Ionospheric data fusion with GNSS, GNSS-RO and satellite altimetry based on machine learning

Marcel Iten[1], Shuyin Mao[1], Benedikt Soja[1]
[1]Institute of Geodesy and Photogrammetry, ETH Zurich

1 Introduction

Global ionospheric maps (GIMs) are widely used ionospheric products, especially in Global Navigation Satellite System (GNSS) applications, as they allow for instance to correct for the ionospheric delays in single-frequency applications. The global distribution of GNSS data used to describe the ionospheric state is heavily limited to continental regions, leaving oceanic areas with major data gaps. Combining ionospheric estimates from different space geodetic techniques such as **GNSS**, GNSS **radio occultation** (GNSS-RO) and **satellite altimetry** we can improve the GIM quality in regions without GNSS observations.

2 Data

- Global GNSS data from the International GNSS Service (IGS) network.[1]
- GNSS-RO data from the University Corporation for Atmospheric Research (UCAR) of the Constellation Observing System for Meteorology Ionosphere and Climate (COSMIC-2) mission.[2]
- Satellite altimetry data from National Oceanic and Atmospheric Administration (NOAA) of the Jason-3 mission.[3]

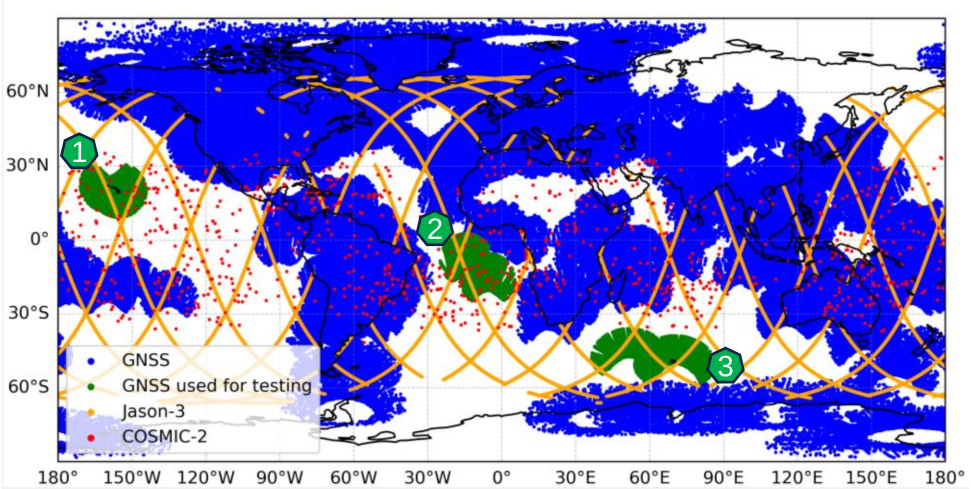


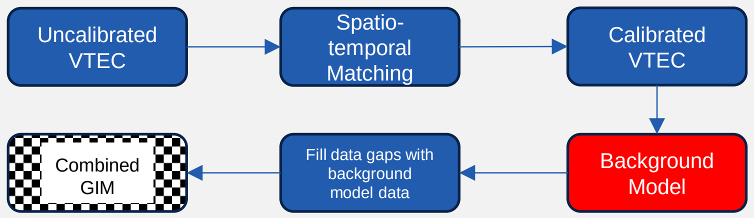
Figure 1: Distribution of Ionospheric observations from different observation techniques for 2024-08-09. Marked in green are the three test regions Hawaii (1), Atlantic (2) and Antarctic (3).

3 Method

- Neural network (NN) based GIM consisting of 10 ensemble members.[4]
- Loss function according to Laplacian deep ensembles which enables to output the predicted value with an estimated uncertainty.[5]

$$\ell_j = \sum_{i=1}^{N} \left(\log\left(\eta_j(X_i)\right) + \frac{|Y_i - \mu_j(X_i)|}{\eta_j(X_i)} \right)$$

Pipeline to fill data gaps with additional data:



