MS/CS “Green Book’ Report 2024

Section 1: Background

* 1.1 Country

France

* 1.2 Author(s)

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* 1.3 Organisation

Météo-France

* Section 2: Summary of major highlights

Météo-France makes extensive use of products supplied by the ECMWF. One need that has emerged is that of a long (~1 year) period of data with the new cycle sufficiently in advance of an IFS version upgrade in order to assess the consequences on Météo-France’s downstream products and recalibrate the latter.

Section 3: Forecast Products

3.1. Direct use of ECMWF forecast products

* a) Medium Range (e.g. for high impact weather forecasting)

Simulated vertical profiles are computed from raw IFS outputs, and used as a diagnostic by some human forecasters.

* b) Extended Range (monthly)

ECWMF extended-range forecast maps for temperature, precipitation and atmospheric circulation for weekly averages (ensemble mean and significance) over Western Europe, and France in particular, are analysed and used to provide information on shorter-term ranges than the seasonal time scale. These products are particularly useful for stakeholders in the water sector.

* c) Long Range (seasonal)

Long range seasonal forecast charts and data from ECMWF and the Copernicus Climate Change Service are retrieved and analysed in the elaboration of the Météo-France seasonal forecast bulletin each month.

More specifically, 200 hPa velocity potential and streamfunction fields are plotted for each initial month and monthly and seasonal forecast times. Months 2-4 ensemble mean SEAS5 forecasts are included in the Regional Climate Center technical bulletin for comparison with other seasonal forecast providers and analysis of robustness of teleconnection patterns.

Geopotential height at 500 hPa and mean sea-level pressure are also compared to Météo-France system 8 outputs and other C3S models as part of a consensus bulletin based on expert analysis. Consistency amongst seasonal forecast systems is one ingredient of an increased confidence in the favoured seasonal outlook.

* d) CAMS and Fire-related output (ecCharts mainly)

None to report.

3.2. Cycle 48r1

* a) Positive impacts of model cycle 48r1

We have no specific positive impacts to show with the 48t1 model cycle. Nevertheless, tests were carried out prior to the last CAMS-Global cy48r1 switchover, showing a neutral impact (Figure 1).

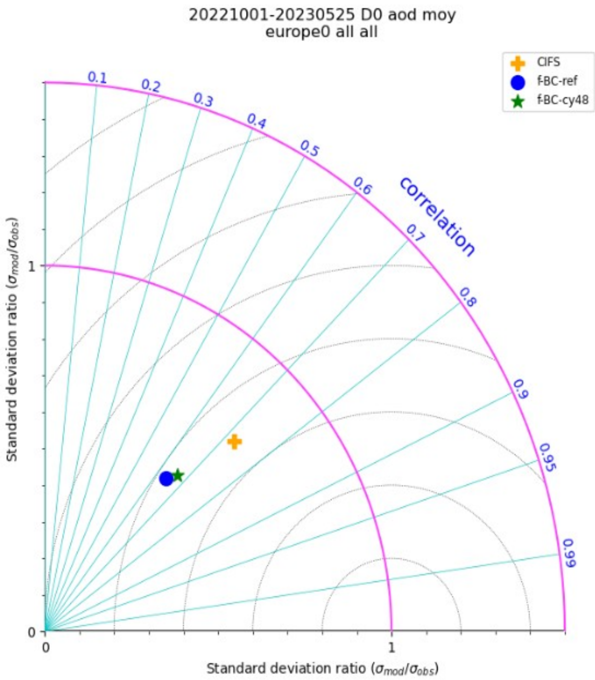

Figure 1: Taylor diagram showing the neutral impact of using chemical boundary conditions (BC) from CAMS Global (CIFS on the diagram) on the AOD simulated on the CAMS Regional domain by MOCAGE using BC from cycle 46 (f-BC-ref on the diagram) and from cycle 48 (f-BC-cy48 on the diagram). Reference data: MODIS Land-Ocean AOD

* b) Negative impacts of model cycle 48r1

Post-processed ENS temperatures using the method described by Taillardat (2021) are used for anticipating possible heat waves over France at a medium-range horizon. They were badly altered right after the June 2023 change (Figure 2) – necessitating urgent patches since up to 3 degree biases were observed in some places.

