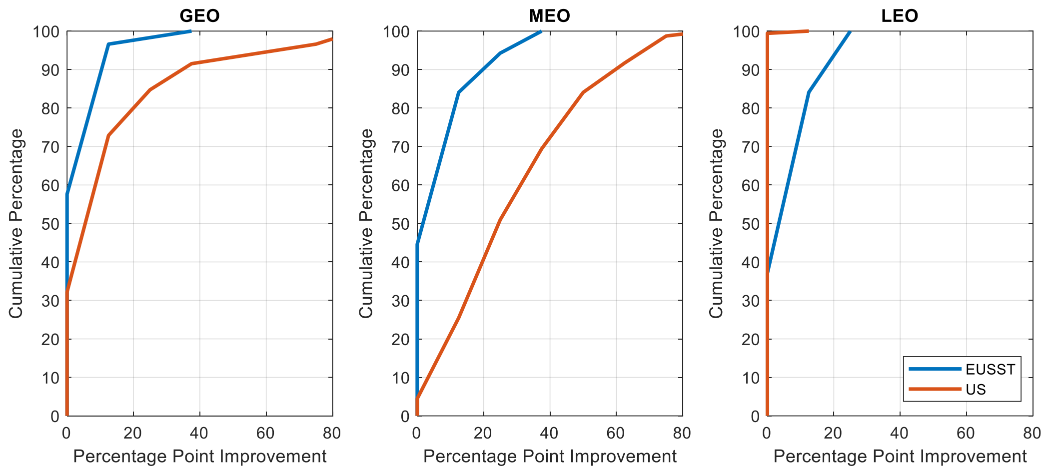

Fig. 5. Orbit coverage improvement for combined dataset over individual EUSST or US datasets

5. PREDICTION ERROR FOR SATELLITES WITH REFERENCE ORBITS

This section presents the analysis of orbit prediction accuracy using the different datasets for the chosen reference satellites, in this case, Galileo-21 and Sentinel-3A. These are operational satellites for which precise orbit determination products are available during the period of analysis, achieving accuracies to the centimeter level (and thus a negligible level of error for the comparisons in question). The main goal of this section is to use these precise ephemerides as ground truth to validate the orbit determination and orbit comparison methodology proposed in this work, as well as to assess the accuracy performance that can be achieved for the different datasets as compared to the real orbit of the objects.

The general methodology for orbit determination and prediction was described in Section 3. In the case that an independently developed reference orbit is available, we do not have to create a synthetic reference to evaluate prediction accuracy. Instead predictions using the state vector resulting from the orbit determination are simply predicted 1-, 2-, and 3-days from the epoch and compared directly to the reference position. It is still important to avoid time-phased periodic differences by computing the residuals RMS over a single orbital revolution centered on the desired comparison epoch.

In order to show the accuracy improvement achieved with data fusion, Fig. 6 and 7 below describe the relative accuracy improvement as compared to the data fusion for both reference satellites, as a function of the day of the year, for the three different propagation epochs of analysis. The improvement in accuracy is computed as follows:

$$\left|\overrightarrow{\Delta x}\right|_{RMS}^{wrt\ fusion} = \left|\overrightarrow{\Delta x}\right|_{RMS}^{dataset} - \left|\overrightarrow{\Delta x}\right|_{RMS}^{fusion}$$

Therefore, the improvement in accuracy is measured as the difference between the accuracy achieved with a single dataset versus the combined dataset, in relative terms. A positive value of the metric indicates that the data-fusion RMS metric is smaller than the single dataset RMS, or, in other words, that the data-fusion orbit predictions are more accurate.

