EGNOS PERFORMANCE PREDICTION (EPP)

-using machine learning -

NAVISP Agenda/Introduction Slide

- Presenters:
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  - Jiří Doubek (Iguassu Software Systems)
  - János Nemes (GeoX)
  - Csongor Fekete (GeoX)

Project introduction

- Objective: investigate and demonstrate the use of ML in the GNSS context
  - Current GNSS performance simulations are often either:
    - High-end simulations: complicated and time-consuming
    - Macro-model based: simplistic, fast, calibrated (less generic)
  - Use ML to predict GNSS performance
    - Faster and easier to use than high-end simulators
    - More performant than macro models
- Application is proposed by the tenderer

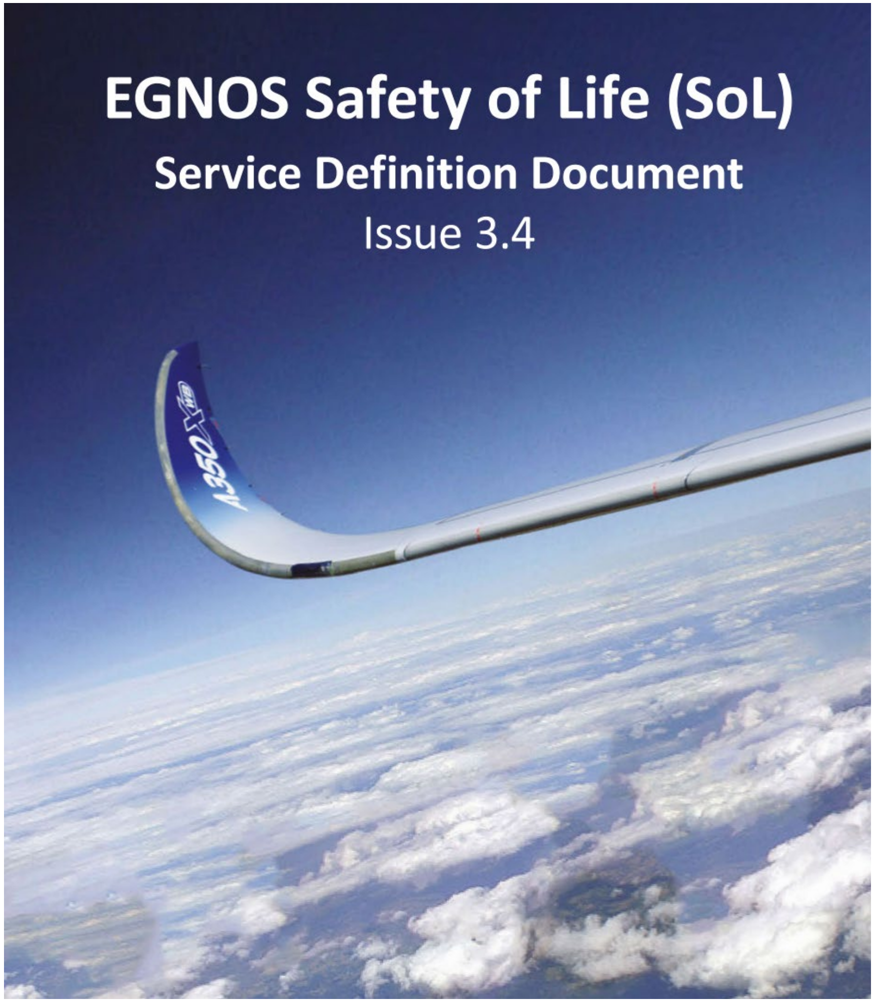
The Team

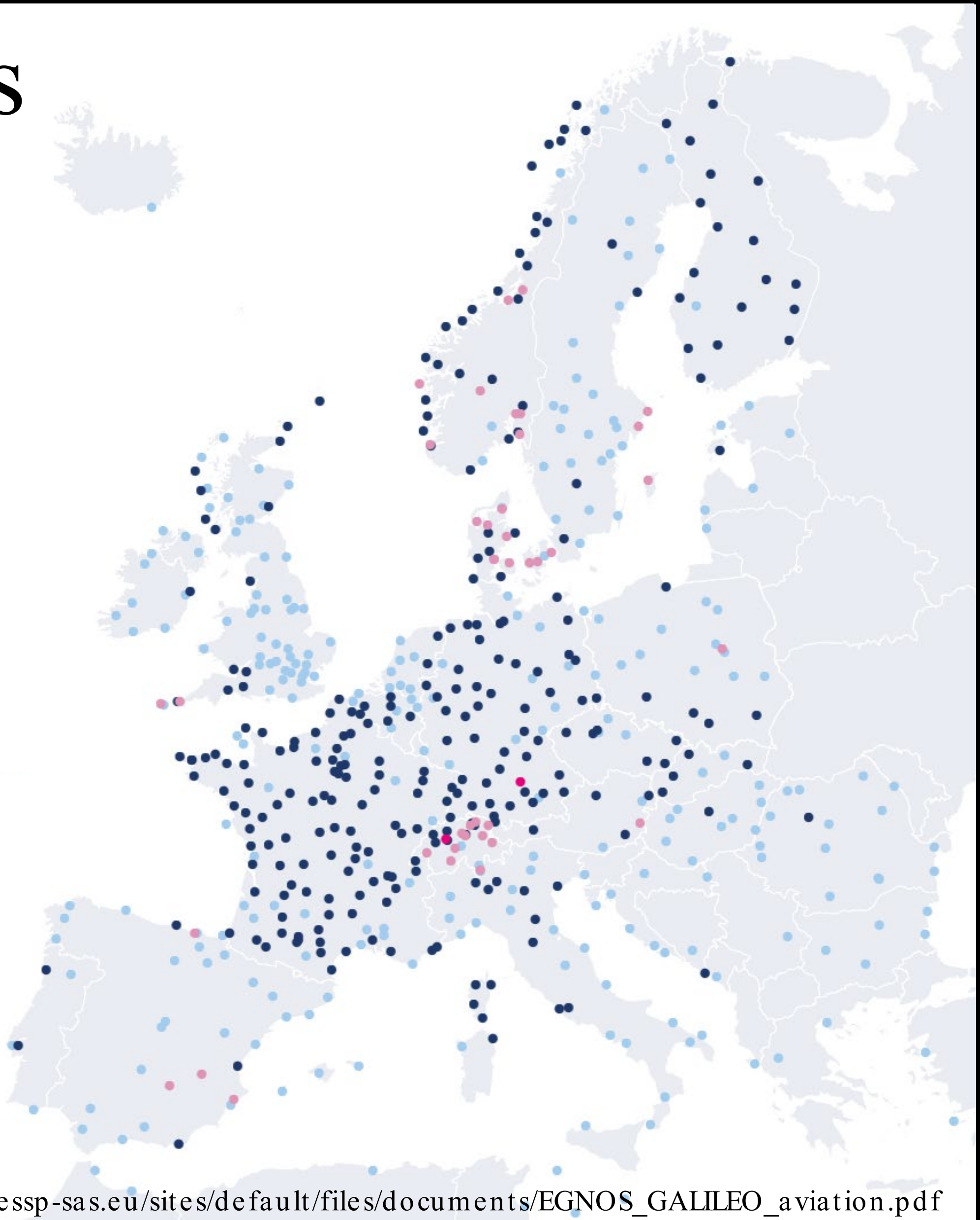
- Iguassu Software Systems (Prague, CZ)
  - EGNOS expertise, GNSS tooling for ESA
- GeoX Kft (Budapest, HU)
  - Machine Learning expertise
- Integricom (Leiden, NL)
  - Error modelling and prediction expertise
    - Including ionosphere, orbits and clocks
  - (RAIM) prediction systems expertise
  - Project management

