THE IMPACT OF THE NEW NRLMSIS 2.0 ON RE-ENTRY PREDICTIONS

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ABSTRACT

On average, two small tracked debris objects re-enter the Earth's atmosphere every day and burn up. Fortunately, only some very large objects re-enter Earth's atmosphere in a year, while objects larger than 1 m, such as satellites or spent rocket bodies, re-enter about once a week. Some pieces of these large space debris objects that re-enter the atmosphere in an uncontrolled way can reach the ground and pose a risk to the population; A risk which is however several orders of magnitude smaller than commonly accepted risks in daily life. ESA's Space Debris Office provides information on upcoming and past re-entries to a wide target audience, including national protection agencies, researchers, and the general public via a web-based portal [1]. ESA also participates in and hosts a re-entry data exchange platform for the IADC (Inter-Agency Space Debris Coordination Committee).

In order to generate the predictions for a given re-entry, various atmosphere models can be considered. ISO-27582 provides a list of models to be considered, without providing indication on the advantages and disadvantages of each from a re-entry point of view. An update of the NRLMSIS-00 model has been released in 2020, called NRLMSIS 2.0 [2]. In this study we compare this new model to models used in previous studies [3][4] – NRLMSIS-00, DTM-2013 and GOST-2004 – all of them integrated in ESAs fully automated re-entry prediction service [5]. This enables their comparison in terms of the re-entry prediction accuracy on a representative set of objects, taking as reference the real re-entry time as provided by space-track.org when available and otherwise analyse the spread of the results. The main objective of the study is to determine if the new model provides an improvement in the accuracy of the results compared to the older models, and if it is the case, include it in the automatic process employed by ESA to generate its re-entry predictions.

1 INTRODUCTION

The ESA Space Debris Office (SDO) is tasked with the development and research on spacecraft and debris re-entries. ESA has been hosting technical workshops on re-entries since the early 80's, as ESA provides a re-entry service to ESA's member states and has also the responsibility for ESA-registered objects. In addition, ESA, as member of IADC, coordinates the re-entry campaigns of IADC (campaign administration, web-based front-end hosting and maintenance).

To accomplish this task, an automated re-entry predictions process was set at ESA in 1999, with the LASCO (Lifetime Assessment for Catalogued Objects) [4] tool, which computes in a fully automated way the remaining lifetime for all objects in the public TLE catalogue and generates re-entry predictions. The results are accessible for a limited number of people via the DISCOS (Database and Information System Characterizing Objects in Space) web interface [7][8]. Since 2013 the results of the LASCO analysis containing the re-entry predictions for the following two months are more proactively distributed via e-mail to stakeholders. Shortly after, in 2014, a new tool was created, called RAPID, which automatizes the call to separate existing tools that are used to generate more accurate predictions during the last month of a re-entry, and with the capability of additional plot generation. The last step of this modernisation was taken in 2016, with the setup of a two-tier web based data distribution [1] aimed at civil protection agencies, with some contribution for the general public as well as part of ESA's educational responsibility. A more detailed explanation of the capabilities of the tools can be found in [5].

This study is an extension of previous work [2][3] which analysed re-entering objects during a different phase of the solar cycle, and which included 3 atmosphere models. Therefore, it adds an extra atmosphere model and analyses another phase of the solar cycle.

2 ATMOSPHERE MODELS AND SPACE WEATHER

In order to generate the predictions for a given re-entry, various atmosphere models can be considered. ISO-27582 provides a list of models which are worthy of consideration. In previous studies three of the proposed models were used – NRLMSIS-00, DTM-2013 and GOST-2004. In September 2020, an evolution of the NRLMSIS-00 model was released to the public, the new

Proc. 8th European Conference on Space Debris (virtual), Darmstadt, Germany, 20–23 April 2021, published by the ESA Space Debris Office
Ed. T. Flohrer, S. Lemmens & F. Schmitz, (http://conference.sdo.esoc.esa.int, May 2021)

NRLMSIS 2.0 [2]. ESA's re-entry tools have been updated in order to incorporate this new model, which is running in the daily re-entry prediction process since December 2020.