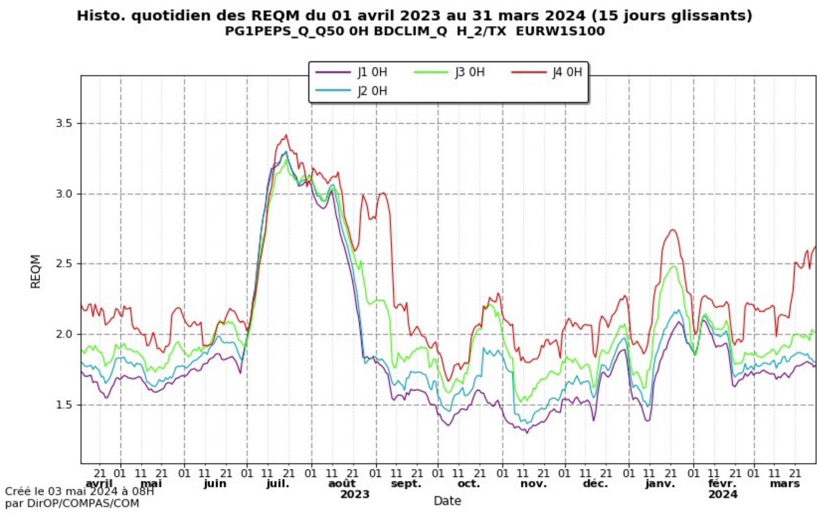

Figure 2: Evolution of RMSE of maximum daily temperature at 2 m (15 day rolling average) of the forecast provided by ENS temperature calibration (median). The reference is provided by the surface station network over France. The forecast for day 1 is shown in purple, day 2 in blue, day 3 in green and day 4 in red.

One possible means of mitigating such impacts could be to provide sufficient data ahead of a change of cycle to train the calibration methods ahead of the switch (see also section 5.a).

We also found out that ENS control member and HRES are not equivalent and significantly diverge after some days.

c) Systematic changes in forecast output since model cycle 48r1 was implemented

3.3: Derived Fields

At the seasonal time scale, weather regimes and variability modes based on SEAS5 mean sea level pressure anomalies are used to produce the following diagrams:

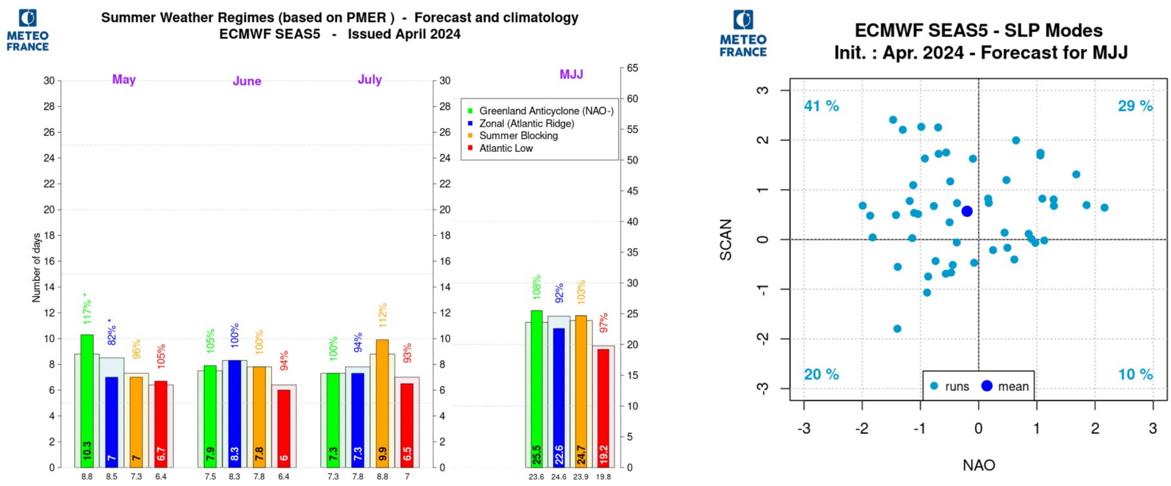

Figure 3: Examples of products derived from ECMWF SEAS5 seasonal forecast outputs: ensemble mean number of days in four North Atlantic Europe weather regimes for forecast months 2 to 4, and seasonal average (left), variability mode indices (modes NAO, SCAN) computed for months 2-4 in each ensemble member (light blue dots) and ensemble mean (dark blue dots).