ESA support

- Many thanks to ESA's support

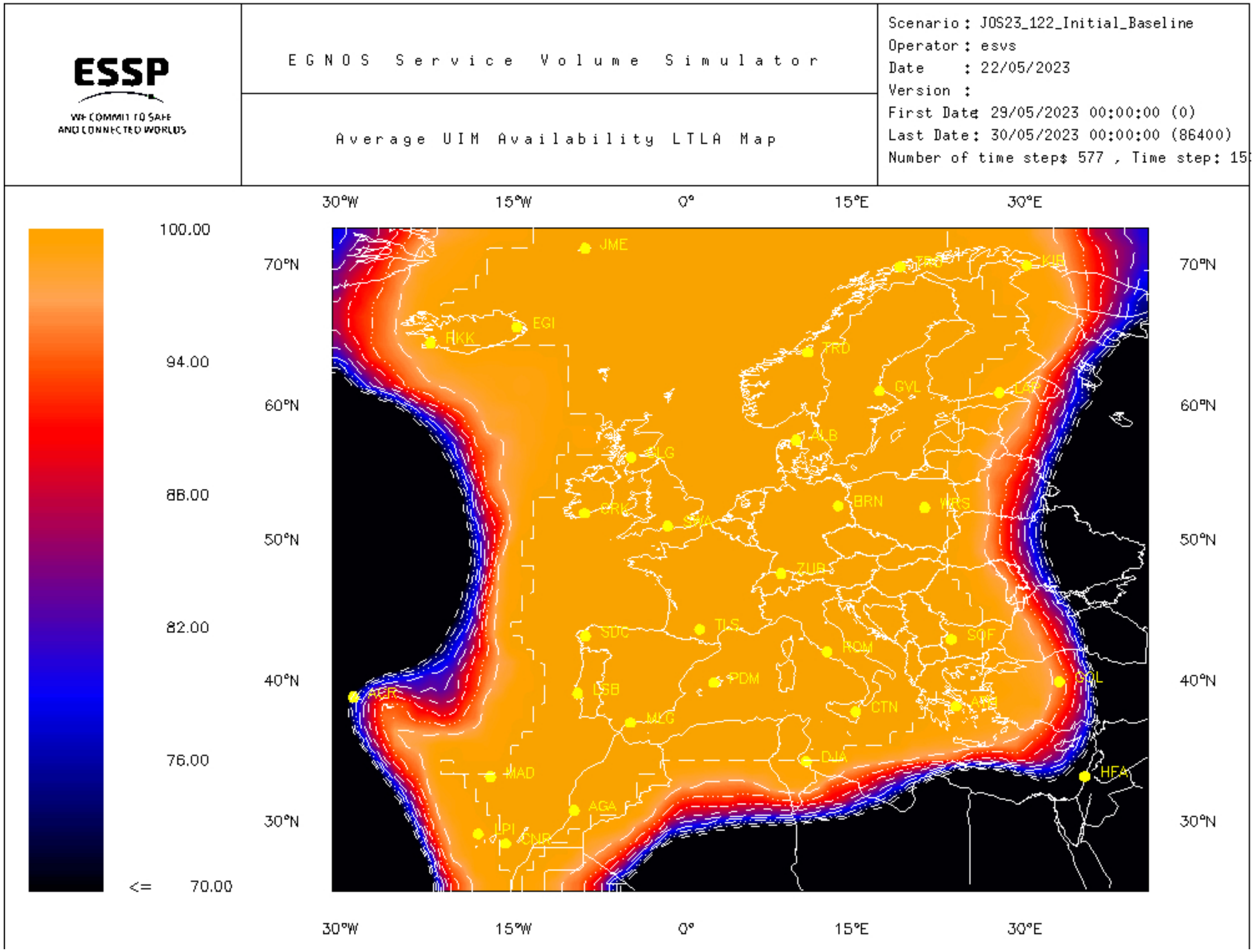
EGNOS Approaches

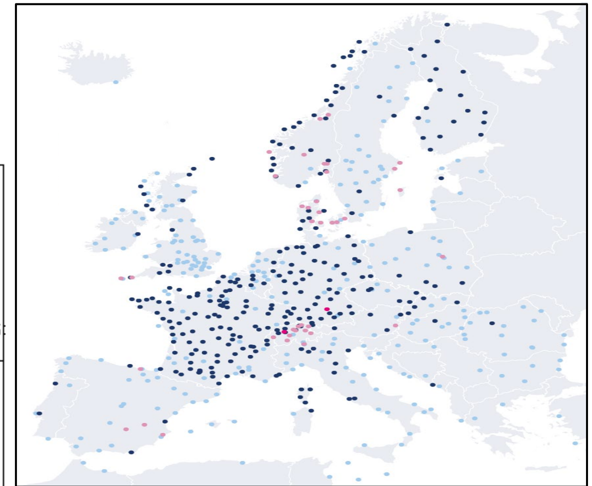




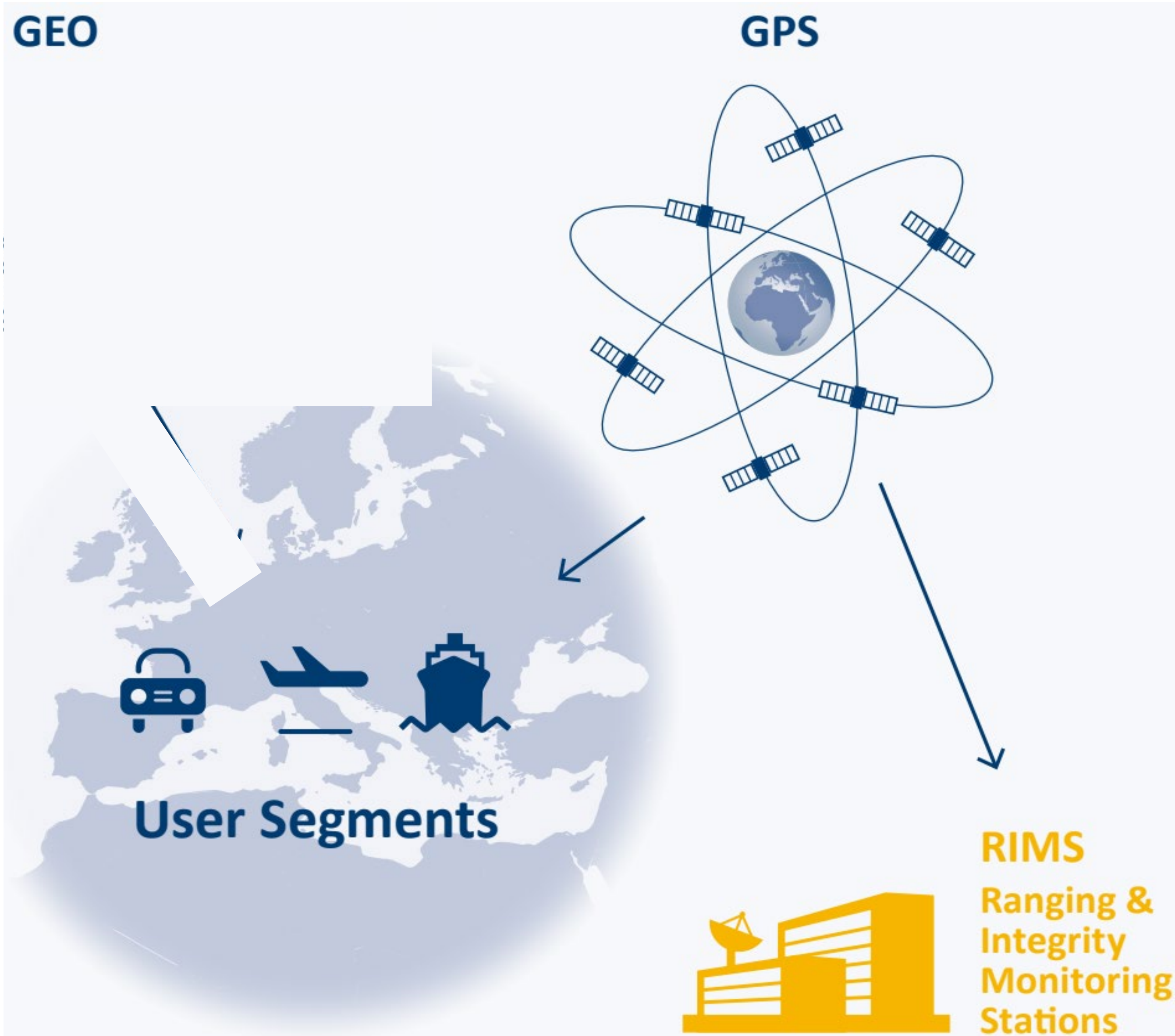
Source: https://egnos-user-support.essp-sas.eu/sites/default/files/documents/EGNOS_GALILEO_aviation.pdf

Predicted Availability





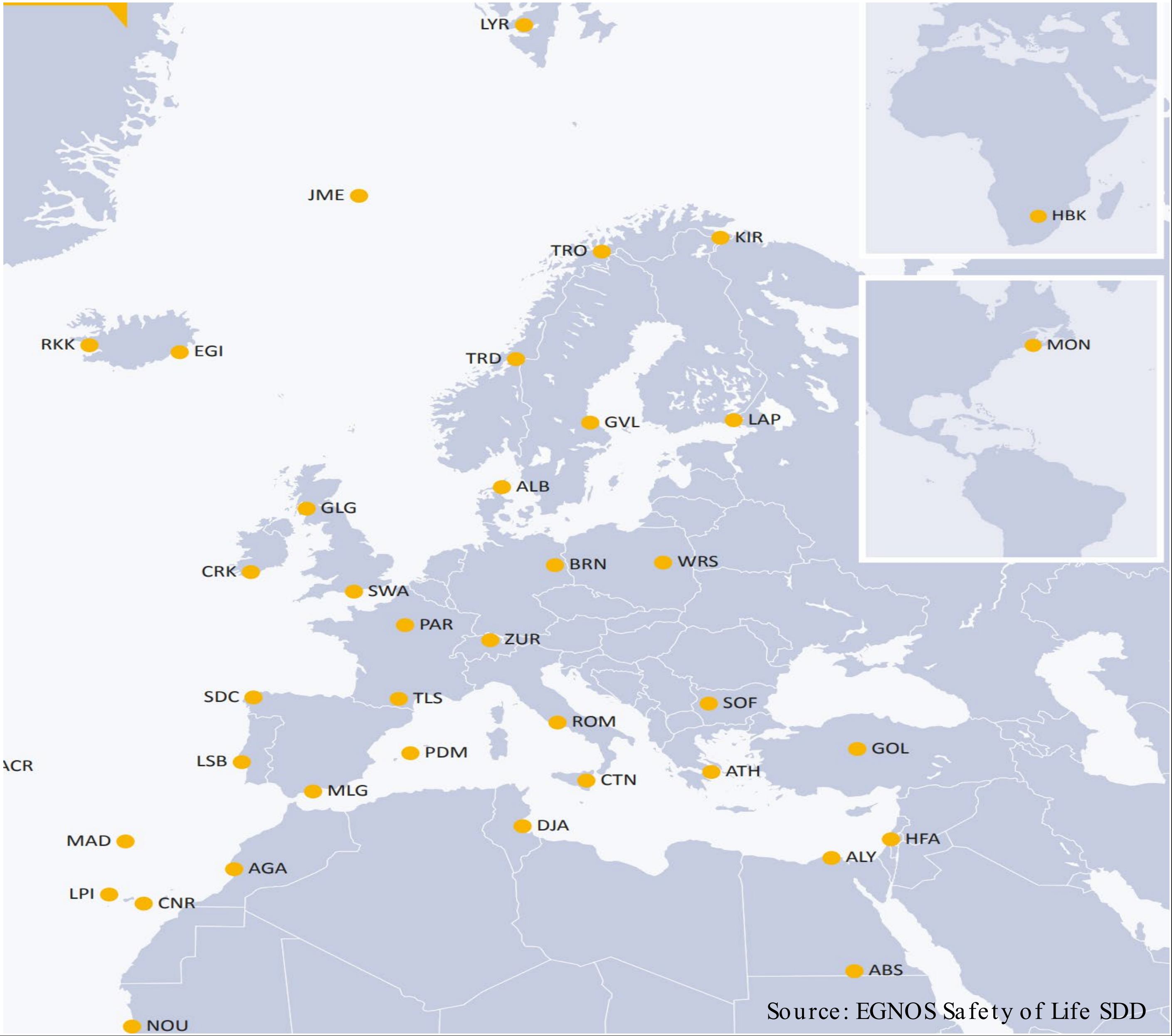
Source: https://egnos-user-support.essp-sas.eu/services/safety-of-life-service/forecast-performance/apvl-availability-performance