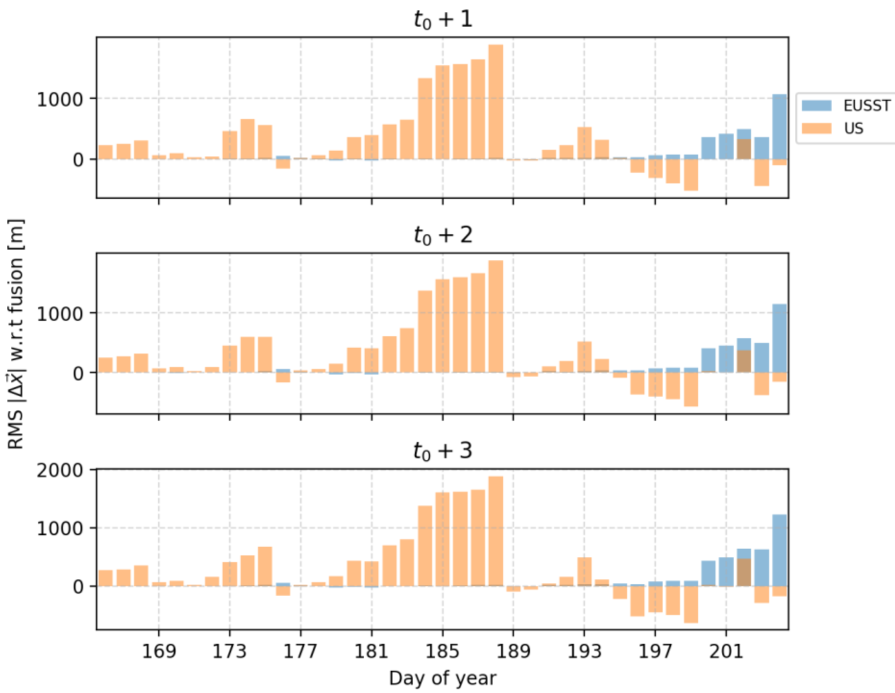

Fig. 6: Relative accuracy for the individual datasets as compared to data fusion for Galileo-21.

At first glance, Fig. 6 shows a generally positive metric of accuracy improvement when the combined dataset is used. This improvement reaches up to 2000 meters as compared to the US dataset in the middle of the analysis period, and up to 1000 meters as compared to the EUSST dataset at the end of the period. Both of these losses in precision are due to periods of data scarcity, leading to significant degradation of the orbit estimation and prediction accuracy. The US dataset has few measurements of Galileo-21 between days 177 and 188 and thus shows decreased accuracy as compared to the combined dataset, which benefits from the EUSST data. On the contrary, EUSST tracking of Galileo-21 stops around day 193, with US tracking filling the gap for the rest of the analysis period. This is seen as an increasing trend in the EUSST dataset error after some days without updates. Thus, generalized benefits of data fusion are shown for this MEO object for both datasets, filling the coverage gaps and improving the accuracy. Moreover, the combination of data not only provides a larger number of measurements and tracking coverage robustness, but also allows a reduction of the update intervals, significantly improving the accuracy.

Fig. 7, which describes the relative accuracy metrics for Sentinel-3A, shows a different scenario. EUSST dataset coverage and measurements distribution issues lead to an accuracy degradation between 100 and 200 meters as compared to the data fusion. In fact, the combined dataset solution is driven mostly by the US dataset contribution, seeing days where the US dataset alone provides even slightly better accuracy than the combined dataset. There are two main reasons for this. On the one hand, there is a clear network capability difference between the US radar network and the EUSST one, which leads the former one to find a small benefit on many occasions. On the other hand, as discussed previously in this paper, the GRAVES sensor is the one providing the highest pool of the EUSST data, outputting observations with a high rate and thus extremely time correlated. This could have been mitigated by the US Track Weighting method, but as already mentioned the US cataloguing system was unable to process bi-static range rate measurement. Moreover, GRAVES' performance was lessened by the fact that the data that could be shared within the frame of this experiment came with suboptimal ionospheric corrections pre-applied. This pulls the combined orbit trajectory towards it, deteriorating the accuracy. This is yet another example of the required effort for a cataloguing system when combining the data of multiple providers. When more data of high quality arrives, providing better geometrical coverage and reducing the weight of other sensors, unseen issues of specific sensors may be pointed out with this insight, where specific treatments such as measurements under sampling or de-weighting are to be applied to make the data combination effective.