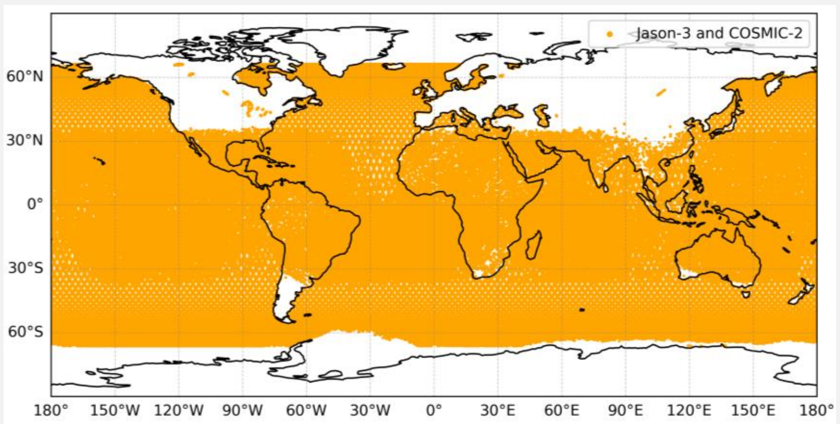


Figure 2: Distribution of Ionospheric observations from Jason-3 and COSMIC-2 over a time period of 80 days used to construct a background model for a specific day.

4 Results

Table 1: VTEC MAE [TECU] for the three test regions by including the local GNSS data into the GIM modelling, excluding local GNSS data, and excluding GNSS data but using background model samples.

Region	Local GNSS included	No local GNSS, no Background	No local GNSS, with Background
Hawaii	1.64	10.59	6.66
Atlantic	2.29	6.27	5.74
Antarctic	0.92	7.22	4.85

Table 2: Single point positioning 3D MAE [m] compared to a dual frequency solution. Evaluated for stations of the test regions for a case with included local GNSS data, no local GNSS data and a case where missing local data is compensated with data from the background model.

Station(Region)	Local GNSS included	No local GNSS, no Background	No local GNSS, with Background
MKEA (Hawaii)	2.67	4.89	3.52
KOKF (Hawaii)	2.12	4.26	3.09
STHL(Atlantic)	2.09	2.45	2.25
ASCG(Atlantic)	3.44	4.36	3.88
CZTG(Antarctic)	1.47	2.26	2.06
KRGG(Antarctic)	2.01	2.59	2.36
KERG(Antarctic)	1.56	2.20	1.96

5 Conclusion and Outlook

- Missing GNSS data significantly reduces the performance of VTEC modelling.
- Using samples from the background model can help mitigate this error to some extent.
- Adapting the loss function can lead to more realistic uncertainty predictions in oceanic areas.
- Background modelling will continue to be optimized and evaluated.

References

1. Noll, C. E. (2010). The crustal dynamics data information system: A resource to support scientific analysis using space geodesy. In Advances in Space Research (Vol. 45, Issue 12, pp. 1421–1440). Elsevier BV. https://doi.org/10.1016/j.asr.2010.01.018
2. UCAR COSMIC Program, 2019: COSMIC-2 Data Products ionprf. UCAR/NCAR - COSMIC, Access date 2024-05-15, https://doi.org/10.5065/T353-C093
3. Lillibridge, John; US DOC/NOAA/NESDIS > Office of Satellite Data Processing and Distribution (2019). Jason-3 Level-2 Operational, Interim and Final Geophysical Data Records (X-GDR), 2016 to present (NCEI Accession 0122595). Interim. NOAA National Centers for Environmental Information. Unpublished Dataset. https://www.ncei.noaa.gov/archive/accession/0122595. Accessed 2025-04-15.
4. Mao, Shuyin, Kłopotek, Grzegorz, Pan, Yuanxin, & Soja, Benedikt. (2024). Global Ionospheric Modeling Using Multi-GNSS: A Machine Learning Approach. ETH Zurich. https://doi.org/10.3929/ETHZ-B-000683664
5. Kiani Shahvandi, M., Mishra, S., & Soja, B. (2025). Laplacian deep ensembles: Methodology and application in predicting dUT1 considering geophysical fluids. In Computers & Geosciences (Vol. 196, p. 105818). Elsevier BV. https://doi.org/10.1016/j.cageo.2024.105818