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# SWAN Executive Summary Report

Space Weather impact on Arctic Navigation

**ESA Contract No. 4000131556/20/NL/AS**

**Forecasting Space Weather Impacts on Navigation Systems in the Arctic (Greenland Area)**


Prepared:

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# 1 Introduction

## 1.1 Purpose

This document is the “SWAN Executive Summary Report” The document is defined as a deliverable item under ESA Contract No. 4000131556/20/NL/AS, Forecasting Space Weather Impacts on Navigation Systems in the Arctic (Greenland Area).

## 1.2 Scope

The SWAN Executive Summary Report summarizes the work performed, and high-lites the major results obtained under ESA Contract No. 4000131556/20/NL/AS, Forecasting Space Weather Impacts on Navigation Systems in the Arctic (Greenland Area).

## 1.3 Reference Documents

| Ref. | Doc. No. | Title | Rev |
|---|---|---|---|
| TN 1.1. | SWAN-CCORE-TEC-D-001 | TN 1.1: Space Weather threats and existing Real time Space Weather services for PNT systems | 3 |
| TN 1.2 | SWAN-NMA-TEC-D-002 | TN 1:2 Product requirements for Advanced Space Weather forecast for PNT in the Arctic region | 3 |
| TN 2 | SWAN-ONERA-TEC-D-004 | TN 2: New methodologies/algorithms for the provision of Advanced Space Weather Forecast/Warning products for PNT in the Artic region | 3 |
| TN 2 ADD | SWAN-SPIRE-TEC-D-001 | TN 2: New methodologies/algorithms for the provision of advanced space weather forecast/warning products for PNT in the Artic region – ADDENDUM | 2 |
| TN 3.1 | SWAN-DTU-TEC-D-005 | TN 3.1: Design Justification Document | 2 |
| TN 3.2 | SWAN-DTU-TEC-D-006 | TN 3.2: Testbed verification and products validation plan | 1 |
| TN 4.1 | SWAN-NMA-TEC-D-007 | TN 4.1: SWAN Implementation and validation report | 1 |
| TN 4.2 | SWAN-NMA-TEC-D-008 | TN 4.2: Demonstrator operation report | 2 |
| TN 4.3 | SWAN-DTU-TEC-D-009 | TN 4.3: Roadmap for implementation of Advanced Space Weather Forecast/Warning products for PNT in the Arctic Area. | 2 |
| TN 4.4 | SWAN-DTU-TEC-D-010 | TN 4.4: Draft scientific publication of the main results of the activity. | 1 |
| FR | SWAN-DTU-TEC-FR-001 | SWAN Final Report | 2 |
| [Fabbro et al., 2021] | | V. Fabbro, Jacobsen, K. S., Andalsvik, Y. L., and Rougerie, S.. GNSS positioning error forecasting in the arctic: Roti and precise point positioning error forecasting from solar wind measurements. J. Space Weather Space Clim., 11:43, 2021. doi:10.1051/swsc/2021024.<br>doi:https://doi.org/10.1051/swsc/2021024. | |
| [Newell et. al, 2007] | | P. T. Newell, T. Sotirelis, K. Liou, C.-I. Meng, and F. J. Rich. A nearly universal solar wind-magnetosphere coupling function inferred from 10 magnetospheric state variables.Journalof Geophysical Research: Space Physics, 112(A1), 2007. ISSN 2156-2202. doi:https://doi.org/10.1029/2006JA012015 | |

# 2 Background

Space weather describes the variations in the space environment between the Sun and Earth. Space weather includes a number of phenomena (Figure 2-1) of the environmental conditions in Earth's magnetosphere, ionosphere and thermosphere due to the Sun and the solar wind that can influence the functioning and reliability of space-borne and ground-based systems and services or endanger property or human health. It includes CME from the Sun, disturbances in Earth's magnetic field, changes in the space environment and geomagnetic storms resulting from eruptions on the Sun. Space weather processes can include non-solar sources such as galactic cosmic rays and changes in the interplanetary magnetic field.