Even though the US dataset does not benefit from the data fusion in this LEO scenario, the impact of data combination has a mild relevance on their solution, but significantly improves the EUSST dataset accuracy. This points out that different cooperation procedures could be proposed for future collaboration, detecting the cases where a certain network is sufficiently accurate on its own and only apply a 1-sided data sharing when appropriate.

Therefore, several benefits of data fusion have been shown with this analysis of orbit prediction accuracy with respect to precise ephemerides. Gaps in the data are covered, improving the estimation and prediction of the orbits when network visibility or availability is reduced. A higher frequency of observations avoids the need for longer propagation arcs. A better diversity of the measurements in terms of geometry and observability allows improved orbit determination accuracy. And, as is shown in Fig. 6 and 7, effectively avoiding very inaccurate estimation at times of data gaps leads to an improvement in the robustness of the SSA system, whose overall benefit exceeds any minor accuracy degradation that may occur if any of the datasets presents undetected biases or inaccurate measurements.

Finally, it is worth remembering that this analysis is performed against precise orbits, known to represent the ground truth. However, in the general case of most SSA activities, the majority of objects are non-collaborative, and a precise ephemeris is not available. Nonetheless, it has been shown in this section that the accuracy and robustness of orbit determination and propagation is expected to be improved when fusing the data. This led to propose the combined dataset orbits as reference to analyze the performance of the individual datasets for the general case of satellites without reference orbit, as was explained previously in Section 3.

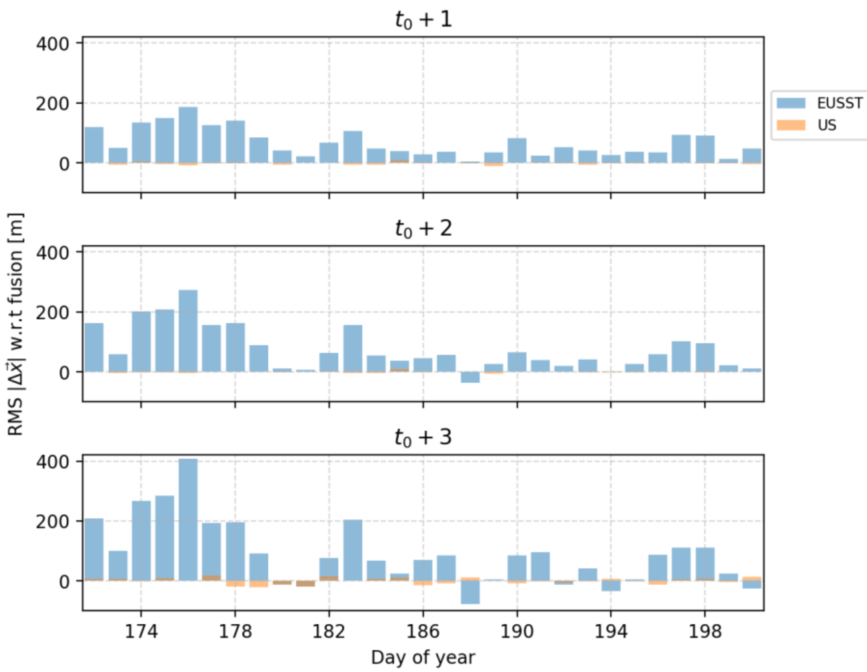

Fig. 7: Relative accuracy for the individual datasets as compared to data fusion for Sentinel-3A

6. PREDICTION ERROR FOR SATELLITES WITHOUT REFERENCE ORBITS

As previously mentioned, the study group chose satellites to cover the three main orbital regimes (GEO, MEO and LEO) with diverse altitudes, eccentricities and inclinations, in an effort to be representative of the global space population and thus of its cataloguing process. Consequently, objects that lack external precision reference orbits were included. This section focuses on the prediction error for these satellites, representative of the general RSO population. The particular process of using the combined dataset solution as a reference orbit has already been explained in Section 3 and it has been shown as appropriate after the analysis of Section 5. One further characteristic of the results presented in this section is the normalization of the prediction error outputs in order to facilitate their public release; they have thus been normalized to a reference accuracy and are unitless, a stratagem that still allows useful relative comparison, which is in fact the particular thrust of this section's analysis.