2.1 NRLMSISE 2.0

NRLMSIS 2.0 is an empirical atmospheric model that extends from the ground to the exobase and describes the average observed behaviour of temperature, eight species densities, and mass density via a parametric analytic formulation. The model inputs are location, day of year, time of day, solar activity, and geomagnetic activity. NRLMSIS 2.0 is a major, reformulated upgrade of the previous version, NRLMSISE-00.

As for the previous MSIS models, it accepts as input either a daily Ap value, or a combination of eight 3 hour Ap values. Both inputs are used for the routine runs, in different configuration modes. This has an effect in the determination of the drag coefficient obtained from the fitting of various states, but none for the propagation from the state epoch until decay, because the solar activity predictions do not predict the hourly Ap values.

2.2 Space weather

ESA's Space Debris Office has its own solar and geomagnetic activity prediction model (SOLMAG) [9], which uses data from past solar cycles to predict the future ones. SOLMAG has a short term prediction algorithm (which covers with predicted daily values only the following solar rotation), and a medium and long term prediction algorithm (for the next centuries, with predicted values provided on a monthly basis). The medium and long-term prediction method implemented in SOLMAG is based on the regression technique of McNish and Lincoln [9], which is similar to that used by Holland and Vaughan [10].

In SOLMAG a daily Ap value is predicted, while in reality, the variations have a much shorter span, and observed data values every 3 hours are provided. It is possible to get better predictions for the very short term (up to three days), based on the expert assessment of the SIDC (Solar Influences Data Analysis Center), which is part of the solar physics research department of the Royal Observatory of Belgium [11]. These predictions are incorporated to the SOLMAG process and provide more reliable data for the last days of a re-entry.

The current analysis has been performed during a period of low solar activity, as can be seen in Fig. 1, although the solar cycle number 25 started in December 2019. Such an analysis would need to be performed during a full solar cycle to understand if the effect is the same in all phases of the solar cycle.

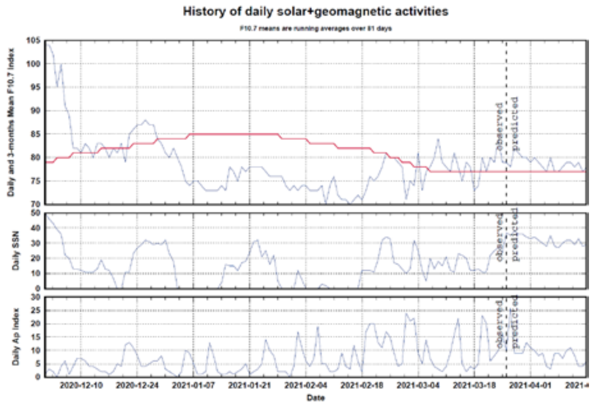

Fig. 1. Observed solar activity (F10.7 daily and 3-month averaged, daily Sun Spot Number (SSN)), and daily geomagnetic activity (Ap) from December 2020.

3 RE-ENTRY PREDICTIONS

For this study, the RAPID system was extended in November 2020 to include the NRLMSIS 2.0 model to the process which automatically performs accurate re-entry predictions using already three atmosphere models (NRLMSIS-00, DTM-2013 and GOST-2004), for all objects for which a lifetime of less than one month was estimated by LASCO. In addition, both the NRLMSIS-00 and the NRMLSIS-2.0 models were set to run with two different configurations, one using the daily Ap values and the other using 3-hourly Ap values. For each of the cases, two re-entry predictions were computed every day, once using only the last 20 US TLEs available and the other one using all the TLE within a given time-span which changed depending on the eccentricity of the orbit and the time to re-entry. Furthermore, all the cases have been repeated a posteriori, once the objects have already re-entered, so that the solar and geomagnetic activity used is the one observed instead of a prediction, in an attempt to separate the errors coming from the predictions of the solar activity and the errors inherent to the process and the atmosphere models.