Source: EGNOS Safety of Life SDD

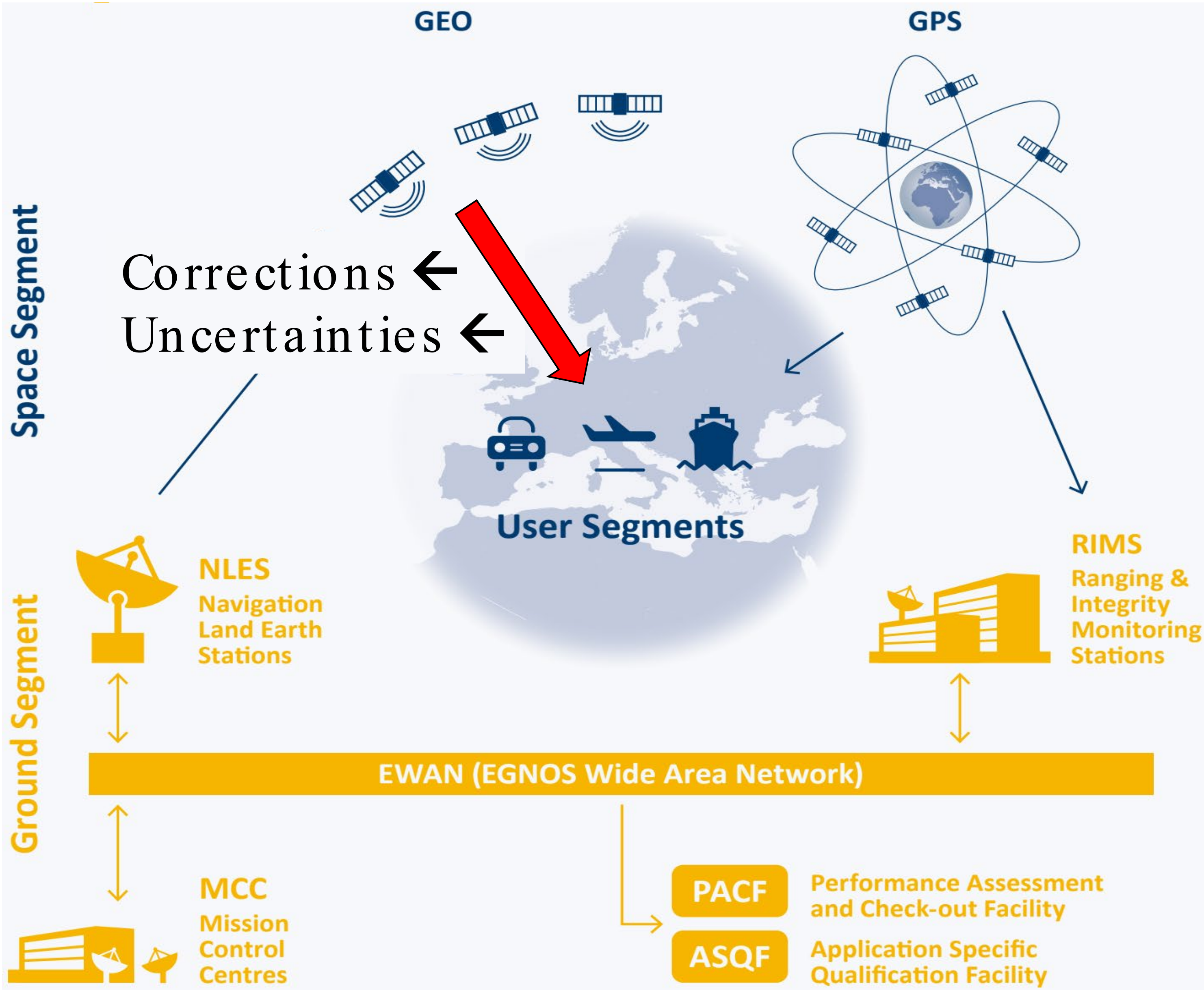
EGNOS v2 Monitoring

EGNOS RIMS Monitoring Stations



Source: EGNOS Safety of Life SDD

EGNOS v2 broadcast



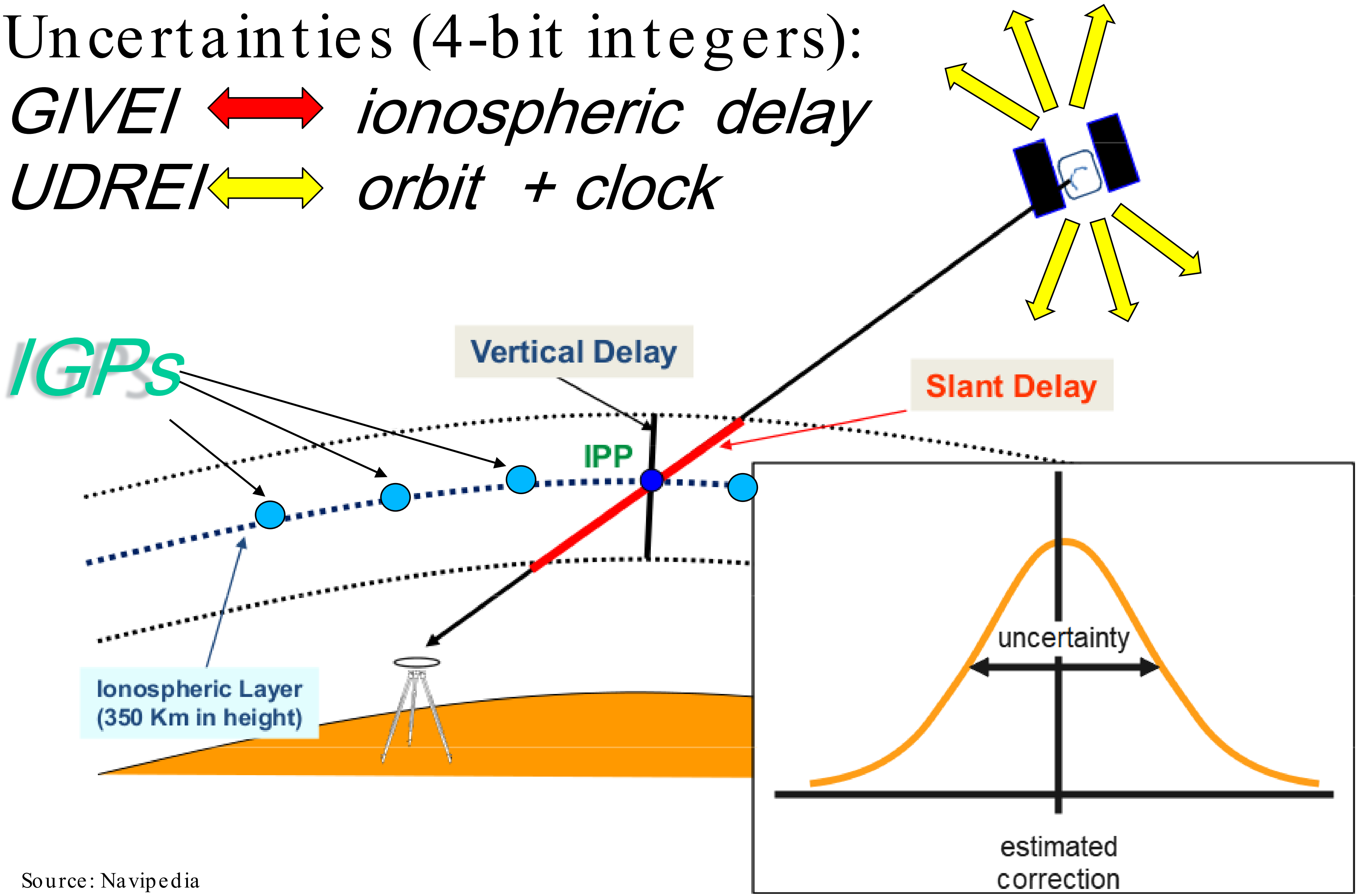
Source: EGNOS Safety of Life SDD

Data since 2014 (EDAS)

Uncertainties (4-bit integers):

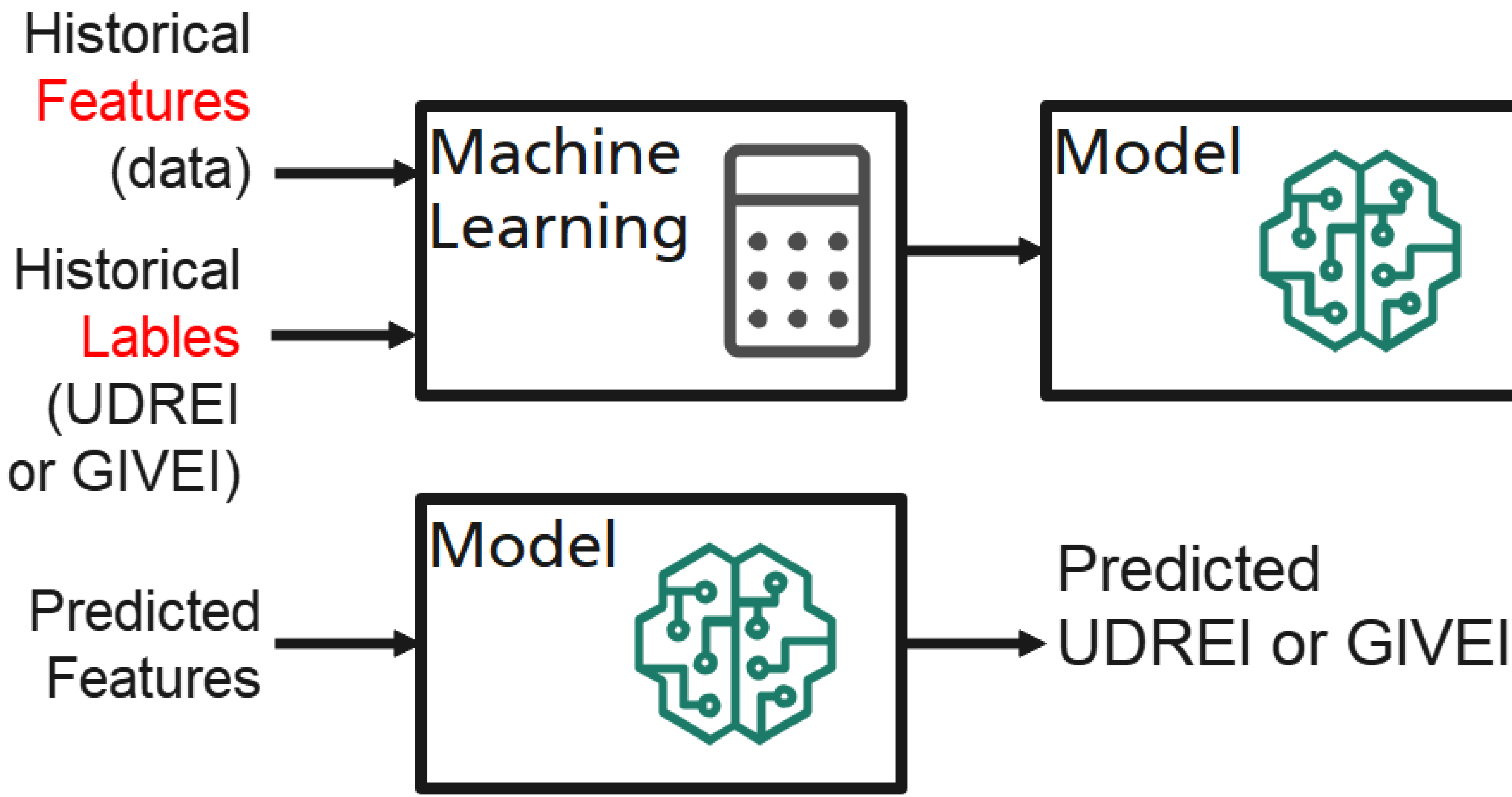
GIVEI ⟷ *ionospheric delay*

UDREI ⟷ *orbit + clock*



Source: Navipedia

Machine Learning: Classification



Data Features

UDREI prediction model inputs:

- Geometry: RIMS locations, number of RIMS in view, DOP
- Multipath variances
- Weather indicators
- Space-weather indicators
- Satellite: position, block, clock type

GIVEI prediction model inputs:

- IGP location
- Number of IPPs, IPP locations near the IGP
- Multipath variances
- Global space-weather indicators
- Local space-weather: TEC values and gradients
- Satellite: position, block, clock type

Data Features

UDREI prediction model inputs:

- Geometry: RIMS locations, *number of RIMS in view* , DOP
- Multipath variances
- Weather indicators
- Space-weather indicators

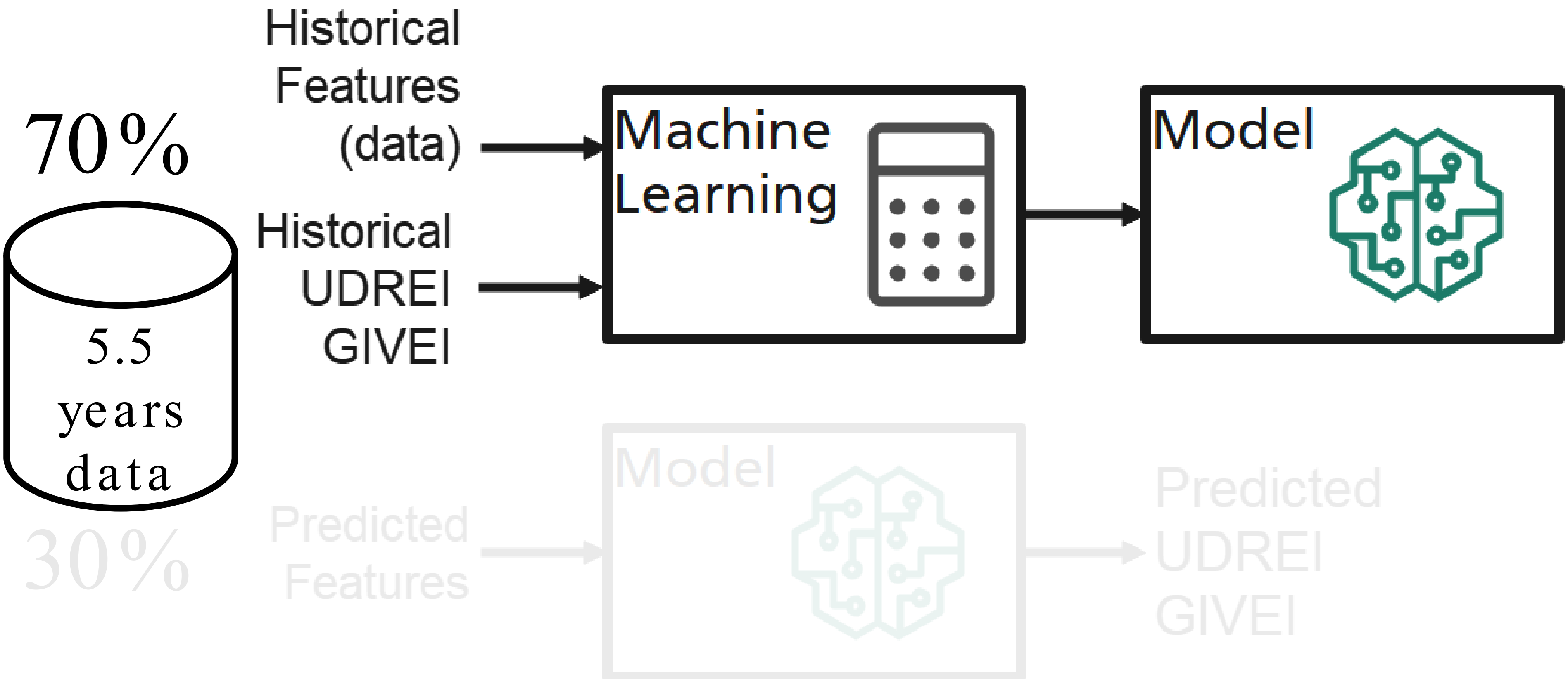
Macro Model :