Two original test objects were, after further analysis, discarded for the following reasons:

- Object 1984-108B, having a mean altitude around 380 km, was originally chosen to represent low-altitude LEO. Unfortunately, the propagation times used for comparison were not suited to that particular regime, as it was found that after even one day of propagation the prediction errors due to atmospheric density uncertainties predominated the entire analysis and swamped any improvements due to more favorable tracking density. A specialized analysis would be required to examine this specific regime with adapted propagation periods, and this was beyond the scope of the present effort.
- Object 2020-018B did not have sufficient observations from either entity during the measurement campaign. Its cataloguing process was thus unable to produce enough prediction points using the US dataset, which made comparison often impossible and the results not meaningful.

Fig. 8: Representation of prediction error vs. number of observations used in OD, both by regime and data provider

With the remaining objects, a first approach was to look at the prediction error as a function of the number of observations used to produce the corresponding orbit determination. Fig. 8 was produced by grouping all prediction errors by orbital regime and dataset used and plotting them against the number of measurements. Note that the graphs are using a log-log scale to accommodate the broad dynamic range of the data. Several inferences suggest themselves in comparing the data distribution from both providers in Fig. 8:

- For GEO objects, both data providers exhibit some predictions that encompass too few measurements to maintain consistency with respect to the reference orbit. Interestingly, the point at which this consistency disappears is different for each provider, confirming that both networks are not equivalent in the way that they provide information. The geographical dispersion of sensors, their respective performances, longitude revisit rate, and measurement frequency are all probably at play.
- For MEO objects, all objects seemed to be provisioned with sufficient observations in the EUSST dataset such that no clear point of inconsistency in the prediction error occurs. The number of observations in the US dataset, however, is an order of magnitude smaller; and a divergence in consistency does occur, roughly at the 100 measurement per fit-span point.
- For LEO, the number of measurements is not that appreciably different across both providers. However, the US dataset clearly performs better than the EUSST one, even with less data; this is a clear consequence of the network disparities discussed in the tracking density analysis.

In examining the results of the combined dataset now, it is already clear that some tracking synergy is taking place:

- The performance of the GEO combined dataset is better across the board. Clearly, the increased amount of measurement data improves the tracking distribution to a point of much better consistency. From this graph alone, it can be seen directly that it performs better in terms of prediction error than either of the provider's individual solutions.
- The MEO combined dataset performs better than the US one, which suffers from a lack of measurement for certain prediction points. Its overall performance relative to the EUSST dataset cannot be assessed in a conclusive manner from this graph alone.
- Inversely, the LEO combined dataset addresses the EUSST data density problem, with better prediction errors across the board; but it does not show clear signs of improvement with respect to the US dataset.