When solar wind reaches Earth, it energizes Earth's magnetosphere and accelerates electrons and protons down along Earth's magnetic field lines where they collide with the atmosphere and ionosphere, particularly at high latitudes (NOAA 2020). Different types of space weather can affect different technologies at Earth. Solar flares can produce strong X-rays that degrade or block high frequency radio waves used for radio communication during events known as Radio Blackout Storms. Solar energetic particles (energetic protons) can penetrate satellite electronics and cause electrical failure. These energetic particles also block radio communications at high latitudes during solar radiation storms. Geomagnetic storms can also modify the signal from radio navigation systems (GNSS) causing degraded accuracy.

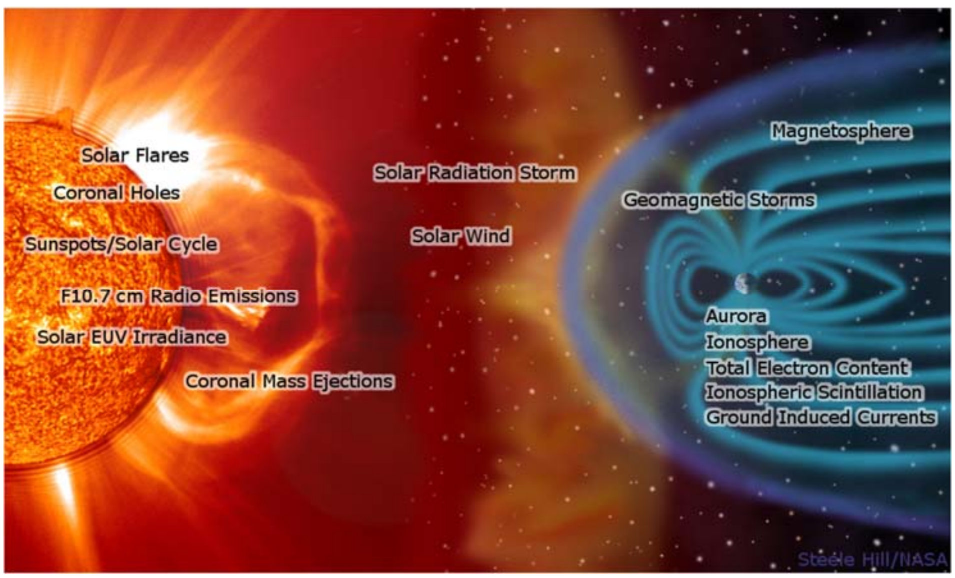


Figure 2-1: Space weather phenomena. Adopted from NOAA.

The forecast of space weather events is becoming more and more important as the reliance on space-based systems is increased. Reliable and timely forecasts can allow mitigating actions to be taken in order to reduce disruptive or harmful consequences of space weather disturbances.

[TN 1.1] provides a review of the literature relevant to positioning, navigation and timing (PNT) as affected by space weather. After a short introduction the note provides some basic information on space weather and ionospheric phenomena focusing on scintillation of L-band signals in the Arctic region including Greenland. It also includes a description of space weather threats and detailed descriptions of relevant models and space weather centers. More than one hundred references covering topics in relevant space weather and PNT topics are identified and used in [TN 1.1].

## 2.1 Space weather threats

A review of threats has been investigated in [TN 1.1], the main threats can be categorized as

- Geomagnetic storms
- Solar radiation storms
- Ionospheric storms
- Solar radio bursts

The relevance of the space weather effects vary with each of the applications of GNSS. Some applications require millimeter accuracy and some only need coarser accuracy. [TN 1.1] describes the most common impact on GNSS/PNT:

- Loss of lock
- Position error
- Timing Error
- SNR and GNSS receiver tracking performance

## 2.2 Existing space weather real-time services

[TN 1.1] identifies and describes available space weather centers. See below:

1. NOAA, Space Weather Prediction Center (https://www.swpc.noaa.gov)
2. Solar wind and geomagnetic activity data from NASA's Coordinated Data Analysis Web (CDAWeb, https://cdaweb.sci.gsfc.nasa.gov)
3. NRCan, Space Weather Canada (https://www.spaceweather.gc.ca). The Geomagnetic Laboratory of Natural Resources Canada is the Government of Canada's headquarters for the Geomagnetic Monitoring Service and the Canadian Space Weather Forecast Centre
4. ESA Space Weather Office and Space Weather Service Network (http://swe.ssa.esa.int/swe)
5. The International Space Environment Service (ISES) (www.spaceweather.org).
6. Russia. http://spaceweather.izmiran.ru/eng/links.html
7. Space Weather Services, Bureau of Meteorology, Australia (http://www.sws.bom.gov.au)
8. Ionosphere Monitoring and Prediction Center, DLR, Germany (https://impc.dlr.de) https://impc.dlr.de/products/total-electron-content/near-real-time-tec/nrt-tec-global/
9. Belgium https://www.spaceweatherlive.com
10. SIDC http://sidc.oma.be/products/meu/
11. Global TEC map https://iono.jpl.nasa.gov/latest_rti_global.html
12. The Norwegian Centre for Space Weather (NOSWE) https://site.uit.no/spaceweather