3.4: Artificial Intelligence (AI) / Machine Learning (ML) techniques

At present, HRES and ENS temperatures are post-processed using ML techniques (random forests, EMOS). Post-processing is made at station locations and the result is spatialised on a kilometric grid. MOS HRES temperatures are also included in the online expert aggregation algorithm that provides the operational temperatures forecasts from day D to D+3. MOS is also performed on stations worldwide (random forests). Next steps will include ENS windspeed/gusts and rainfall calibration. These next steps were due to begin in 2023 but the slow access to ECMWF dataset forced us to postpone them at an undefined date (this will depend on whether the access is made faster or not).

3.5: Dynamical Adaptation

For environmental emergency models, Météo-France uses

- PERLE-IFS weather data from IFS (supplied by the ECMWF on request) then interpolated *via* FullPos at Météo-France for 2 km Meso-NH coupling;
- MOCAGE-Accident weather data from IFS *via* Météo-France analysis and forecast data base (BDAP).

For the MOCAGE OPER model, Météo-France uses

- upper-air weather data from IFS produced by a TC3 task for interpolation on the Europe domain (MACC01) and the vertical grid (60 levels) MOCAGE;
- surface weather data from IFS *via* BDAP;
- interpolation (at Météo-France) of chemical boundary conditions (from CAMS Global) to MOCAGE resolution;
- interpolation (at Météo-France) of GFAS information at MOCAGE resolution (global and regional domains).

ECMWF medium-range ensemble prediction system surface fields are used as forcing for the Météo-France hydrological modelling chain over France so as to provide 15-day outlooks of soil wetness index at the country, regional and department level, as well as snow water equivalent evolution over mountain areas (Figure 4).

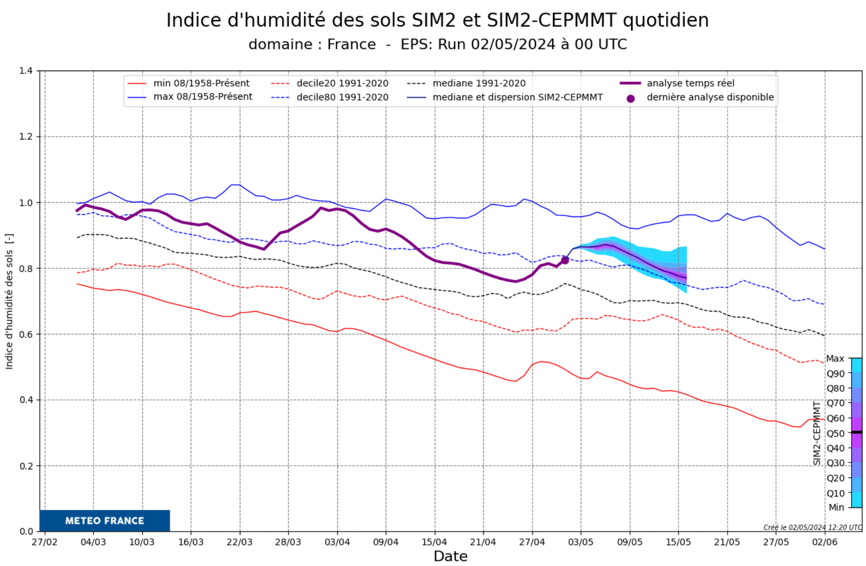

Figure 4: Example of output of the SIM2 surface modelling chain using ECMWF ENS as meteorological forcing: 15-day probabilistic outlook of soil wetness index conditions averaged over France.

HRES analyses and forecasts are used as initial and boundary conditions for some limited-area AROME instances.

3.6: Data-driven (AI) models

* a) ECMWF's real-time AI model initiative

The ECMWF's initiative to deliver AI model outputs on eccharts is interesting to assess the relevance and limitations of such forecasts compared to physical models. Researchers and forecasters watch them regularly, although they are not integrated in the production chain nor in the decision-making process.

*** b) Use of AI forecasts for operational purposes**

None so far as part of routine operations, but these forecasts are being examined in certain cases to assess their relevance.