RIMS-> UDREI
IPPs -> GIVEI

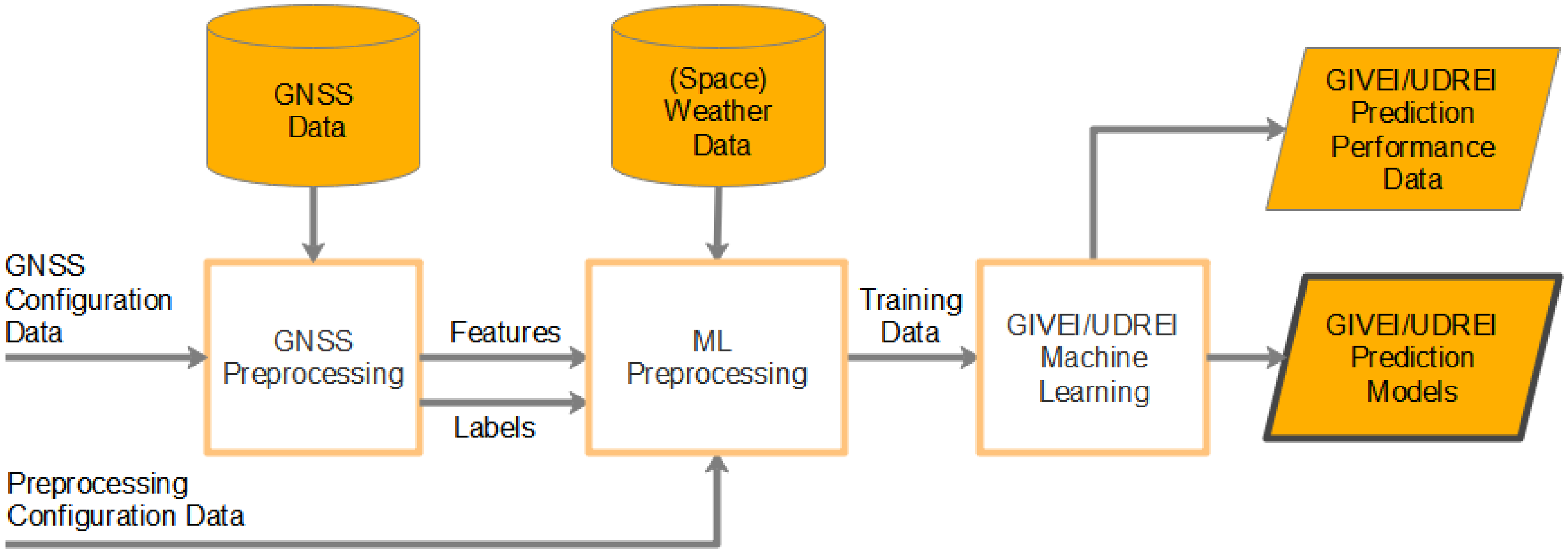
GIVEI prediction

- IGP location
- *Number of IPPs*, IPP locations near the IGP
- Multipath variances
- Satellite: position, block, clock type
- Global space-weather indicators
- Local space-weather: TEC values and gradients

Training and Performance Validation



Training Infrastructure



GNSS Preprocessor

GNSS data preparation for ML:

- Labels (GIVEI, UDREI) and features generation
- 3 operational modes: training, prediction and labels only

Input data:

- All modes: time interval, RIMS, multipath
- Training
  - Source: EDAS (SBAS, RINEX), IONEX, SBAS
  - Training period: 2014-2022
  - Multiprocessing, 3 machines, few weeks to generate all training data
- Prediction: almanacs, NANU, IONEX, PRN and iono masks, RIMS outages, prediction time: <90 min for 1 day

GNSS Preprocessor

Output data:

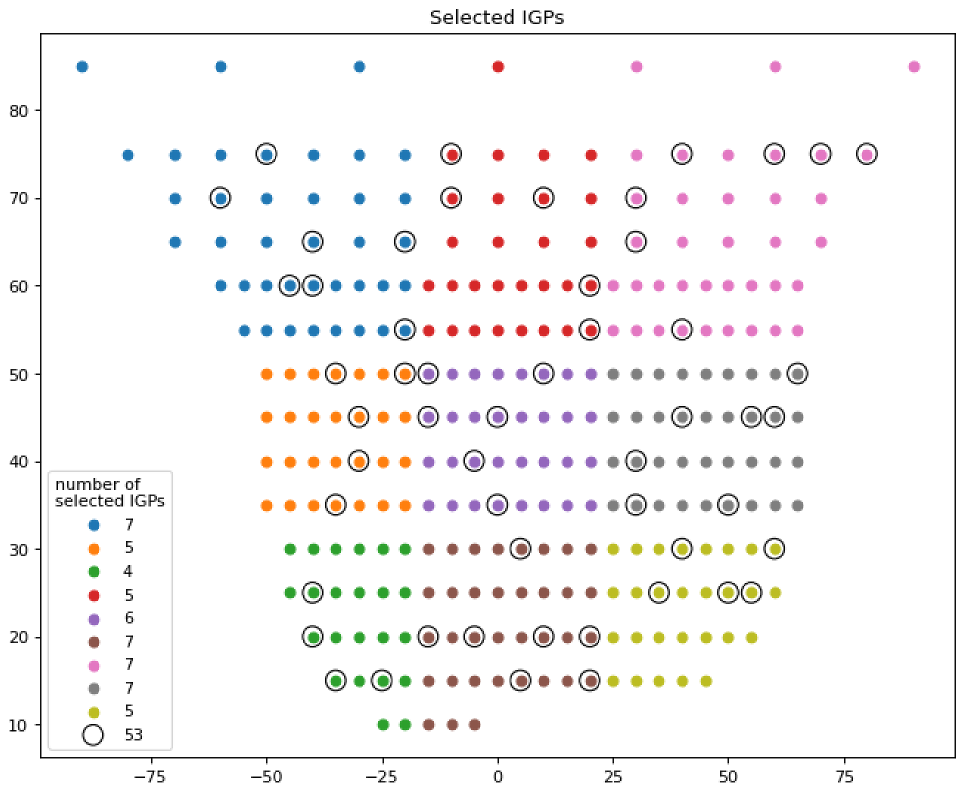
- Labels (training and label mode): UDREI for all satellites and GIVEI for all IGPs
- Features (training and prediction):
  - IPPs: monitoring, IPP coords, PRN, multipath
  - IGPs: IPP list, TEC data, sun position, local time
  - Satellites: ECEF, PRN mask, IPP list, reverse DOPs, monitor flag
- Format: JSON (zip), one file per hour, one folder per day

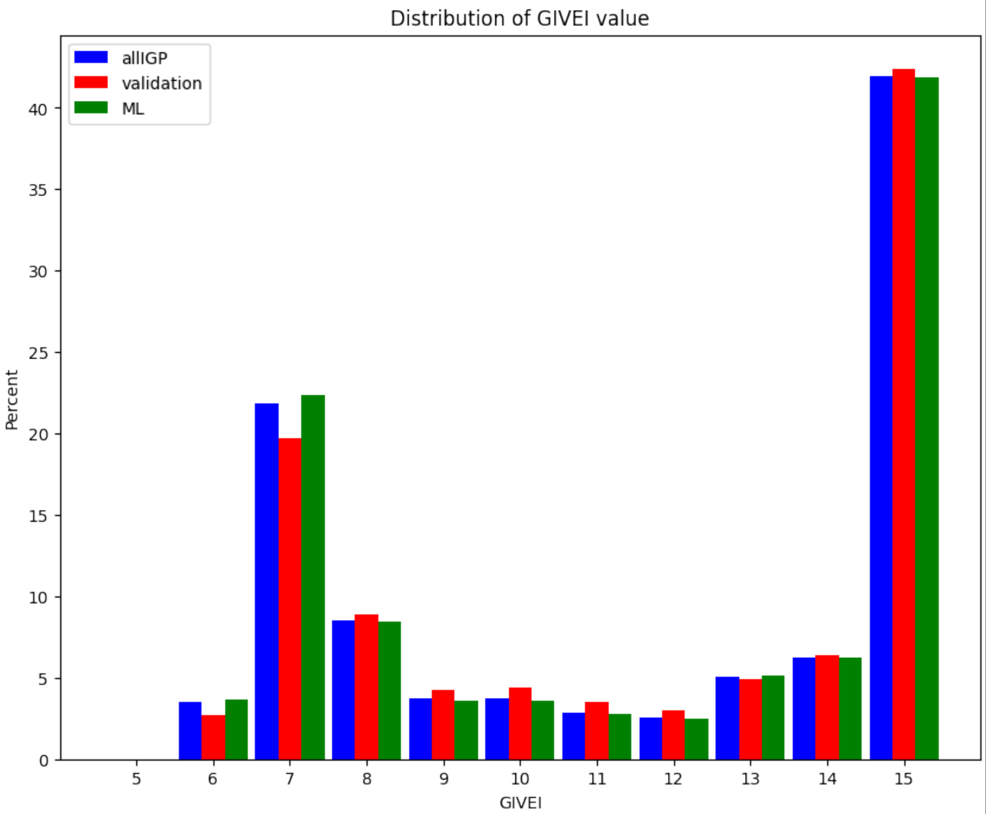
Training data: 5.5 years required

GIVEI	Full Training Period
6	13252789
7	71180842
8	27882026
9	12464735
10	12806314
11	10002505
12	9140517
13	17183772
14	21173503
15 (not mon.)	139458929

UDREI	Full Training Period
5	9201619
6	3393117
7	1097350
8	342445
9	134305
10	92853
11	**53381**
12, 13, 14	23652991