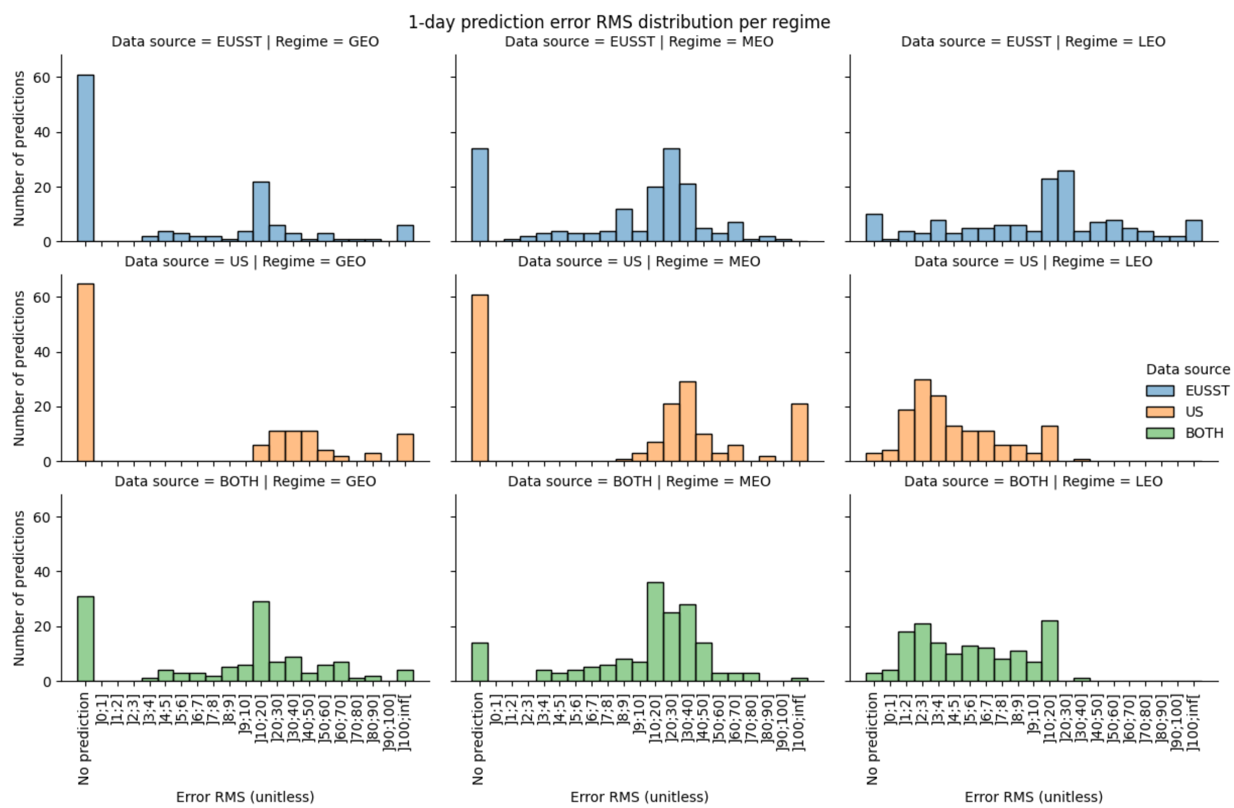

Fig. 9: Prediction error distribution across orbital regimes for each data provider

Fig. 9 presents the prediction error distribution, considering the days in the study period in which no prediction could be issued for each dataset. Results are shown only for a 1-day propagation period, as these comparative results are only marginally different for the 2-day and 3-day periods. The graphs again are categorized by data provider and orbital regime. The first x-axis bin accounts for days in which no prediction could be made; and the following prediction error bins are then sized logarithmically, using the same unitless error as in Fig. 8. Finally, the last x-axis bin gathers all the points with a prediction error above the unitless value of 100, at which point the prediction was judged unsuitable to be used for an orbital safety product.

These error distributions allow for additional assessment of the benefits (or lack thereof) gained from data fusion:

- In GEO, in addition to the global prediction error improvement, it is observed that both providers have around 60 instances in which the lack of data does not allow the production of a new orbit. This figure is roughly halved for the combined dataset; so the fused dataset has the combined benefit of better prediction accuracy as well as providing more consistent temporal coverage across the study period.
- In MEO, the fused dataset has a slightly better error distribution than the EUSST solution, but not of such a degree to advance this as an obvious improvement. Of course, this conclusion must retain as its context that the reference orbit is a synthetic one rather than a precise ephemeris; and therefore smallish differences in prediction error evaluated against a synthetic truth ephemeris remain inconclusive. Nonetheless, the temporal coverage is again much better, as the days without a prediction decrease from 34 to 14. When compared to the US dataset, it is clearly superior in both error distribution and temporal coverage.
- For LEO, however, it appears that no benefit is gained from the data fusion, relative to the US dataset. Some predictions appear worse, while others are slightly improved; and the error distribution is even slightly worse overall, with a more pronounced peak in the [10;20] bin. As can be seen from Fig. 8 and also from Fig. 3 and 4, very little extra information is provided by the two participating EUSST radars compared to the coverage already provided by the US network alone. As for MEO, it is not possible to confirm which of the two solutions (combined or US data alone) is objectively better. A larger statistical sample and a reference trajectory that is less correlated to the predicted one would probably help to resolve this question. As expected, the gain in prediction error is significant when compared to the EUSST dataset, yet the temporal coverage is only marginally better.