Section 4: Verification

4.1 Raw model output from ECMWF, and other operational models/ensembles

a) Short Range and Medium Range

ARPEGE (Météo-France global deterministic model), AROME-France (Météo-France regional deterministic model over France) and HRES are compared with a synthetic indicator adding the Brier Skill Score (BSS) against the persistence forecast for 4 parameters: gusts above 40 km/h, 6h-accumulated rain greater than 0.5, 2 and 5 mm (Figure 5). The reference is provided by the surface station network over France and the scores are averaged over a window of 12 months. AROME performs better than ARPEGE and HRES. This is explained by the higher resolution of AROME-France (1.3 km) which allows the explicit simulation of deep convection in comparison with the global models HRES and ARPEGE, which use a cumulus scheme. The indicator of all models shrunk in 2022 and 2023 due to uncommon meteorological conditions (drought over France), making the persistence (used as reference in the BSS) harder to beat. ARPEGE performs better than those of HRES because of:

- changes in ARPEGE in the middle of 2022 (46t1), implying a reduction of overforecasts of slight rains; HRES continues to largely overforecast slighter rains (Figure 6);
- changes in IFS in the middle of 2021 (47r2), increasing the overforecast of slight rains and causing the overforecast of moderate rains (5 mm/6 h); moderate rains were not biased before the change (Figure 7).

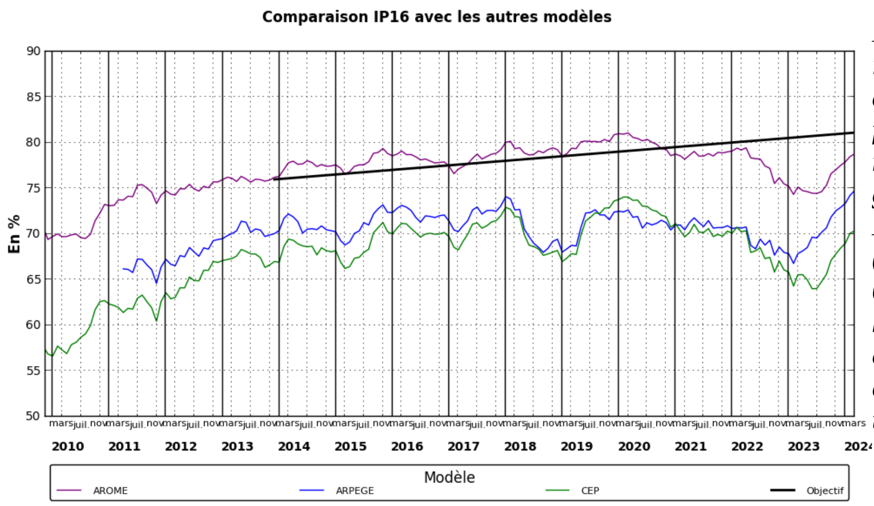

Figure 5: Synthetic quality indicator built with the BSSs against the persistence forecast for 6 h accumulated rains and maximum wind gusts for ARPEGE (blue), HRES (green) and AROME (purple). The thresholds are 0.5, 2 and 5 mm/6 h and 40 km/h, respectively. The black curve indicates the quantitative goal assigned to the operational model.

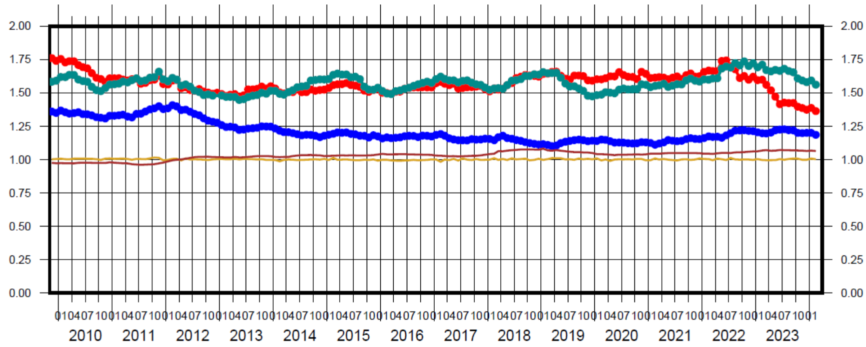

Figure 6: Evolution of frequency bias for 6 h accumulated rain greater than 0.5 mm (12 month rolling average) for ARPEGE (red), HRES (aquamarine) and AROME (blue). The reference is provided by the surface station network over France.