Current space weather predictions are focused primarily on five areas (Wu 2020):

1. Solar flares and eruptions impacting communications, radar, and GNSS receivers;
2. Radiation storms affecting airlines, astronauts, satellites, and communications;
3. Disturbances in Earth's magnetic field impacting electric power grids, GNSS, satellites, and airlines;
4. Atmospheric heating from increased short-wavelength radiation which shortens the lifetime of low-Earth orbiting satellites; and
5. Ionospheric storms, which degrade navigation systems, GNSS dependent technologies, and high frequency and satellite communications.

Many space weather events are forecasted, but with minimal lead time because of a lack of real-time data and limited model capabilities. Hence, further development is required to enhance the forecasting. Especially in the Arctic regions.

# 3 Advanced space weather forecast for PNT in the Arctic region

## 3.1 Requirements definition for advanced space weather forecast for PNT in the Arctic region

Based on the analysis of the existing services and on the impact of space weather on PNT in the arctic, [TN 1.2] & [FR] presents the results of a "gap analysis" between the existing ESA Space Weather Customer Requirements Documents (CRD) and the identified threats to PNT in the Arctic [TN 1.1]. As a result of this gap analysis a set of specific requirements were set up for the Space Weather impact on Arctic Navigation (SWAN) forecasting service to be implemented, [TN 1.2].

The requirements have been established within the following categories:

- Data requirements
- Functional requirements
- Performance requirements
- Presentation requirements
- Operational requirements

These requirements [TN 1.2] have formed a solid baseline for the design, implementation and test of the SWAN testbed. Further, after the verification and validation process for the forecasting model has been carried out, the requirements baseline has also made it more evident where further developments are needed to propagate this Arctic forecasting service into an operational system.

## 3.2 Data sources, methodologies and algorithms considered for SWAN

### 3.2.1 Data sources

The SWAN project has investigated a range of various ground and satellite-based sensors for obtaining data relevant for space weather forecasting. [TN 2 ADD] describes and categorizes the identified data sources and also priorities the relevance of these sources in relation to an actual real-time forecasting service. (This is also described in further detail in [FR])

There are many practical issues associated with the different types of data. These can be broken down into four main areas:

1. Data availability and timeliness
2. Data location
3. The predictive capability of the data
4. How well suited the data is for use in the machine learning (ML) methods to be developed under the SWAN project

The first two of these can be determined from inspection of the data; point three must be assessed using pre-existing scientific literature; and point four is specific to this project. To guide the development of SWAN a scoring matrix has been that aims to prioritize which data types just be used. The scores indicate clearly that developing the use of solar wind, 1Hz ROTI and magnetometer data is appropriate for the SWAN project. (Detailed descriptions and analysis of the various data sources have been performed in [TN 2 ADD]).

Figure 3-1 show the location of the GNSS receivers as well as the Magnetometer stations used to create the required SWAN Database for input to and validation of the proposed forecasting service. The stations marked in green to the left, are the Magnetometer stations, which also were considered as part of the input data in the database. However, for the empirical modelling, this data was again disregarded.

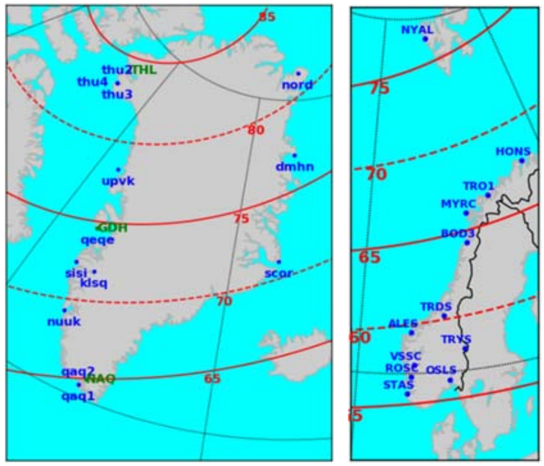


Figure 3-1: The locations of the NMA GNSS receivers, GNET receivers in Greenland as well as magnetometer stations used in Greenland.

