Thermosphere and satellite drag **NB: this topic is not in the 2015 Roadmap**

NB2: thermosphere for drag calculation specifically

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1. Introduction

The main uncertainty in aerodynamic drag calculation of objects in low Earth orbit (LEO) is due to the

2. Sources of uncertainty in drag calculation and forecasting

2.1 Upper atmosphere models (Tim, Jia, Sean)

There are two categories of upper atmosphere thermosphere models, low-resolution empirical (e.g.,

2.2 Upper atmosphere data (Tim, Jia, Sean)

The greatest limitation to improving thermosphere models today is inconsistency between datasets,

2.3 Solar activity: measurements and forecasts (Thierry)

One of the two primary drivers of upper atmosphere heating is the absorption of solar radiation in the

2.4 Geomagnetic activity: measurements and forecasts (Yuri, Ruggero)

The Kp Index (Bartels, 1949; Mayaud, 1980) is a measure of global geomagnetic activity used to drive

2.5 Satellite shape and aerodynamic coefficient modeling (Piyush)

The drag coefficient is a component of a more general aerodynamic coefficient and characterizes the

2.6 Orbit extrapolation and uncertainty propagation (Fabian)

Uncertainty in orbit propagation grows from the starting epoch due to uncertainties in the semi-major

2.7 Operational concerns (Stijn, Katherine, Scott)

Operational nowcasts and forecasts of satellite orbit prediction and conjunction analysis require

3. Conclusions and recommendations

3.1 Upper atmosphere models

3.2 Upper atmosphere data

3.3 Solar activity: measurements and forecasts

3.4 Geomagnetic activity: measurements and forecasts

3.5 Satellite shape and aerodynamic coefficient modeling

3.6 Orbit extrapolation and uncertainty propagation

3.7 Operational concerns

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Figure captions

Figure X. Typical error samples and probability density estimates after 10 days of propagation. Left: accounting for density uncertainty, right: neglecting it (Source: Schiemenz et al. 2020c).

Figure KP1. Figure 7. K-fold Cross Validation root mean square error (RMSE) for the data models described as a function of the forecast horizon time. The solar wind-based model has the lower RMSE than Kp-based models, while the recurrence model outperforms the solar-wind based model for longer horizon times. The full model provides a smooth transition between the recurrence and solar-wind models (adapted from Shprits et al., 2019).

Figure KP2. Accuracy of different data models as a function of forecast horizon for (a) ($Kp \leq 4$), and for (b) $Kp > 4$ (adapted from Shprits et al., 2019).

Figure KP3. Comparison of models obtained with different regression methods: RMSE (top) and correlation coefficient (bottom) (adapted from Zhelavskaya et al., 2019).