In summary, there are 18 combinations between atmosphere models (NRLMSIS-00, NRLMSIS 2.0, DTM-2013 and GOST-2004), quantity of TLE (20 TLE or variable number according to time span) and use of space weather data (daily or hourly Ap, predictions or observations (a posteriori)) which have been analysed. The following list includes the cases and the names used in the plots to identify them:

- NRLMSIS-00 with daily Ap values and 20 TLE (NRLMSISd)
- NRLMSIS-00 with daily Ap values and variable time span (NRLMSISds)
- NRLMSIS-00 with daily Ap values, 20 TLE, a posteriori (NRLMSISda)
- NRLMSIS-00 with 3-hourly Ap values and 20 TLE (NRLMSISh)

- NRLMSIS-00 with 3-hourly Ap values and variable time span (NRLMSIShs)
- NRLMSIS-00 with 3-hourly Ap values, 20 TLE, a posteriori (NRLMSISha)
- NRLMSIS 2.0 with daily Ap values and 20 TLE (NRLMSIS2d)
- NRLMSIS 2.0 with daily Ap values and variable time span (NRLMSIS2ds)
- NRLMSIS 2.0 with daily Ap values, 20 TLE, a posteriori (NRLMSIS2da)
- NRLMSIS 2.0 with 3-hourly Ap values and 20 TLE (NRLMSIS2h)
- NRLMSIS 2.0 with 3-hourly Ap values and variable time span (NRLMSIS2hs)
- NRLMSIS 2.0 with 3-hourly Ap values, 20 TLE, a posteriori (NRLMSIS2ha)
- DTM-13 with 20 TLE (DTM)
- DTM-13 with variable time span (DTMs)
- DTM-13 with 20 TLE, a posteriori (DTMa)
- GOST-04 with 20 TLE (GOST)
- GOST-04 with variable time span (GOSTs)
- GOST-04 with 20 TLE, a posteriori (GOSTa)

In order to compare the different models in terms of re-entry prediction accuracy, we have taken an unbiased set of objects for which the real assessed re-entry time and an uncertainty window is provided by space-track.org. From beginning December 2020 until mid-March 2021, this accounts for 22 objects.

3.1 Individual results

We can analyse the results for each individual object separately and use the real re-entry time as reference to compare the different methods. We compute the relative error as the difference between the re-entry prediction epoch and the real re-entry epoch, divided by the remaining time from the prediction until the re-entry. An example thereof is shown in Fig. 2. In this first approach, there is no clear indication that a method provides better results than another, as it varies from object to object.

In a first order attempt to determine if there is an influence on the quality of the predictions as a function of the time to re-entry, we have grouped the predictions for each object in two groups according to the time: i.e. from 28 to 14 days before re-entry and from 14 to 0 days, to follow the solar rotation period present in atmosphere models as well.

To assess commonalities between objects, the Spearman correlation coefficient between the relative error and the time to re-entry is computed for each method listed in section 3, assessing monotonicity in the dataset. Fig. 3 shows one of these correlations, for all the objects and test cases analysed. Although for some cases it seems that there is no correlation, for others the correlations are quite strong, even in the a posteriori cases.

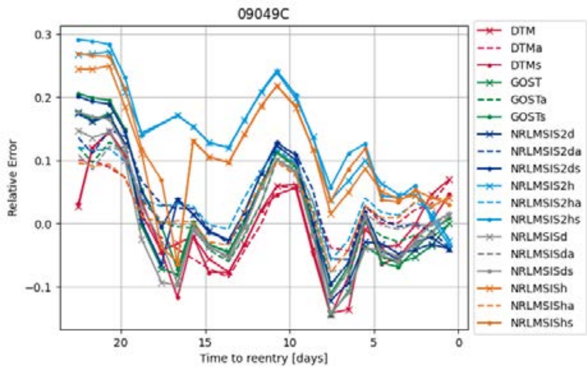

Fig. 2. Relative error for the re-entry predictions of object 2009-049C (Fregat) as a function of the time to re-entry.

