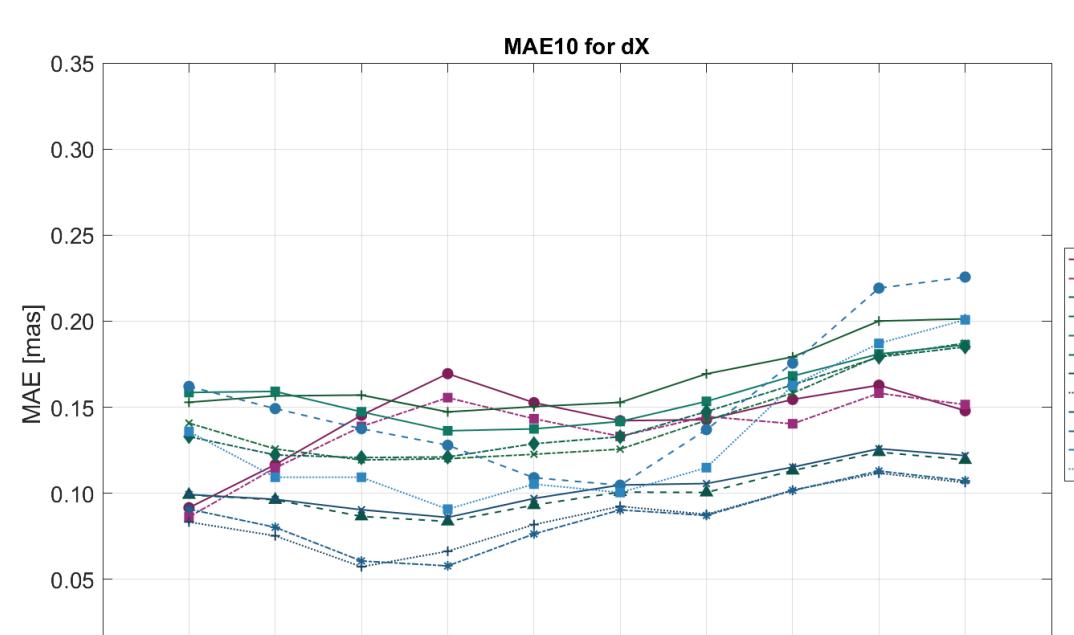


Fig. 4: 10-day-ahead MAE for dX and dY predictions, evaluated against the IERS 20 C04 solution.

3

Recent Publications and Highlights by AI4EOP Members

This section spotlights peer-reviewed work from AI4EOP members that is directly advancing EOP forecasting. The papers fall into three complementary themes: (A) deep-learning architectures that learn patterns end-to-end from time series; (B) hybrid / physics-aware models that fuse ML with geophysical knowledge and signal decomposition; and (C) campaign & evaluation studies that set fair, reproducible standards for comparing methods. Together, they show clear progress on short-term horizons (~1–10 days), improved operational readiness, and better methodological rigor for benchmarking.

End-to-end models learn short-term EOP dynamics directly from the time series. Multi-task CNNs share structure across PMx, PMy, and LOD, trimming Day-1/Day-10 errors versus single-task LSTMs. ConvLSTM with driver inputs (IGS Rapid LOD, EAM) adds operational context and boosts skill at 10–30 days, making near-real-time use practical.

Inputs	QR	Highlight
Guessoum et al., 2025 (C04)		Multi-task CNN ↓ error vs LSTM (short-term).
Yu et al., 2025 IGS Rapid LOD + EAM		NRT ConvLSTM best on mid-term LOD.

Coupling ML with geophysics consistently helps: GPR+GA with AAM/OAM/HAM/SLAM improves short-horizon UT1-UTC/LOD; MCSSA+ARMA strengthens Day-1 and long-term LOD; PM derivatives (x, y) trim errors; colored-noise handling boosts credibility. A recent JoG study further upgrades the driver by refining 10-day EAM with a lightweight NN corrector, cutting Day-10 MAE by 26.8% (x-pole), 15.5% (y-pole), 27.6% (dUT1), 47.1% (ΔLOD).

Community benchmarks clarify what works and how to compare fairly. PCC analyses show PMy is generally more predictable than PMx, with LS+AR+EAM among top performers and some methods beating IERS at short leads. Crucially, reported MAE depends on the reference series (C04-14/20, Rapid, IGS), so the reference must be stated for any result.

Focus	QR	Highlight
Kur et al., 2024 2nd EOP PCC (PM)		PMy > PMx predictability; LS+AR+EAM competitive; some beat IERS at short leads.
Partyka et al., 2025 Reference choice		MAE shifts with C04-14/20 vs Rapid/IGS → always report reference.

¹ Federal Agency for Cartography and Geodesy (BKG), Frankfurt, Germany. ² Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN), Warsaw, Poland. ³ University of Alicante, Spain. ⁴ International Hellenic University, Serres, Greece. ⁵ University of Tehran, Tehran, Iran. ⁶ National Geographic Institute (IGN), Spain. ⁷ Institute for Satellite Geodesy and Wroclaw University of Environmental and Life Sciences, Wroclaw, Poland. ⁸ Indian Institute of Technology Kanpur, Kanpur, India. ⁹ GNSS Center, Wuhan University, Wuhan, China. ¹⁰ AGH University of Krakow, Krakow, Poland. ¹¹ Shanghai Astronomical Observatory (SHAO), CAS, Shanghai, China. ¹² Estação RAEGE de Santa Maria, Associação RAEGE, Azores, Portugal. ¹³ University of Southern Mississippi, USA. ¹⁴ National Technical University of Athens, Athens, Greece. ¹⁵ East China University of Technology, China. ¹⁶ Nottingham, Nottingham, UK. ¹⁷ University of Tasmania, Hobart, Australia. ¹⁸ Technische Universität Berlin, Institut für Geodäsie und Geoinformationstechnik, Berlin, Germany. ¹⁹ Xinyang Normal University, China. ²⁰ University of Mines and Technology, Ghana. ²¹ National Time Service Center (NTSC), Chinese Academy of Sciences (CAS), Xian, China. ²² Oregon State University, Corvallis, USA. ²³ China University of Mining and Technology, China. ²⁴ Henan University, China