The ROTI data from GNET and NMA Stations used in the framework of this project corresponds to the period [2010-2020], covering most of the 24th solar cycle.

For the actual space weather forecasting service, two approaches have been considered for the development of operational forecasts [see detailed descriptions in TN 2]:

1) An empirical approach based on prior work by project partners, and
2) a novel machine learning approach.

The following sections gives a summary on the developments performed in this relation, the results obtained from the verification and validation of the developed approaches to forecasts, as well as the proposed forecast service (Implemented testbed), which is one of the main results of the project. (This is also described in further detail in [FR])

### 3.2.2 SWAN empirical approach

The High lAtitude disturbance Positioning Error Estimator (HAPEE) model was used as baseline for the empirical approach. It is described in Fabbro, Vincent et al. (2021). It is an empirical, statistical, model that can forecast the probability distribution of ROTI for the near future, using solar wind measurements as its real-time input. HAPEE is forecasting ROTI index (characterizing ionosphere disturbances occurrence at high latitudes) and can propose a forecasting of PPP error (Precise Positioning Error).

The original HAPEE model is based on data from GNSS receivers in Norway and provides a forecast for the coming hour. Figure 3-2 indicates the output of the original HAPEE 1-hour forecasting data

The extended model which has been developed during the SWAN project has improved the forecast to around 3 hours and has also extended the applicable area to cover not only Norway, but most of the Arctic by including Greenland (See Figure 3-1).

To update HAPEE model, new ROTI data from the GNET network of GNSS receivers have been processed, to be used together with NMA network ROTI data. This very large set of data allows covering the $24^{th}$ solar cycle and magnetic latitudes from 55 up to 85 degrees.

This ensures a much better statistical characterization of the scintillation events than the previous version of HAPEE model.

As a 3-hour forecast was requested, all statistical regression had to be re-run with a different configuration. Also, the database used to build the model was extended by the addition of data from the GNET network in Greenland. An optional extension of the algorithm transforms the output from ROTI distributions to distributions of PPP positioning error, using an empirical model. (This is also described in further detail in [FR])

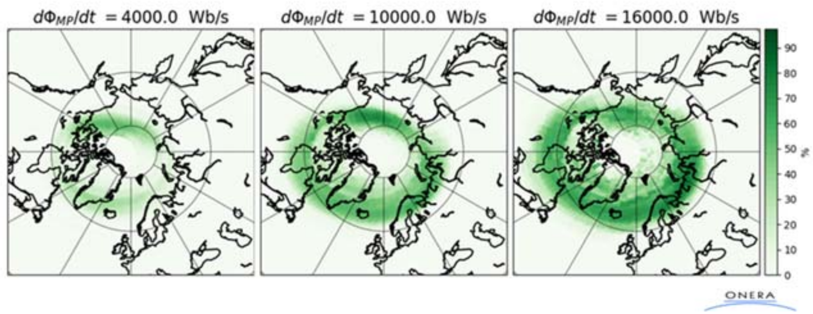


Figure 3-2: Probability of ROTI index to exceed the value 1 during the next hour calculated with HAPEE, from solar wind conditions measured at Lagrange Point 1 (L1).

### 3.2.3 SWAN machine learning approach

The relevance of machine learning was also studied in detail in the context of the SWAN project (See [TN 2]). Machine learning is normally defined as the group of algorithms trained using an example database in order to find rules, which in time allow them to perform the same task for new data. Three types of machine learning tasks depending on the feedback signal can be distinguished: supervised learning, unsupervised learning and reinforcement learning. In the context of SWAN an investigation of the LSTM algorithm to forecast time series has been performed and A state-of-the-art review on machine learning algorithms has been performed to justify the choice of LSTM algorithm.

Important properties of LSTM are:

- It captures the long-term dependencies.
- Modelling of series temporal structure is done directly.
- It allows variable length inputs and/or outputs.
- It can address multivariate problems and multi-step prediction.