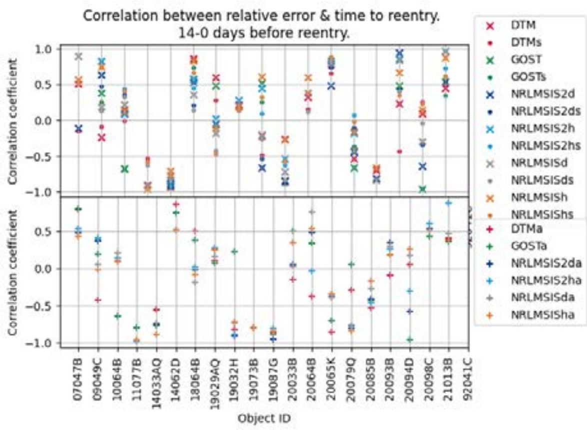

Fig. 3. Correlation between the relative error and the time to re-entry for predictions done 14 to 0 days before re-entry.

3.2 Statistical approach

The strong and distinct correlations observed for most objects between time to re-entry and relative error, notably as well in the cases where the space weather activity was already known and used, is to be explained by the systematic absorption of error into the drag coefficient estimation coupled to the use of moving windows on observational datasets. An overview of such influences can be found in [12].

Therefore, expanding on the relative error, we introduce the relative model error (RME) by the simple observation that we need an object independent reference instead of an absolute re-entry time. For each of the prediction epochs, the method which has the smallest relative error is considered as the reference, and all other methods are then translated accordingly (by adding or subtracting the relative error of the reference method). This requires the prediction epochs to be constant across the methods and conserve prediction accuracy as expressed in delta relative error between the methods. This metric is therefore free of the evolution pattern which was observed between the relative error and the time to re-entry, as can be seen in Fig. 4, which is the RME evolution for the same object as in Fig. 2.

By construction, an RME of 0 implies that the method was the closest to the absolute truth, i.e. the a posteriori identified re-entry epoch, at a given prediction epoch. The ideal method thus has a central tendency, whichever one we want to use, close to zero and minimised spread around it. In order to compare different methods, the empirical distribution functions of the RME for the two time groups, 28-14 and 14-0, are constructed. Examples are given in Fig. 5 and Fig. 6. Other methods produced similar shapes bounded in RME as a priori, relative errors above 50% had been removed from the data set, affecting less than 1% of the data in both time groups and non-systematically distributed across the methods. No parametric distribution was identified which could convincingly describe the observed empirical distributions for all methods. Hence to compare the different populations, a rank test needs to be employed.

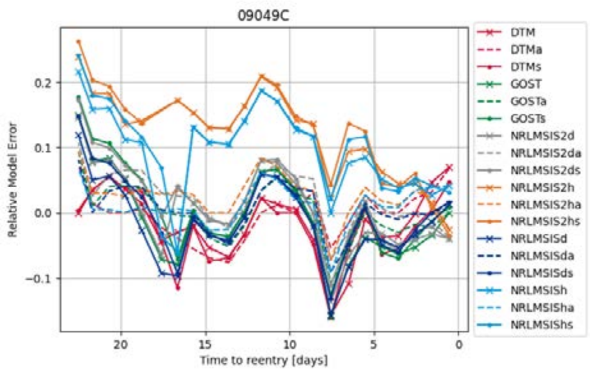

Fig. 4. Relative model error for the re-entry predictions of object 2009-049C (Fregat) as a function of the time to re-entry.