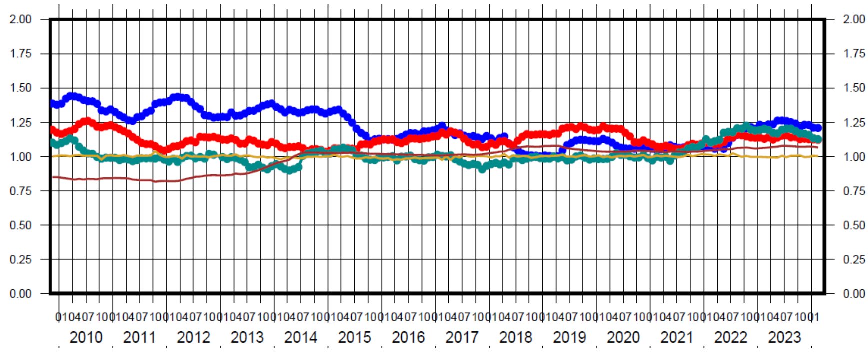

Figure 7: Evolution of frequency bias for 6 h accumulated rain greater than 5 mm (12 month rolling average) for ARPEGE (red), HRES (aquamarine) and AROME (blue). The reference is provided by the surface station network over France.

With regard to chemical/fuel data from CAMS, as previously stated, impact studies are systematically carried out to evaluate/adapt MOCAGE OPER production. No systematic verification is carried out by Météo-France during ECMWF version upgrades (apart from technical tests) for IFS meteorological forcings, for lack of sufficient replay/reforecast data, in particular.

b) Extended Range (Monthly) and Long Range (Seasonal)

At the monthly time scale, flow-dependent prediction skill for near-surface temperature over Europe in former ECMWF S2S and CNRM S2S systems was investigated by Ardilouze et al. (2021).

Several long range forecast scores for surface variables and modes of variability for SEAS5 are shown on the Météo-France seasonal.meteo.fr website, alongside Météo-France operational seasonal forecast system scores.

4.2 <u>Post-processed</u> products and/or tailored products delivered to users

ARPEGE and HRES raw and post-processed daily temperatures (minimum and maximum, at 2 m) are compared through RMSE calculated over surface stations in France (Figure 8 and Figure 9). The post-processing clearly improves daily temperature forecasts; the benefit of post-processing increased these last years. Even if ARPEGE and HRES do not have the same performance for the maximum daily temperature, the quality of the associated post-processed forecasts is roughly similar.

The quality of maximum daily temperature forecast of HRES has decreased these last years, linked to the deepening of its cold bias (not shown).
The forecast provided by the online expert aggregation algorithm performs better than raw and post-processed forecasts of ARPEGE and HRES.

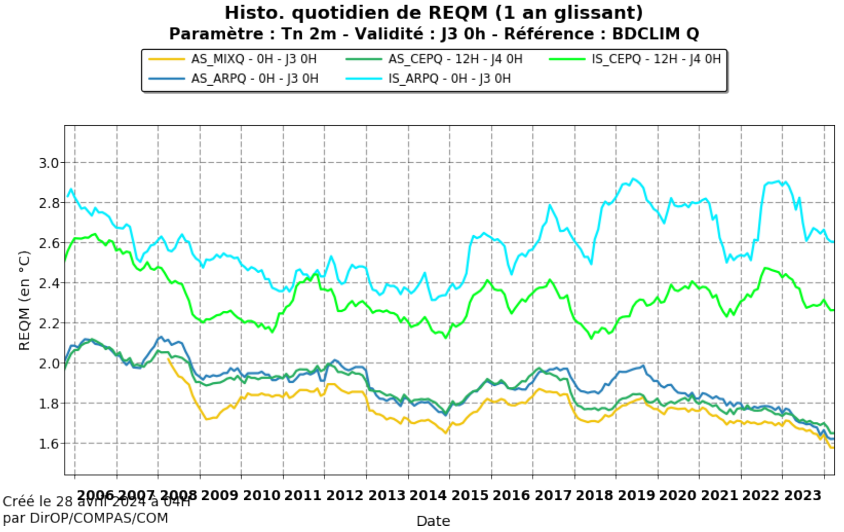

Figure 8: Evolution of the RMSE of minimum daily temperature at 2 m (12 month rolling average). The reference is provided by the surface station network over France. Raw forecasts of ARPEGE and HRES are shown in light blue and green, respectively. Post-processed forecasts of ARPEGE and HRES are in dark blue and green, respectively. The RMSE of the forecast provided by the online expert aggregation algorithm is shown in orange.