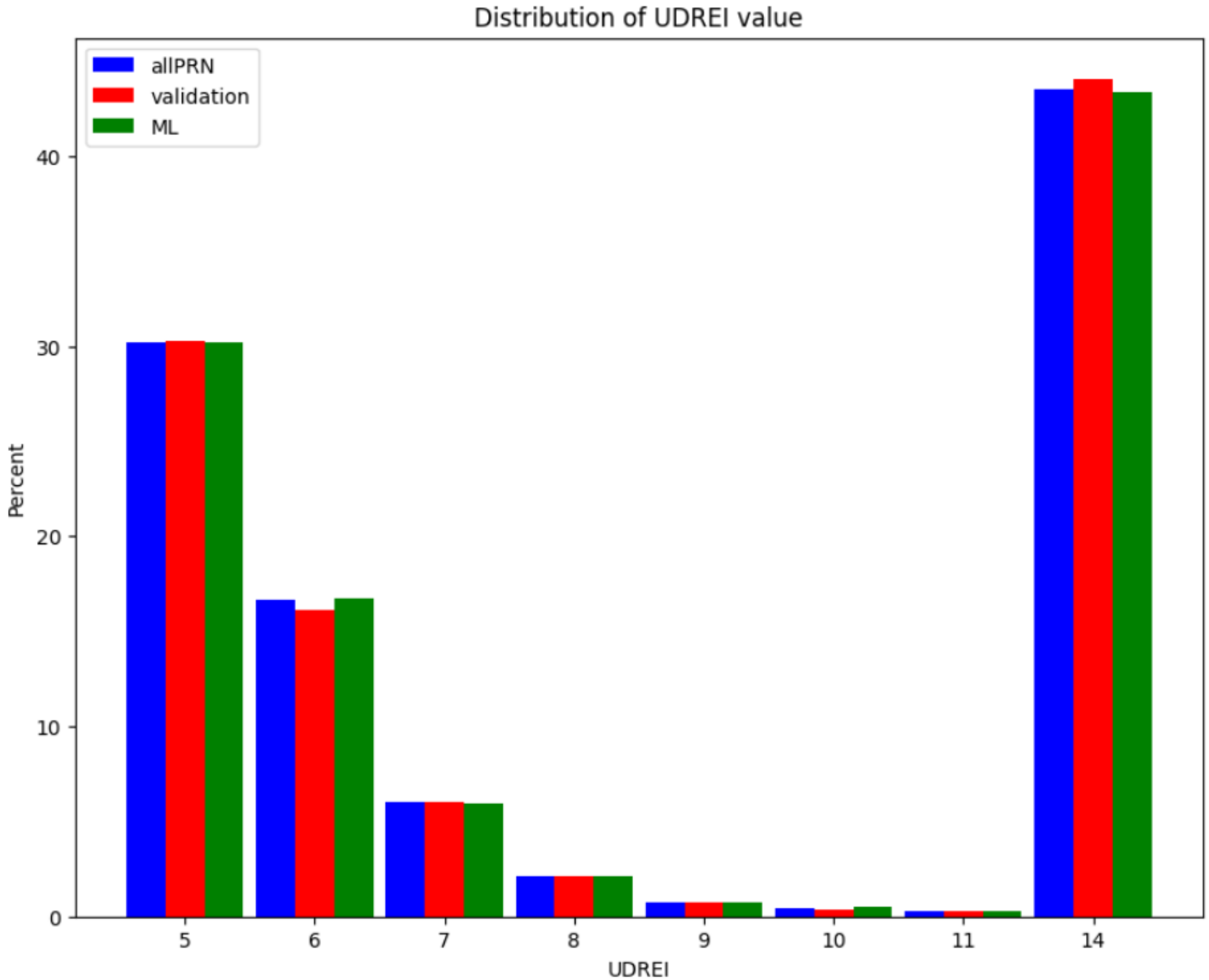
Separate training and validation IGPs



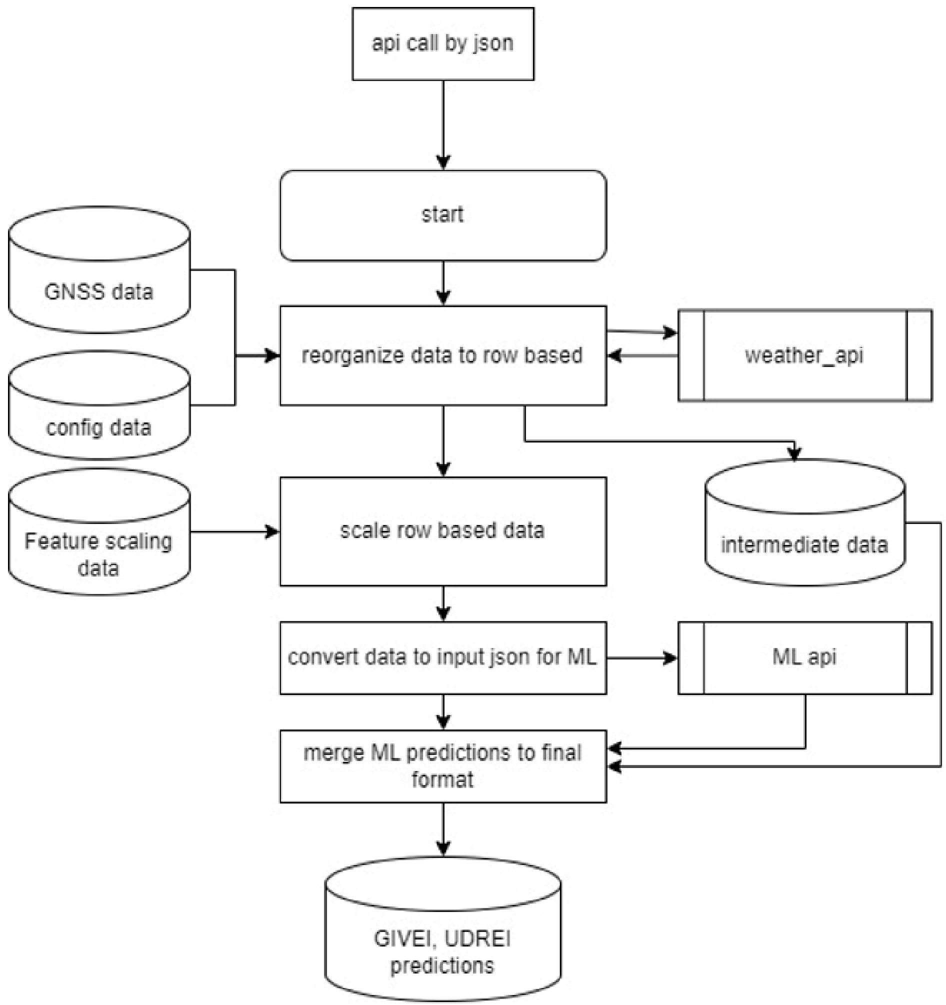


Separate training and validation PRNs

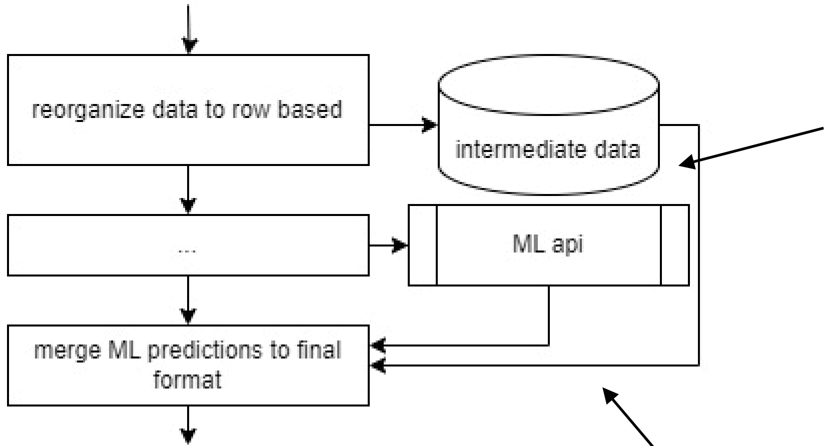
- Random PRNs selected



ML Preprocessing API



Data reorganization

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699_2023_335_2023-12-01T00:00:00;18;2290;432018;2023-12-01T00:00:00;35.0;-45.0;0;0
700_2023_335_2023-12-01T00:00:00;18;2290;432018;2023-12-01T00:00:00;40.0;-45.0;0;1
701_2023_335_2023-12-01T00:00:00;18;2290;432018;2023-12-01T00:00:00;45.0;-45.0;0;2
702_2023_335_2023-12-01T00:00:00;18;2290;432018;2023-12-01T00:00:00;50.0;-45.0;0;2
703_2023_335_2023-12-01T00:00:00;18;2290;432018;2023-12-01T00:00:00;55.0;-45.0;0;1
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18;2290;432018;2023-12-01T00:00:00;35.0;-45.0;15
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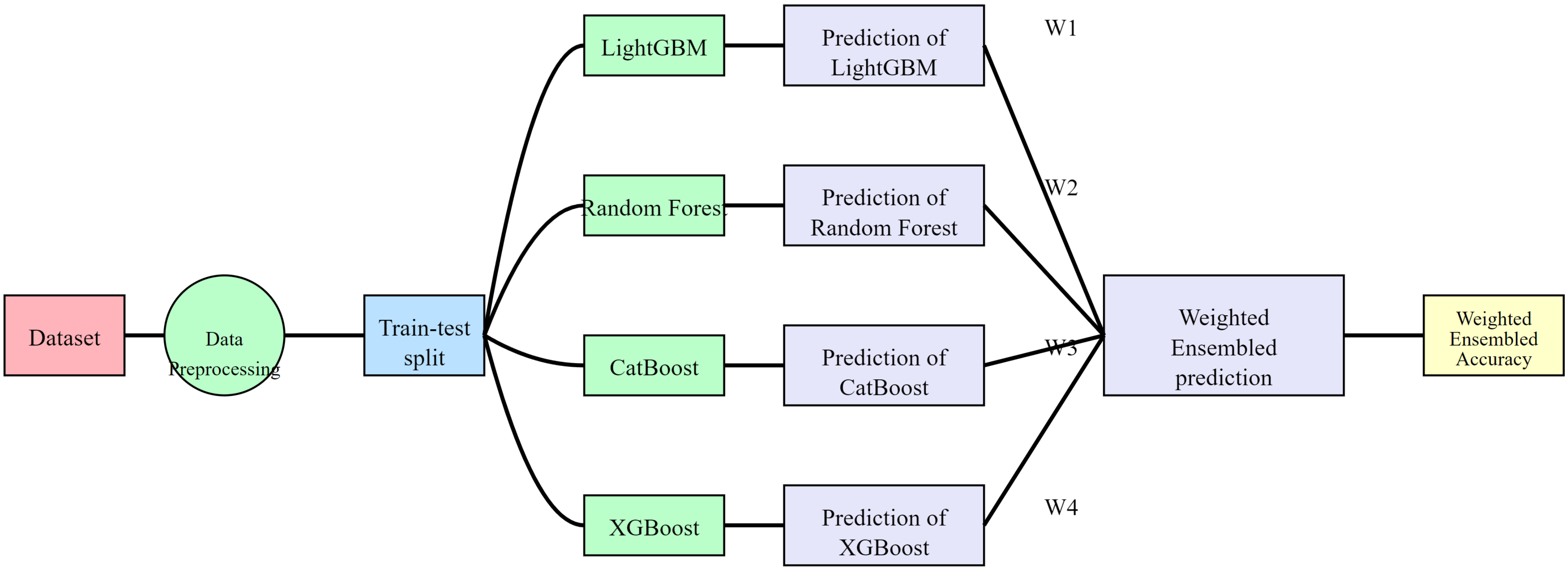
18;2290;432018;2023-12-01T00:00:00;50.0;-35.0;15
```

Machine-learning Modelling

- 4 Models tuned (Givei/Udrei, Normal/Extreme)
- Fine tuning
- Hypertuning
- Additional models, algorithms have been tested:
  - Gradient Boosted Decision Trees
  - XGB
  - Random Forest
  - Logistic Regression
  - Multilayer Perceptron
  - Mixed CNN+MLP
- Final cycle with complete DataSet