The method has been matched to the problem and preliminary results has been presented. The LSTM NN cannot be considered and deployed as an operational service in the frame of the SWAN project as it requires further analysis to improve the performance of the method. However, The SWAN project has highlighted the feasibility of using the method and has also shown the great potential of such a solution for future deployment

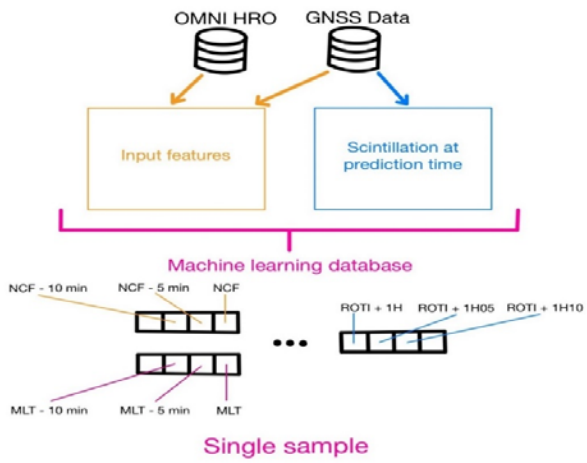


Figure 3-3: Critical components of the machine learning approach.

The critical components of the machine learning approach are shown in Figure 3: the construction of the machine learning database, and the generic illustration of the input features and the variable to be predicted, the ROTI index.

Figure 3-4 shows a comparison of observed ROTI with 1-hour predicted ROTI from the LSTM model. Note that the figure shows only a part of the validation dataset, and thus must be considered as an example. The predictions correctly react to the disturbed periods (i.e. generate larger values during the disturbed periods), but do not match the amplitudes of the peaks.

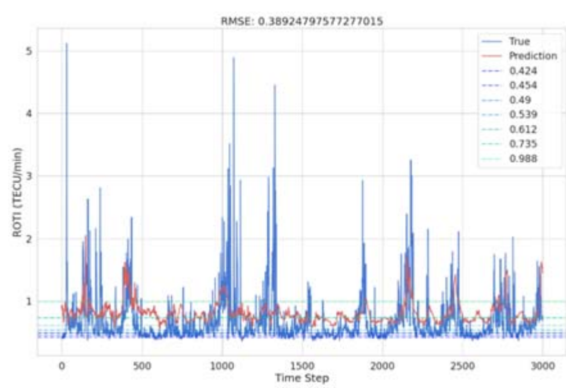


Figure 3-4: Observed ROTI vs predicted ROTI from the LSTM model.

To illustrate this in another way, we compute the standard skill scores using the entire Test dataset. The skill scores are the Probability of Detection (POD), the False Alarm Rate (FAR), the Accuracy (ACC), the True Skill Score (TSS) and the Root-Mean-Square Error (RMSE).

Table 3-1: ML model prediction skill scores, considering the condition ROTI > 0.988.

| POD | FAR | ACC | TSS | RMSE |
|---|---|---|---|---|
| 0.19 | 0.61 | 0.86 | 0.15 | 0.38 |

Table 3-1 shows the skill scores when considering the condition ROTI > 0.988 TECU/minute (i.e.; how well does the model predict the peaks?). A perfect model would have POD = 1 and FAR = 0. As can be seen in the table, the current ML model has a substantial number of failed detections and false positives when tested in this way.

Figure 3-4 shows that the LSTM NN manages to capture the global trend. However, the prediction of scintillation event levels is not accurate enough to use for an operational system. Nevertheless, the model indicates that with more tuning it is very likely that the correlation of the predicted values vs the actual values will increase. (This is also described in further detail in [FR])

## 3.3 SWAN testbed design, implementation and test

A major objective for the project was the demonstration of usage of the forecast method by establishing a prototype of a forecast service “The SWAN Testbed”. The design is described in detail in [TN 3.1].

Due to the complexity of implementing and adjusting the machine learning processor within the available resources in the project, the consortium decided to exclude this added feature from the implementation process. However, as the results turned out to be promising, it is recommended to continue this effort in future projects.

The service was built on the forecasts supplied by the extended HAPEE algorithm, using archive data to provide forecasts for previous times (hindcasts), but also designed in a way that allows integration of real-time data feeds in the future. The implementation is described in detail in [TN 4.1].