As one would expect, the benefits of data fusion are maximized when data scarcity comes into play. In some situations, like the GEO cases that were examined in this study, the combination is better than either of its parts; and the act of sharing data is a mutually beneficial process. In others, it is more of a one-sided approach, where one provider is filling in the data gaps of the other. In some cases, no improvement could be measured convincingly; but likewise there was no evidence of a statistically significant deterioration of the solution either.

It is important to note that all results in this section rely on the predictions made by the EUSST cataloguing system. A similar approach using predictions stemming from the US cataloguing system revealed that results were largely in line with the EUSST ones, save for the LEO case. As discussed previously, this was expected since one limitation that we encountered was that the US cataloguing system was not suited to readily process bi-static radar measurements. For the sake of simplicity and consistency, only the EUSST estimates were used to produce Fig. 8 and 9.

As a technical summary, Table 3 below gives a synthetic view of how the fused dataset performs with respect to the individual providers:

Table 3: Synthetic summary of the fused dataset's performance vis-à-vis those of the individual providers

		EUSST		US	
		Temporal coverage	Prediction error	Temporal coverage	Prediction error
Combined	GEO	Significant improvement	Significant improvement	Significant improvement	Significant improvement
	MEO	Significant improvement	Inconclusive	Significant improvement	Significant improvement
	LEO	Slight improvement	Significant improvement	No improvement	Inconclusive

7. CONCLUSIONS

The analysis of orbit accuracy using precise ephemerides as reference showed that that the precision and robustness of orbit determination and propagation is improved when combining the data, solving data gaps, coverage, network availability issues and reducing the update intervals. For instance, it has been seen how the US can significantly benefit from EUSST data in the case of Galileo-21 to cover the data gaps, whereas EUSST can improve the quality of their products for Sentinel-3A when adding data from the US radars network, which provides wider coverage and geometry. The combined dataset solution, once proven generally more accurate and robust than the individual datasets, has been used as reference to estimate the orbits accuracy of the rest of satellites under analysis.

The benefits of data fusion are maximized when data scarcity comes into play. In some situations the combination is better than either of its parts, and the act of sharing data is a mutually beneficial process. In others it is more of a one-sided approach, where one provider is filling in the data gaps of the other. Overall there are significant benefits to data sharing at the observation level both in temporal coverage and improved prediction accuracy. Also while some technical coordination is needed, this solution has the advantage of being readily applicable by any operational entities that have some level of proficiency in orbital cataloguing.

8. FUTURE WORK

The next step in assessing the benefits of data sharing might be to examine how the accuracy and realism of the covariance using combined data compares to that based on the covariances for the separate contributors. Assuming favorable results, a sharing process experiment could be applied to selected real world predictions of close approach events. Additionally, given the recent interest in the industry in the direct fusion of data products, a salutary future task would be for ephemerides to be developed first using just the US or EUSST data (representing the ephemeris that each would generate using merely their own data) and then to attempt direct fusion of these ephemerides into a single product (perhaps following the approach of [2]), which would then be compared to an OD that used the entire observational dataset. Such an experiment would represent the operational scenario in which ephemeris or Conjunction Data Message data fusion would actually take place, so it therefore would serve as a telling evaluation of direct data product fusion techniques.

9. ACKNOWLEDGEMENTS

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