4. CONCLUSIONS

In this paper we demonstrated the feasibility of an empirical model based on 20 years of HASDM outputs, taking advantage of nearly two solar cycles of satellite drag observations from ~70 calibration satellites. The resulting model, META-HASDM, does not yet outperform leading empirical models such as Jacchia-Bowman 2008. However, we have identified several methods for enhancing META-HASDM including additional parameters such as location relative to the Oxygen-Helium transition. In addition to this, we have published the HASDM-compatible drag coefficient model along with an altitude dependent correction function. Using this model along with the publicly released HASDM database or with the new META-HASDM density model presented here, results in drag predictions that are unbiased on average with respect to observations.

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