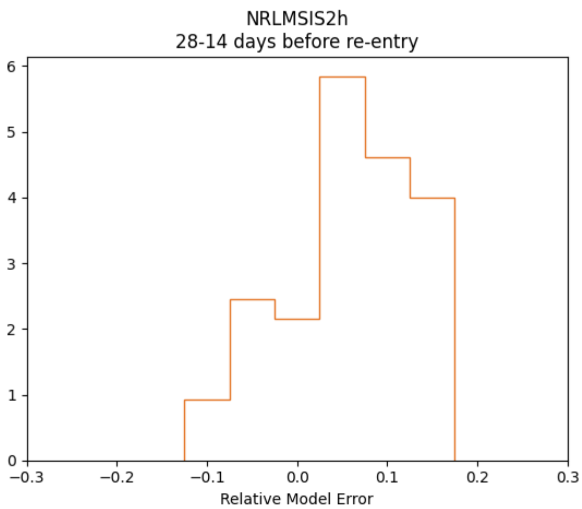

Fig. 5. Empirical distribution function of the NRLMSIS2h in the 28-14 group.

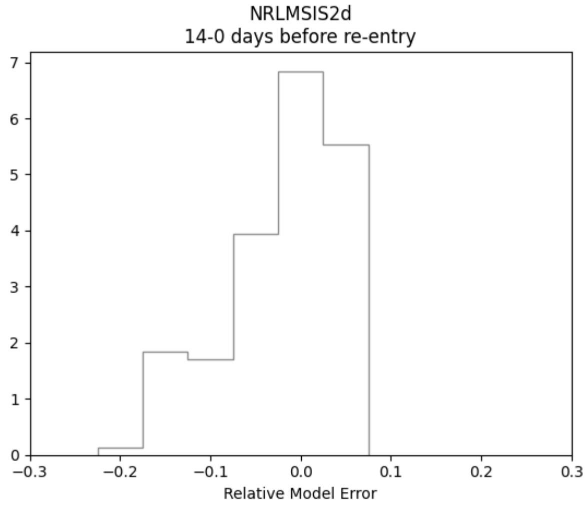

Fig. 6. Empirical distribution function of the NRLMSIS2d in the 14-0 group.

In Fig. 7, Fig. 8 and Fig. 9, box plots are provided for the different empirical distribution functions for the two different time groups, plus a third group for 5-0 days before re-entry. These boxplots have their whiskers correspond to the 10th and 90th percentile, uncertainty box identified by the 25th and 75th percentile, the median indicated as a flat black lines, and a 95% confidence interval around the median identified by the notched part of the box corresponding to 10000 bootstrap samples of the median. Visual grouping is done by colour for the atmosphere models, fit methodologies go after each other.

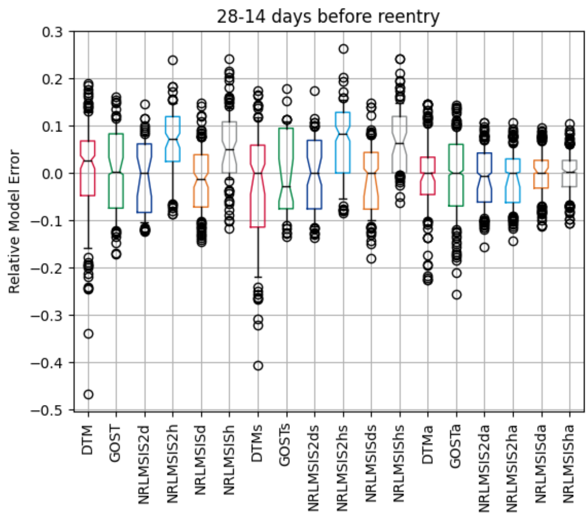

Fig. 7. Boxplot of the empirical distribution functions per method in the 28-14 group.