- Documentation
- Paper published

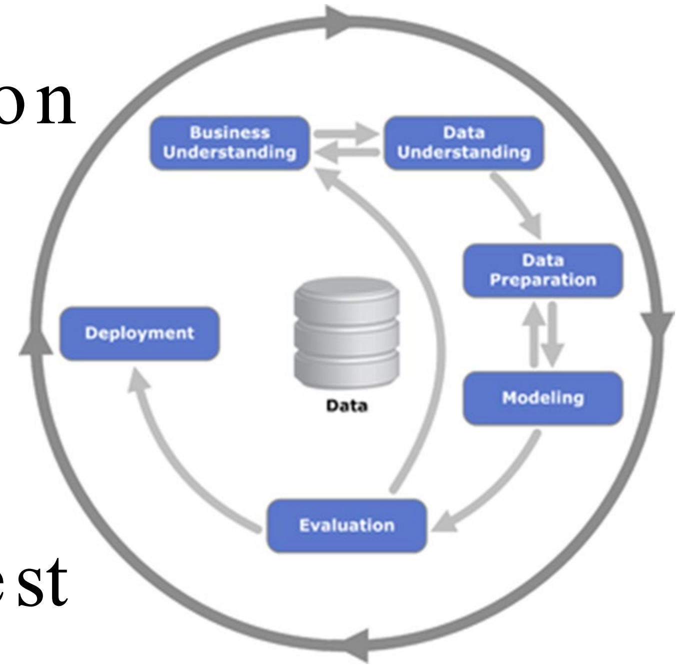
Library	Algorithm	GIVEI List	GIVEI Image	UDREI Row
TensorFlow+Keras	CNN	N	Y	N
Catboost	Catboost	Y	N	Y
XGBoost	XGBoost	Y	N	Y
LightGBM	LightGBM	Y	N	Y

Ensembling models

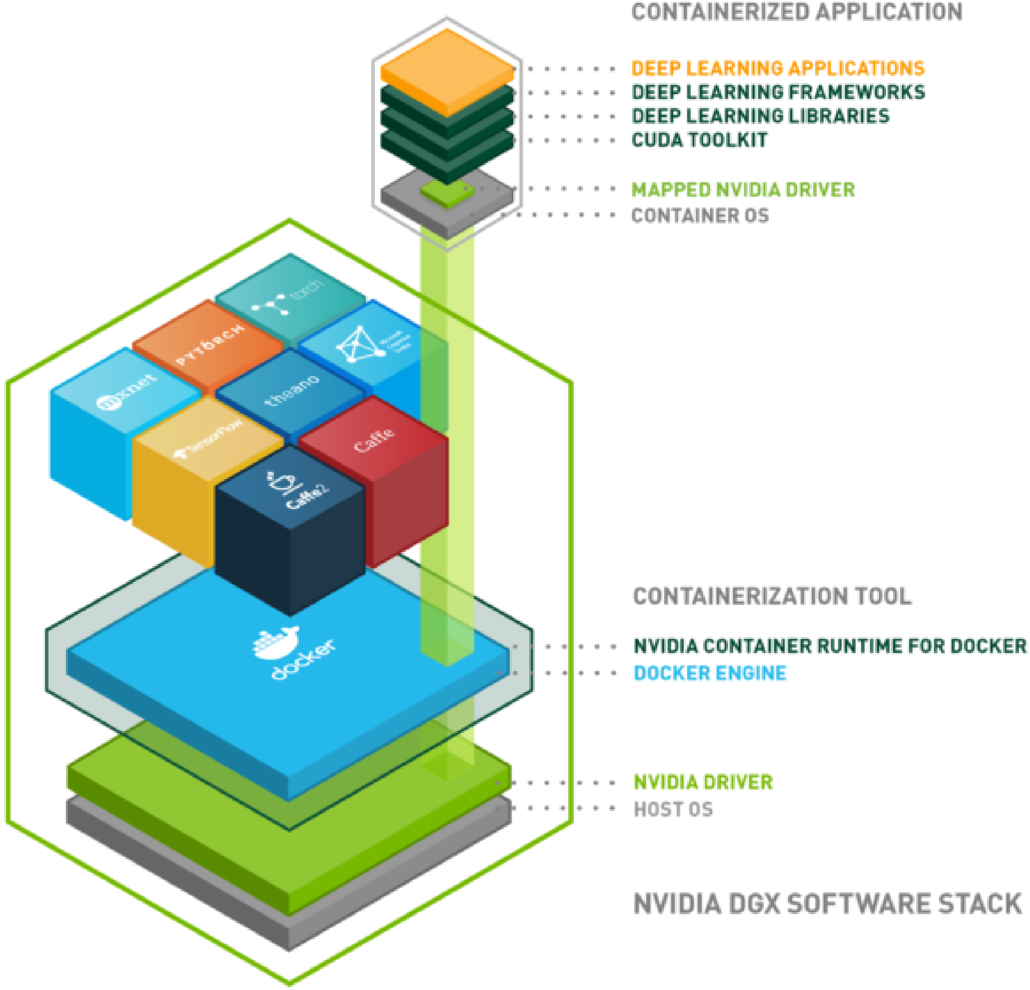


Evaluation

- Evaluation Scripts have been completed
- Fine tuning: 117k+ model iteration
  - 4 models
  - 7 algorithms
  - ~200-400 hyperparameters sets
  - 14 data /feature set version
- Best performing models with best parameters have been deployed to inference environment
- Documentation

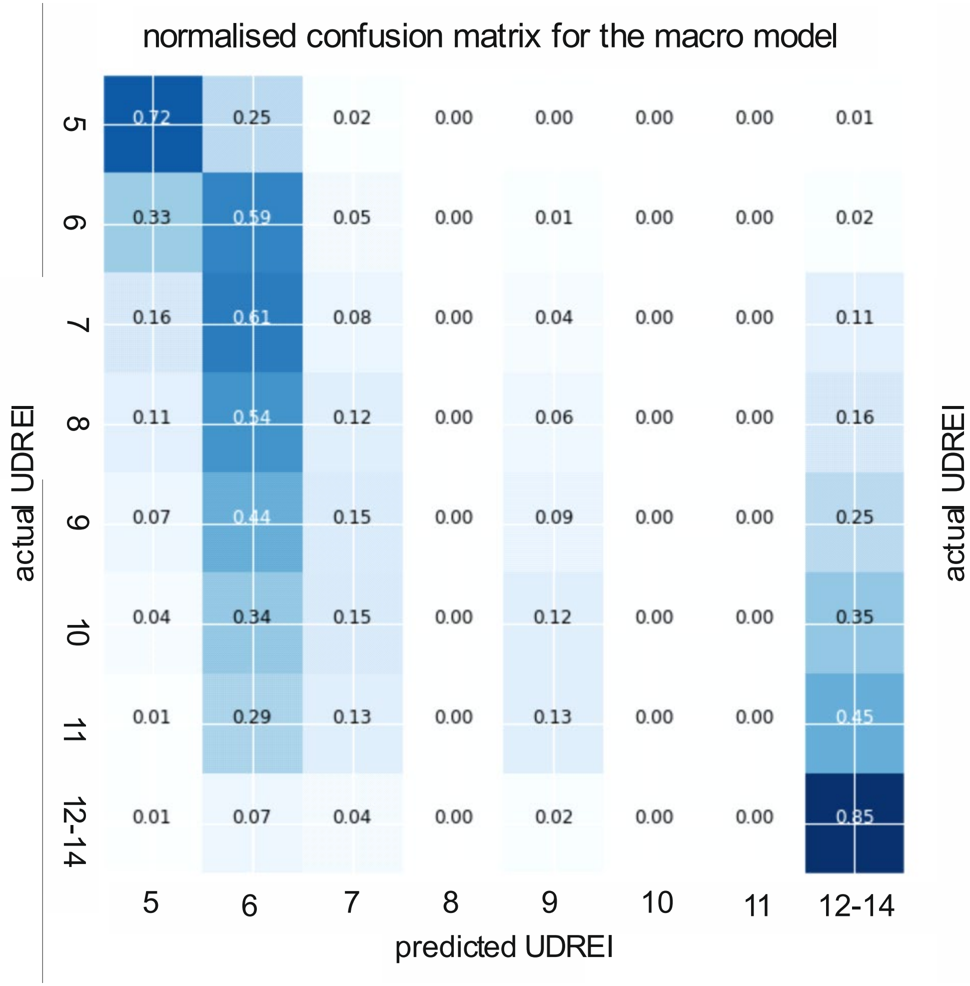


Docker Environment

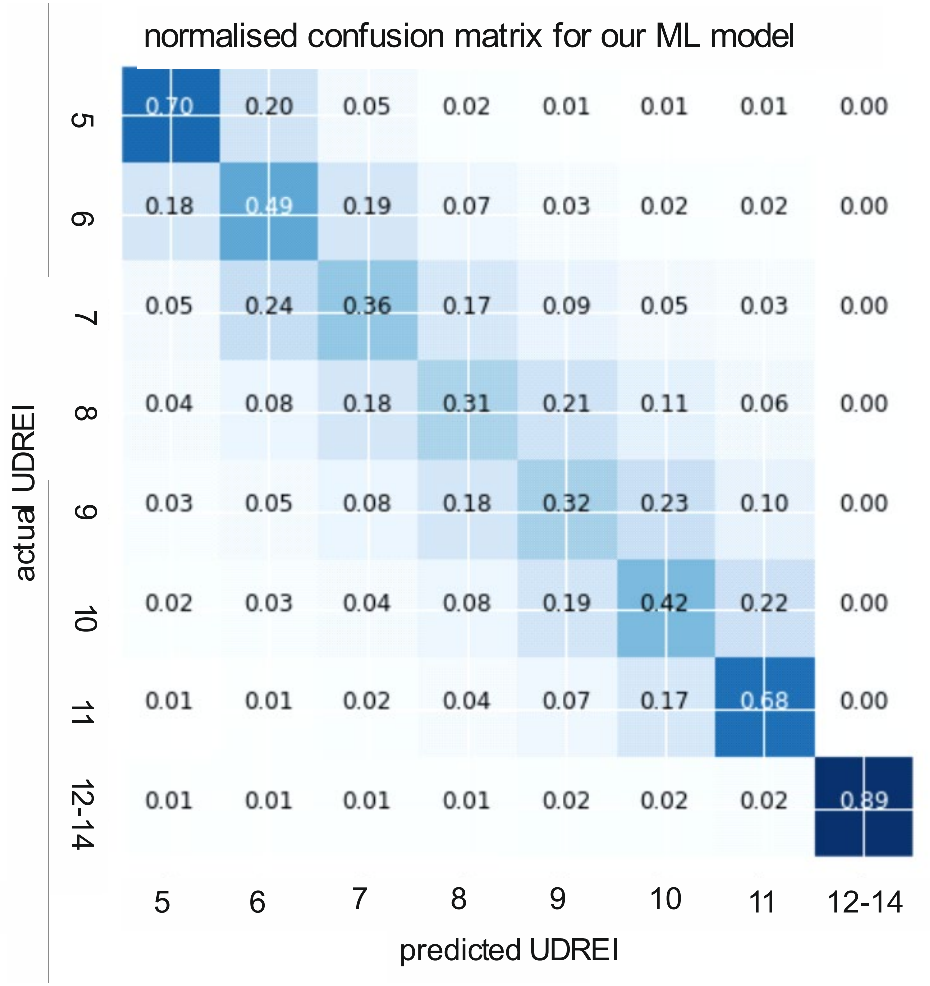


- Ensures identical dev test prod environments
- Service transportability
- Scalability with kubernetes
- GPU usage for faster Inference

ML prediction results: UDREI

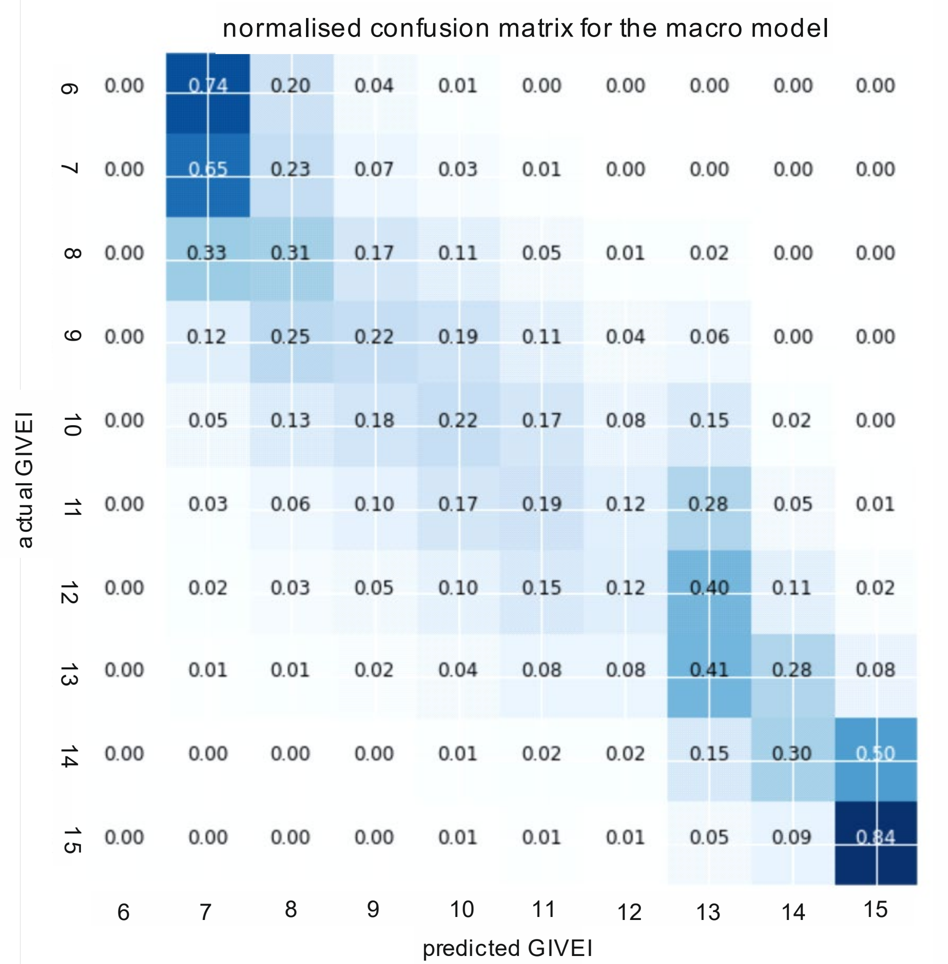


Macro model

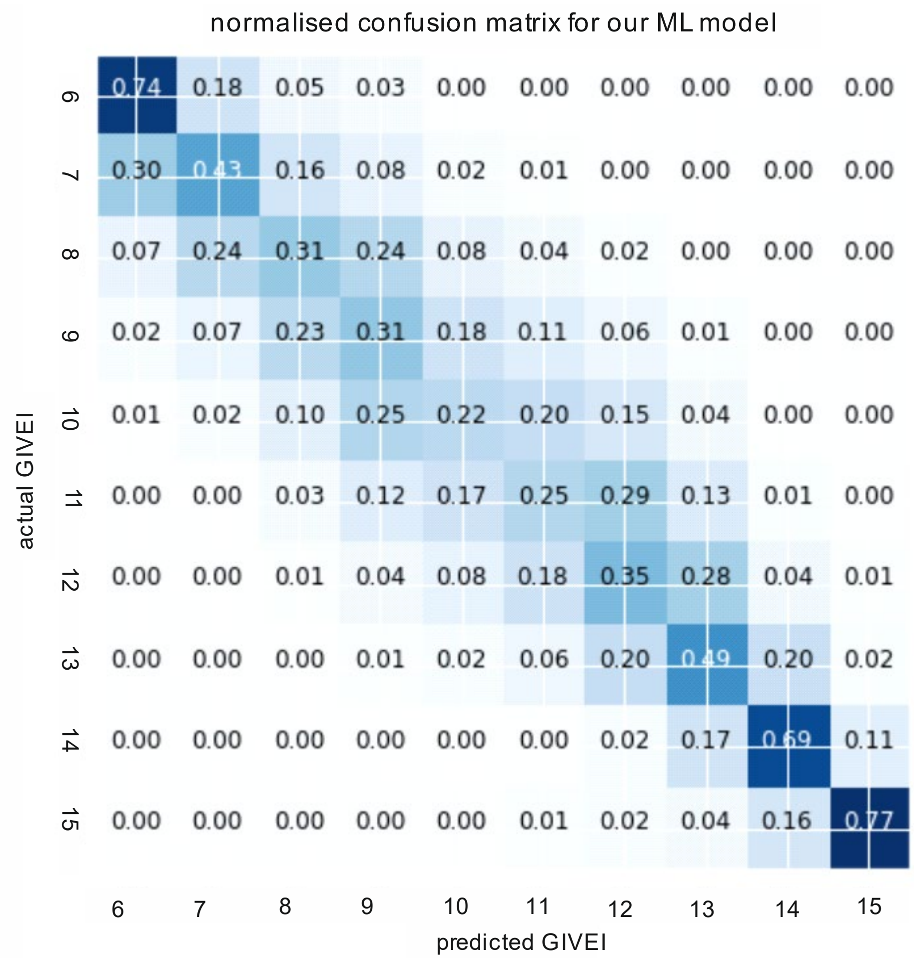


ML model

ML prediction results: GIVEI



Macro model



ML model

EGNOS User Performance

Uncertainties:

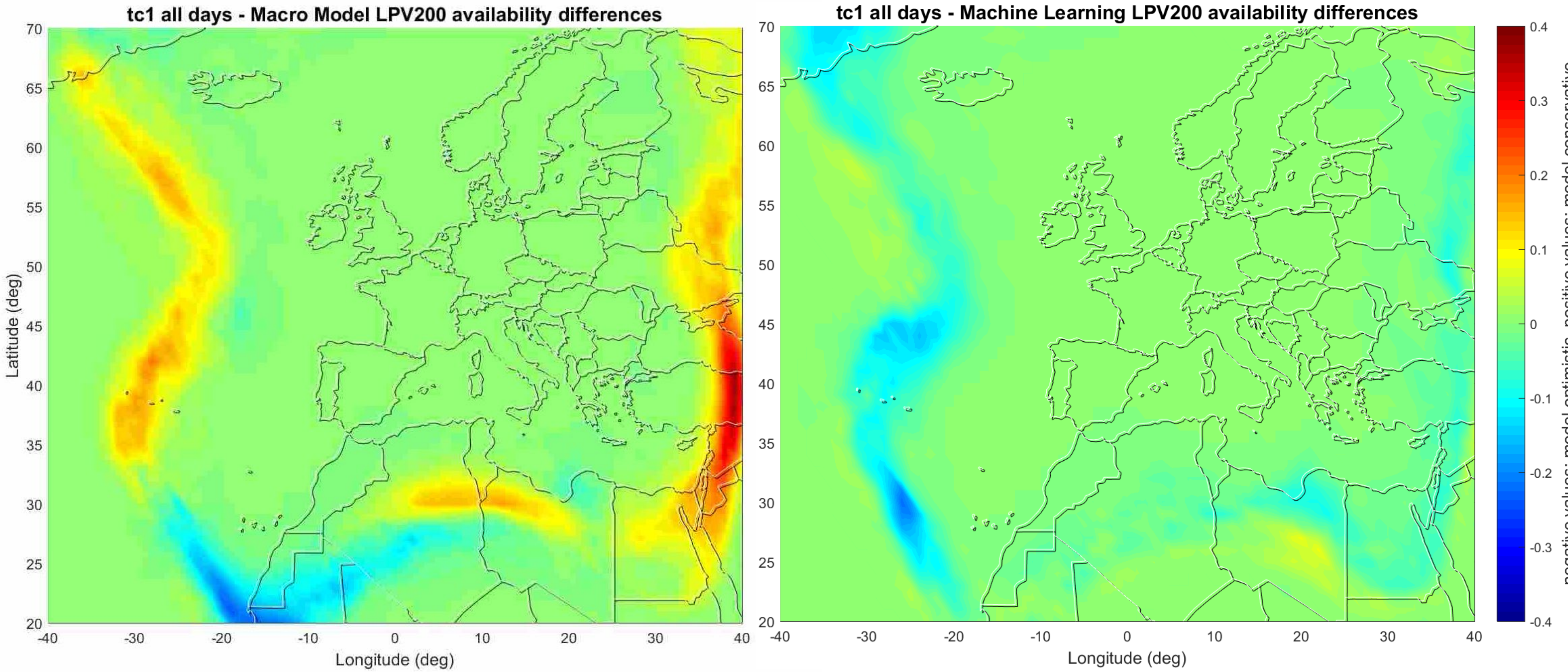
GIVEI *ionospheric delay*

UDREI *orbit + clock*

Performance Evaluation Module

- Two step process:
  - Compute protection levels (‘max. position error’) for each of three streams:
    - EGNOS Broadcast/Simulated Broadcast
    - Machine Learning Predictions
    - Macro Model Predictions
- Compute statistics and plots
- Availability: ‘sufficiently low protection levels to fly the operation’

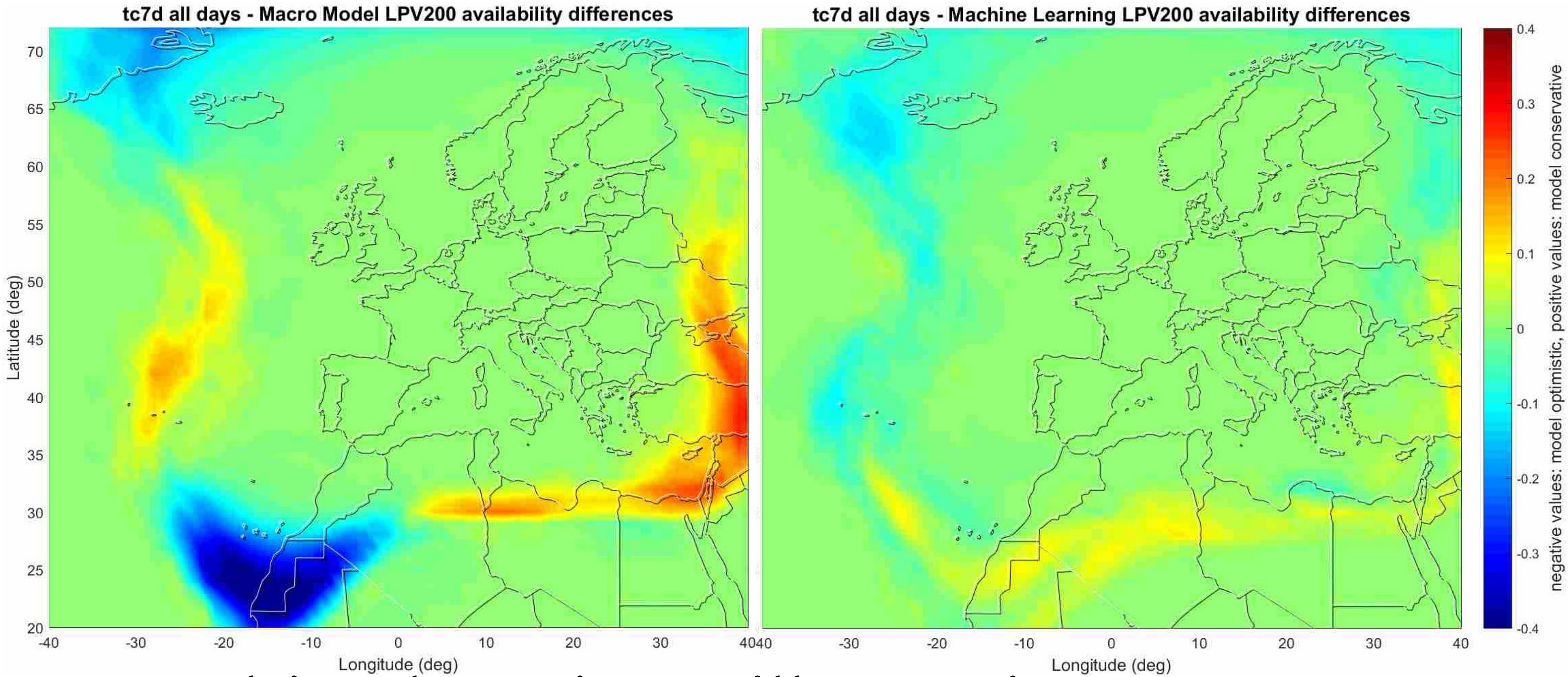
Example 1a: LPV200 availability



- Machine learning clearly superior

Note: normal (quiet) ionosphere, *historical* (space) weather

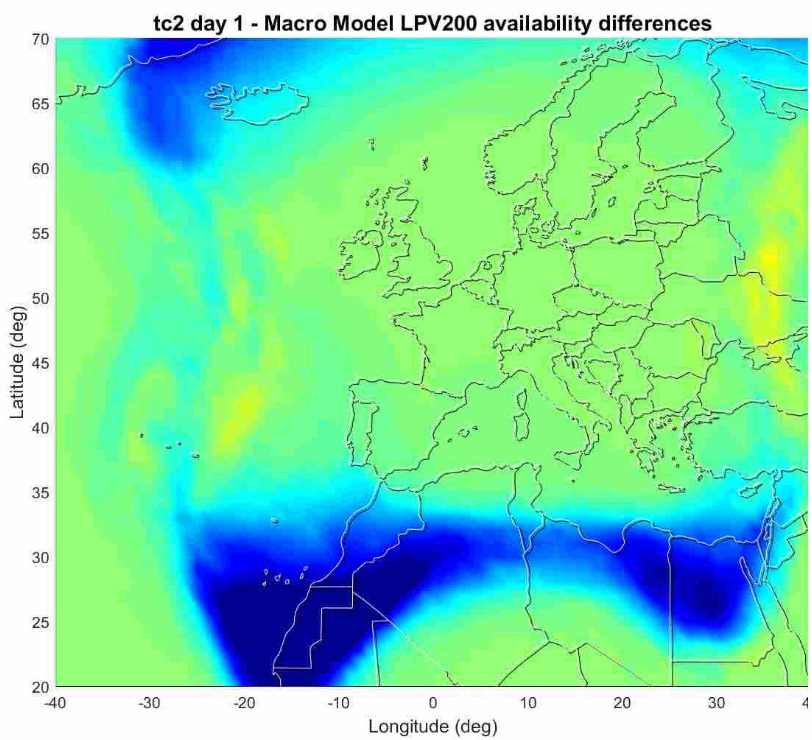
Example 1b: LPV200 availability

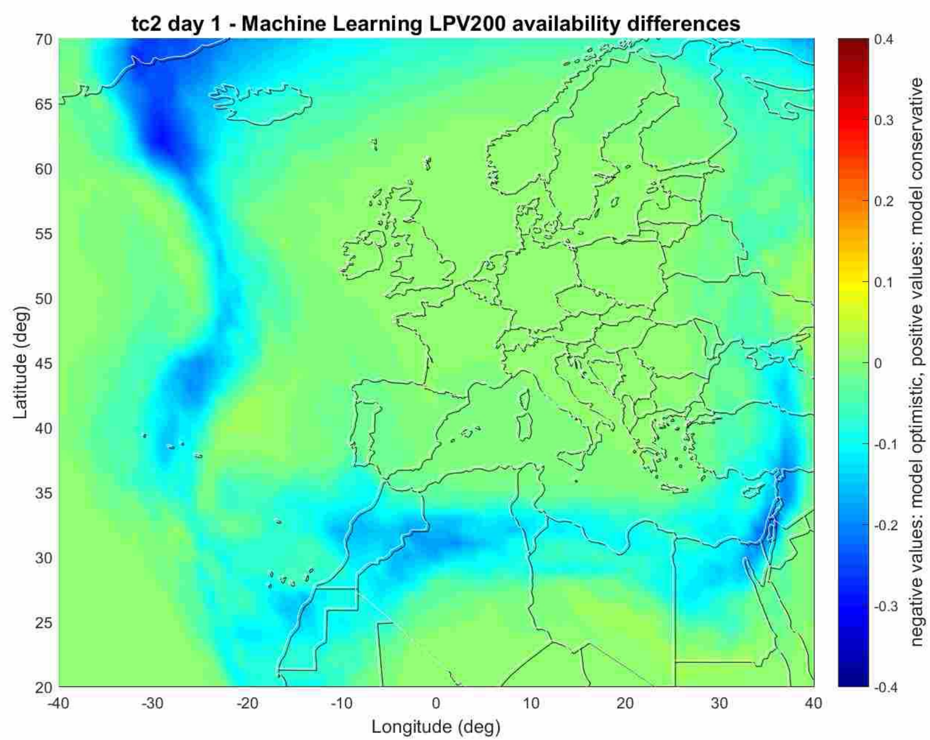


- Machine learning still superior

Note: normal (quiet) ionosphere, *forecast* (space) weather

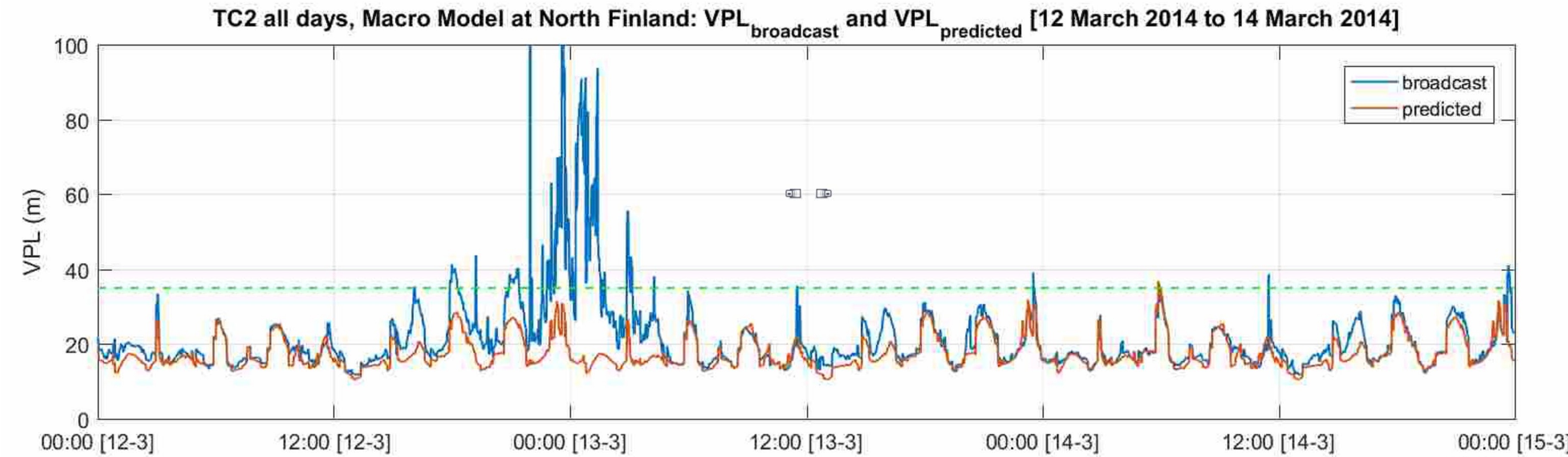
Example 2: active ionosphere

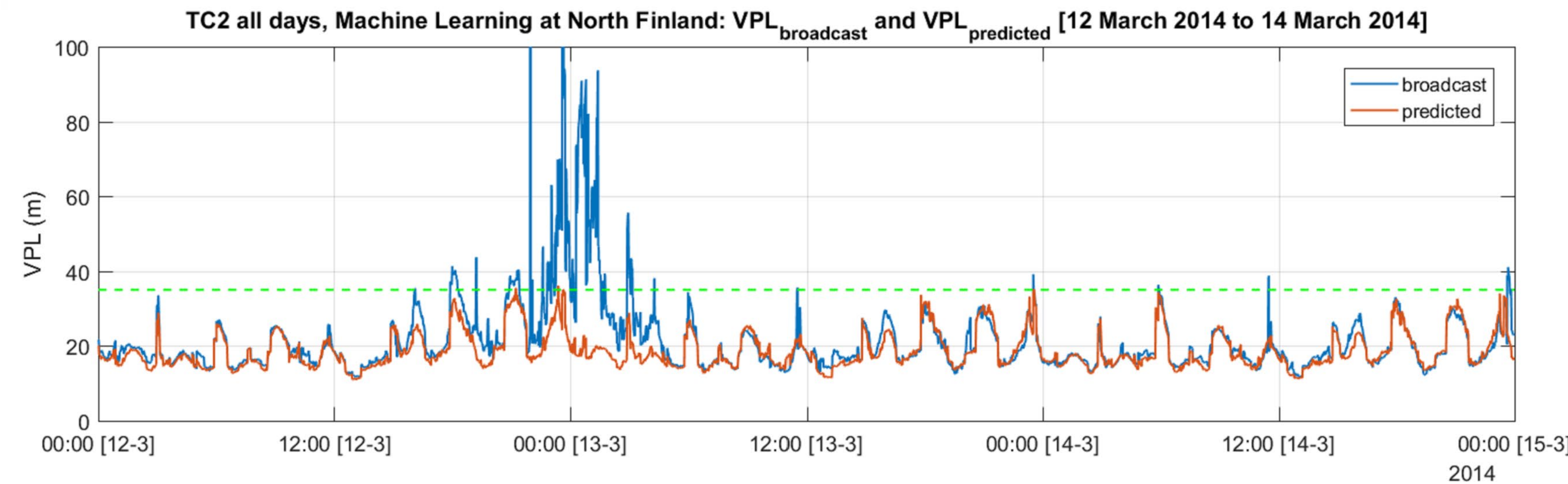




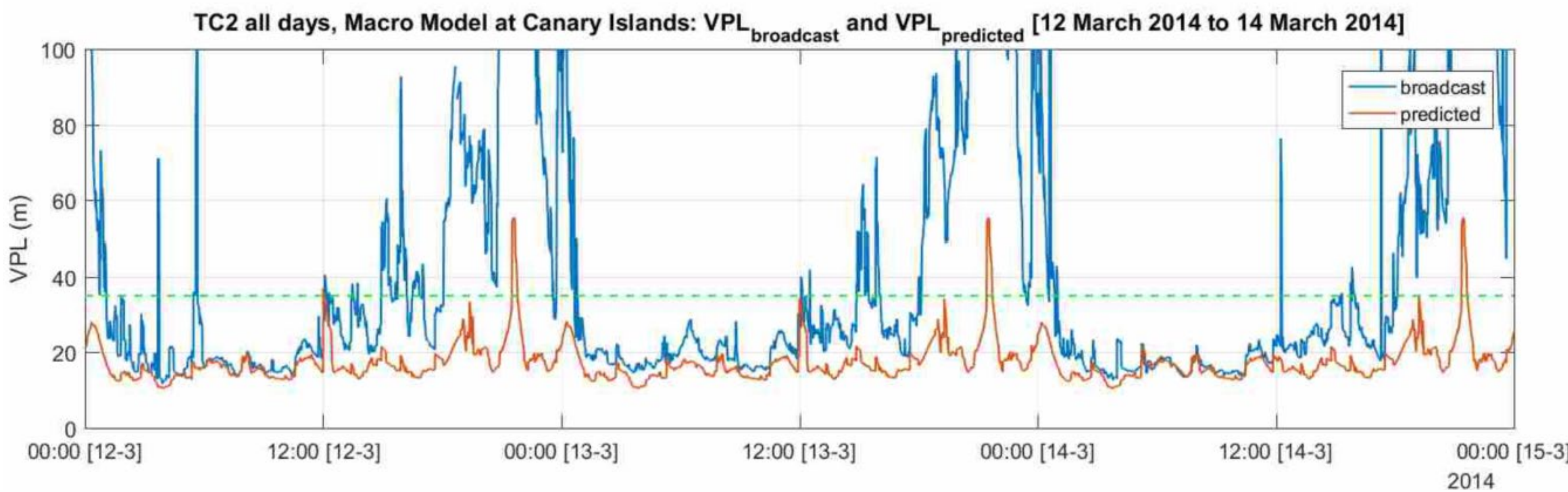
Note: active ionosphere, historical space weather

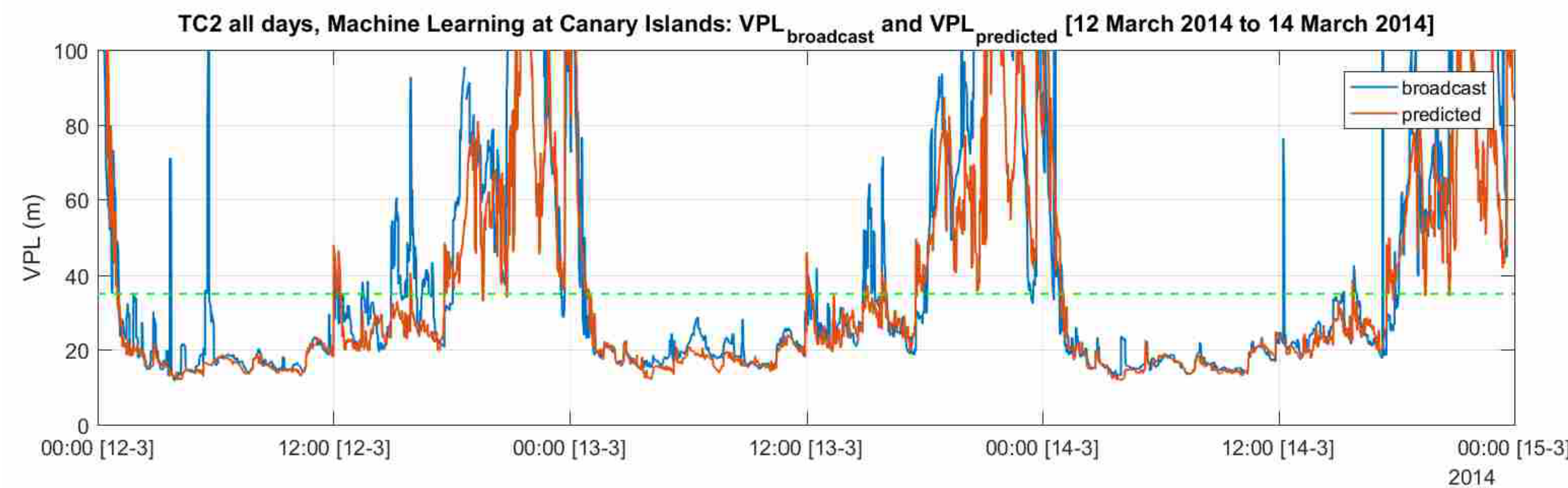
Active ionosphere: Finland





Active ionosphere: Canary islands





Summary: faulty prediction percentages

Faulty Predicted LPV200 availability (percentages)		
Year-DOY	**Macro Model**	**Machine Learning**
2016-261	6.3	4.4
2016-262	6.1	4.4
2016-263	5.4	4.1
2017-001	5.2	4.1
2017-002	6.2	4.9
2017-003	5.4	4.5
2017-004	6.1	5.2
2017-005	6.1	5.0
2017-006	5.8	4.4
2017-007	6.3	5.2
2017-008	5.7	4.7
2017-009	5.8	4.4
2017-010	5.9	4.4
2017-011	5.8	4.4