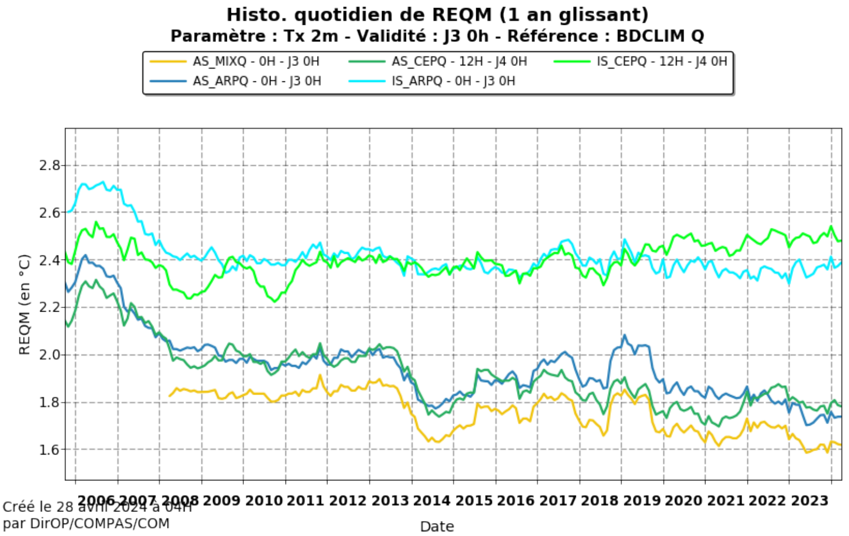

Figure 9: Evolution of the RMSE of minimum daily temperature at 2 m (12 month rolling average). The reference is provided by the surface station network over France. Raw forecasts of ARPEGE and HRES are shown in light blue and green, respectively. Post-processed forecasts of ARPEGE and HRES are shown in dark blue and green, respectively. The RMSE of the forecast provided by the online expert aggregation algorithm is shown in orange.

4.3 <u>Subjective verification</u>

Subjective verification bulletins for the seasonal range are prepared each month for the past trimester. These are included on the seasonal.meteo.fr website (password protected) and available upon request.

4.4 Case Studies

a) Case Study 1

b) Case Study 2

Section 5: Output Requests

a) Product request 1: Data sets over long periods of time

For a variety of uses, Météo-France needs replays/reforecasts over long periods, on the order of a year. Hereafter are two examples of use.

Météo-France needs at least one year's worth of data on chemical boundary conditions to prepare for the MOCAGE OPER switchover. This replay must be available no later than 4 months before the switchover, to allow time for evaluations to be carried out and for production to be adapted if necessary. This need has already been indicated to CAMS Global as part of the CAMS2_40 (CAMS regional) contract, and concerns all 11 regional models participating in this service.

As explained in section 3.2 for heat wave forecasts at a medium-range horizon, forecast data for a long enough time period are needed for proper calibration of model outputs before a new ECMWF model goes live. Otherwise, it can lead to systematic errors in the MOS technique and introduce critical biases.

b) Product request 2: Crossing Point Forecasts

A valuable product to disseminate in the future would be the Crossing Point Forecasts.

Section 6: References

Ardilouze, C., Specq, D., Batté, L. and Cassou, C., 2021: Flow dependence of wintertime subseasonal prediction skill over Europe. *Weather Clim. Dyn.*, **2**, 1033–1049, 2021 https://doi.org/10.5194/wcd-2-1033-2021

Taillardat, M., 2021: Skewed and mixture of Gaussian distributions for ensemble postprocessing. *Atmosphere*, **12**, 966. https://doi.org/10.3390/atmos12080966

Section 7: Additional comments and Feedback

The ENS temperatures calibration, that provides Météo-France forecasts from day 4 to day 14, has been very negatively impacted in June 2023. This calibration needs to be trained again, but this is hampered by the lack of reforecasts as stated above, and also the fact that daily ENS outputs are too large to be stored on an a single magnetic tape. As a result, ENS data requests on MARS usually fall in timeout.