Figure 3-5 shows an overview of the components of the service as it has been built.

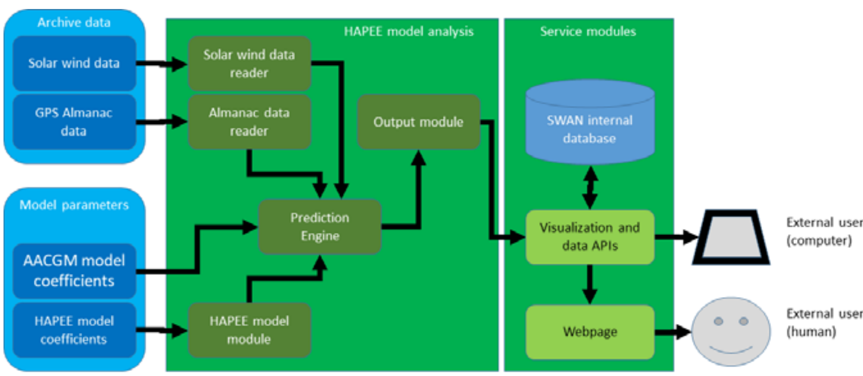


Figure 3-5: Overview of service components and data flow.

Solar wind data and almanacs are the dynamic inputs to the processing, while the model parameters are static sets of coefficients. The AACGM coefficients are a part of the AACGM library (Shepherd, 2014). The HAPEE model coefficients define a realization of the HAPEE model. The HAPEE model analysis modules reads the various input data, perform the calculations to provide forecasts, and transmits the output to the database of the forecast service. The service modules comprise a database which holds all produced forecasts, data transformation into a format suitable for visualization, APIs for both internal and external data access, and a webpage. External users can connect to the human interface (webpage), or directly to data APIs (intended for machine-to-machine communication). For a future real-time service, real-time solar wind measurements and almanac data would be processed on a periodic basis. The processing time for a single set of data is less than one minute. We note that solar wind data is available in near-real-time from the NOAA SWPC data service (currently available at https://services.swpc.noaa.gov/products/solar-wind/).

The Prediction Engine module uses the input modules to acquire input data, and to perform some calculations (notably, calculating geographic IPP coordinates). For the calculation of geomagnetic coordinates, it uses the AACGM library. The Prediction Engine module will, given date and time as well as solar wind parameters, calculate maps of forecasted probabilities to exceed thresholds as follows:

- From Solar Wind Data, calculate coupling function value
- For each grid point of the map:
  - Calculate geomagnetic coordinates for IPPs seen from that grid point
  - Retrieve HAPEE model parameters for the current coupling function and set of geomagnetic coordinates
  - For each defined threshold, calculate the probability to exceed it
- Package results and send it to the output module

Figure 3-6 show a screenshot of the prototype forecast service webpage.

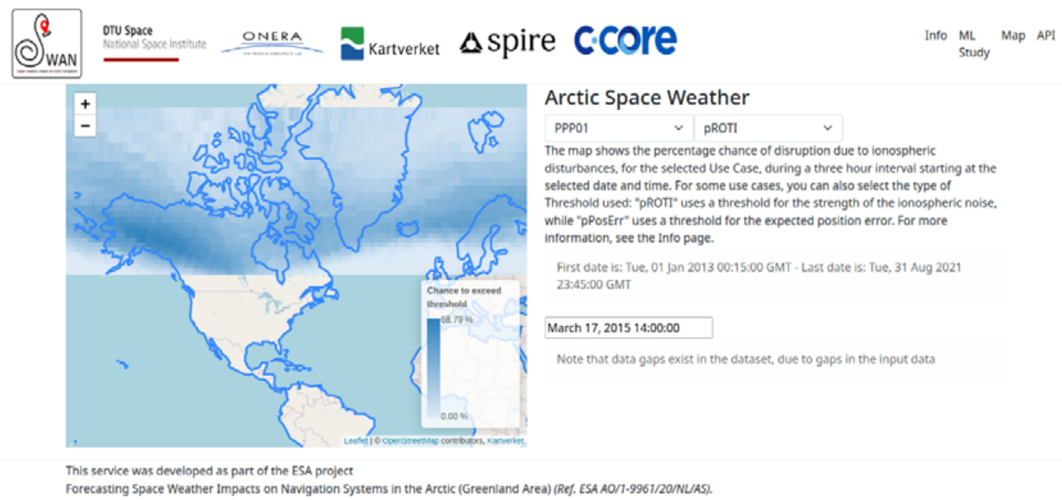


Figure 3-6: Screenshot from the forecast service page.