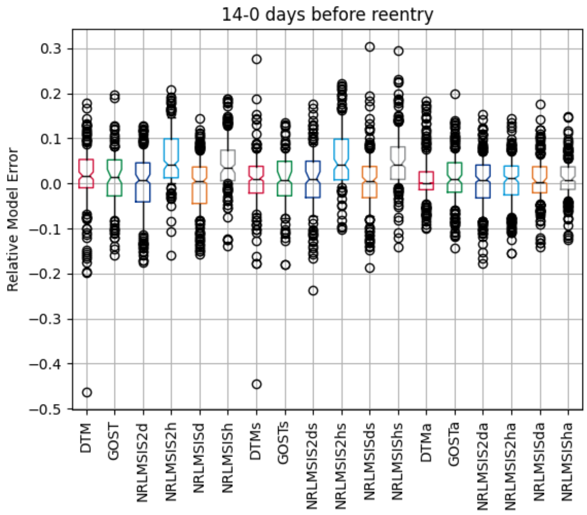

Fig. 8. Boxplot of the empirical distribution functions per method in the 14-0 group.

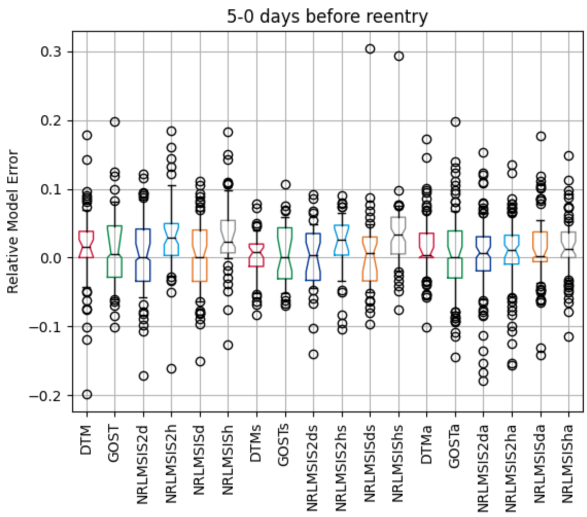

Fig. 9. Boxplot of the empirical distribution functions per method in the 5-0 group.

Two statistical comparison methods are used to try to distinguish the optimal method. The Kruskal-Wallis (KW) H-test, i.e. one-way analysis of variance, is employed to test the null hypothesis that the population median of the groups are equal. The Kolmogorov–Smirnov (KS) test is employed to test the null hypothesis that 2 independent samples are drawn from same continuous distribution.

3.2.1 28-14 days before re-entry

For the statistical analysis of 28-14 days before re-entry (see Fig. 7), the only two groups which could reject the null hypothesis are the NRLMSISh and NRLMSIS2h (the two NRLMSIS models using 3-hourly Ap values), and this is due to the fact that these models are performing worse than the other models for the a priori cases, i.e. using SOLMAG predicted space weather. For the a priori cases, the better performance seems to be obtained with NRLMSISd and NRLMSIS2d (again, the two NRLMSIS models, but using daily Ap values instead of 3-hourly ones).

For the a posteriori cases, with known space weather, the KW test reveals no optimal method, and the KS test shows that the NRLMSISE-00 results (both for daily or 3-hourly Ap) are differentiable from the NRLMSIS-2.0 models, and also from the GOST model, but not from the DTM. All models perform much better a posteriori than a priori, but DTM seems to be the best performing one, followed by the NRLMSIS-00 models.

Also, comparing the models between a priori and a posteriori results, the KW test shows that GOST, NRLMSISd and NRLMSIS2d cannot reject the null hypothesis. This is because the median is similarly close to 0 for all cases of these models.

In summary, from the limited sample size of re-entering objects analysed for this work, the NRMSIS2d model provides the median closest to 0 with the minimal spread for the 28-14 time group when using a priori data, while a posteriori the NRLMSISd and DTM methods are better.

3.2.2 14-0 days before re-entry

For the analysis of 14-0 days before re-entry (see Fig. 8), the results a priori are the same as for the 28-14 group: the NRLMSISh and NRLMSIS2h are differentiable because they perform worse, while the better performance is obtained with the NRLMSIS models that use daily Ap values.

For the a posteriori cases, the KW test reveals no optimal method, and the KS test shows that only the DTM model is differentiable and performs better.

Also, the KW results across the models are the same here as for 28-14 days: GOST, NRLMSIS2d and NRLMSISd have a median similarly close to 0 for a priori and a posteriori.