2017-012	5.8	4.4
2014-071	9.6	6.1
2014-072	10.9	7.0
2014-073	8.8	5.6
2017-076	5.5	4.5
2017-077	5.9	5.3
2017-078	5.5	5.2
2017-078	5.6	5.1
2017-080	5.4	5.0
2017-081	5.4	4.3
AVERAGE	**6.3**	**4.9**

Fault percentages, lower is better

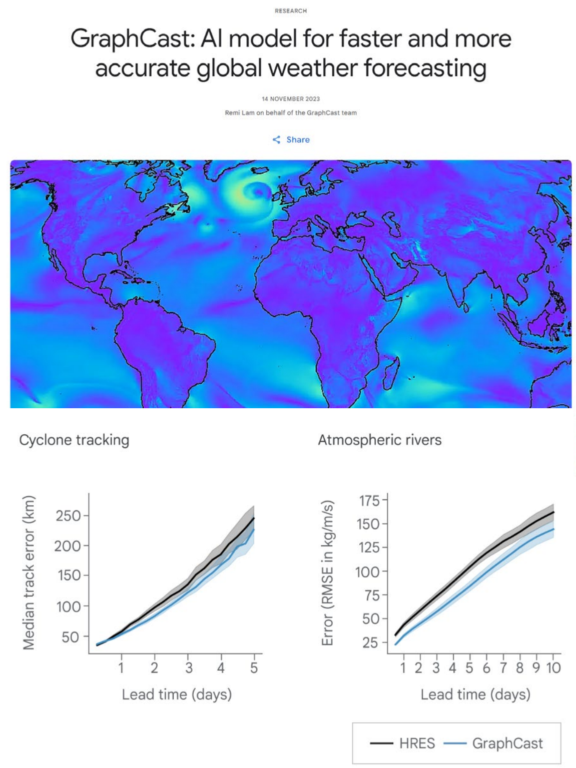
- Machine learning superior throughout

Opportunities to further improve

- Include additional features
  - Improve weather/space weather data
  - IGP locations (?)
- Fine-tune use of RIMS data to get closer to actual data use when there are outages
- Include scintillation risk considerations
- Improve speed
- Use position-domain performance metrics
  - Not trivial, can be computationally expensive

Improve (space) weather data

- Improve (space) weather forecast model (e.g. Google Deepmind GraphCast)
- Benefits
  - Scintillation probability
  - Dense Data for deep models
  - Higher resolution
  - Time series incorporated



Summary and conclusions

- Our Machine Learning models improve EGNOS performance prediction with respect to existing Macro Models
- Overall improvement is significant in both ‘UDRE/GIVEI’ and protection level/availability domains
  - Further improvements are feasible
- There is a computational cost
  - Not limiting for envisioned application(s)
  - Can still be significantly improved