The user selects the use case (”PPP01”) and threshold type (”pROTI”) in the dropdown boxes, and the date and time, and a forecast map is displayed to the left. The map is dynamic, supporting panning and zooming. At the top right are links to information pages about the service itself, the machine learning study, and the APIs for direct data access.

The model and the implemented testbed for the forecasting service has been verified and validated with very promising results, which is also described in [TN4.1]. The testbed is also described in further detail in [FR]

### 3.3.1 SWAN verification and validation

The requirements in [TN 1.2] were written for the future completed service. As the main focus of the current project was algorithm development, not all of the aspects of the complete service were achieved during this project. The specific definition of each of these requirements are defined in [TN 1.2]. the verification process and plan is defined in[TN 3.2] and the actual verification process and specific tests including compliance statements for each defined requirements are described in detail in [TN 4.1]

HAPEE extended model and hence the forecasting service has been validated statistically, by defining a “validation dataset” composed of ROTI data not used during the model regression

During the regressions of the HAPEE model, including NMA and GNET ROTI datasets, covering all stations (cf.

Figure 3-1) and data between years [2007-2019]):

- 80% of the whole database of ROTI data has been considered for the regression of the HAPEE model,
- 20% of the whole database of ROTI data has been kept for the validation. This part of the database is called the 'validation dataset".

Considering this large database, a statistical comparison has been proposed on the validation dataset.

HAPEE is also proposing a statistical forecasting of the occurrence of PPP error to be exceeded. This part of the model has been regressed on NMA data only, and is tested on GNET PPP errors computed by the Gipsy code. As the generated database of error is corresponding to few events, long term statistics cannot be derived. However, an exercise of comparison has been performed and shows generally good results.

In summary, based on the data available and the analysis performed in [TN 4.1] chapter 5 we currently claim compliance to the Requirement SWAN_REQ_DATA_007

# 4 Conclusions and future work

The SWAN project has successfully implemented a statistical method (HAPEE) for predicting the occurrence of GNSS disturbances in the polar region. Furthermore, an alternative method using a more sophisticated machine learning (ML) model has been investigated.

The ROTI database was extended by the addition of data from the GNET GNSS receiver network in Greenland. The output of the HAPEE model is probability distributions of ROTI or position error, which can be combined with a threshold to quantify the risk of exceeding that threshold within a period of time. A realization of the HAPEE model for a 3-hour forecast was generated, and a prototype of an operational service based on this was created. The service provides forecasts both via a machine-to-machine API, and as a graphical view on a webpage. The provided forecasts were validated, with very good results for the ROTI forecasts and promising results for the position error forecasts.

The main results of the SWAN project can be accessed via the SWAN testbed

https://swan.kartverket.no/

The statistical method is robust and an online service has been developed which is verified and validated based on the defined project requirements.

A machine learning approach using a LSTM NN was investigated. The results are very promising regarding the timing of the disturbed periods, but are struggling to correctly predict the amplitudes of the disturbances. Further work on this topic is expected to improve the performance.

The suggested ML model paves the way for a new kind of operational service based on data driven methods. Even with a simple approach linking one type of solar wind data, magnetic local time and the ROTI, the LSTM NN should be able to blindly depict and learn a coarse regular pattern, which is the strength of this approach. Hence, a smart complementarity between a physically-based method like the HAPEE model and data-based techniques like the LSTM NN seems a way to improve predictions of such very complex phenomena.

[TN 4.3] SWAN Roadmap describes in detail ideas for future enhancements and developments in relation to space weather forecasting in the Arctic, but the following list indicates where future work is required.

- Work on the HAPEE-based service for adoption of SWAN results into the ESA S2P Space Weather Service Network.

- Work on the machine learning approach to mature the technology for the forecasting service.
- Future work on additional data sources for the Space weather service required e.g. space-based GNSS measurements, space- and ground-based magnetic data.

Further details on the project and the implementation of the SWAN testbed etc. can be obtained from the SWAN Final Report [FR].