In summary, for the 14-0 time group, the same method as for the 28-14 group (NRLMSISd) provides the median closest to 0 with the minimal spread for the a priori data, while a posteriori the DTM method is slightly better.

3.2.3 5-0 days before re-entry

A third group has been added, from 5-0 days before re-entry (see Fig. 9), to try to identify if there is a better differentiation between the models very close to re-entry.

However, for the a priori cases, the results are the same as for the two previous groups: the NRLMSISh and NRLMSIS2h are differentiable because they perform worse, while the better performance is obtained with the NRLMSIS models that use daily Ap values.

For the a posteriori cases, the KW test reveals no optimal method, and the KS test shows the only differentiable pair is DTM and GOST, though they cannot be differentiated from any other model. All models perform much better a posteriori than a priori.

Also, comparing the models between a priori and a posteriori results close to re-entry, the median relative model error of DTM, GOST, and the NRLMSIS models using daily values are not differentiable.

3.3 NRLMSIS 2.0 vs NRLMSIS-00

As seen in the previous section, the results obtained with the NRLMSIS 2.0 model for the assessed re-entry predictions do not provide a significant difference compared to the ones of NRLMSIS-00. This could be expected, as explained in [2], "the NRLMSISE-00 thermosphere is largely retained", and the thermosphere is the atmosphere layer where re-entering objects spend most of their time, and it is verified by the similar results provided by the two models. More analysis will be conducted, as the current study uses a small set of data. It has to be noted that the computational time required for a single re-entry object prediction with RAPID using the NRLMSIS 2.0 is 3 to 10 times longer than with the NRLMSIS-00 model.

4 CONCLUSIONS

Three of the ISO-27582 recommended atmosphere models and the new NRLMSIS 2.0 have been set up in the ESA automatic process used to compute re-entry predictions. In order to compare the different models and methods analysed, a limited set of objects which have re-entered between December 2020 and March 2021 have been taken as reference. This thus only cover a fraction of the recently started solar cycle 25. A total of 18 different combinations of atmosphere models, solar activity proxies and observed data have been analysed. These include an a posteriori reprocessing, that has been performed in order to remove the errors due to the wrong prediction of the solar activity, and it has been verified that it provides better results for all models than using the predicted values.

The inspection of the relative error dataset per object does not reveal any method to be better in all the cases, and in addition, for some objects a distinct correlation is observed between the relative error and the time to re-entry. Therefore, a the relative model error is introduced which removes this correlation and allows a statistical analysis of the different methods. From the data analysed, which is quite limited and restricted to a small portion of the solar cycle, it seems that the use of NRLMSIS models (either NRLMSIS-00 or NRLMSIS 2.0) with daily solar geomagnetic data provide the predictions with the median closest to 0, for the a priori analysis. Once the solar activity data has been properly calibrated, i.e. a posteriori analysis, the DTM-2013 model seems to provide the best solution, shared with the NRLMSIS-00 models for the 28-14 days to re-entry group. In the days very close to re-entry (less than 5 days), there is no optimal atmosphere model to perform the re-entry predictions. It should be noted that these results are different than the ones obtained in previous assessments [3][4], hence an influence of the period of the solar cycle can be expected. Therefore, one should be careful with extrapolating the knowledge obtained for future events.

The assessment of the new NRLMSIS 2.0, model does not seem to provide any significant improvement in comparison to the other atmosphere models, also not to its predecessor NRLMSIS-00.

Finally, this study has been limited to only few re-entering objects to take into account the new NRLSMIS-2.0 model and it is covering only a small portion of a solar cycle (start phase). ESA has been running predictions with the other 3 models in parallel since 2017 and a more statistical significant data set covering more than 3 years could be used. Even in that case, the solar activity has been very low during the 2017-2021 period (covering the end of solar cycle 24 and the start of a new one). Our automated system will continue to compute re-entry predictions, now also with the NRLMSIS 2.0 model, and we expect to be able to provide more results in the future covering an extended period.

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