

Toward Improved Physics-Based Simulations of the LEO Space Environment using GNSS-Enabled Small Satellites

Eric K. Sutton^{1,1}, Jeffrey P. Thayer^{2,2}, Marcin D. Pilinski^{3,3}, Shaylah M. Mutschler^{1,1}, Thomas E. Berger^{1,1}, Vu Nguyen^{4,5}, and Dallas Masters^{4,4}

¹University of Colorado at Boulder

²University of Colorado Boulder

³Laboratory for Atmospheric and Space Physics

⁴Spire Global, Inc

⁵Spire Global

November 30, 2022

Abstract

Satellite-atmosphere interactions cause large uncertainties in low-Earth orbit determination and prediction. Thus, knowledge of and the ability to predict the space environment, most notably thermospheric mass density, are essential for operating satellites in this domain. Recent progress has been made toward supplanting the existing empirical, operational methods with physics-based data-assimilative models by accounting for the complex relationship between external drivers such as solar irradiance, Joule, and particle heating, and their response in the upper atmosphere. Simultaneously, a new era of CubeSat constellations is set to provide data with which to calibrate our upper-atmosphere models at higher spatial resolution and temporal cadence. With this in mind, we provide an initial method for converting precision orbit determination (POD) solutions from global navigation satellite system (GNSS) enabled CubeSats into timeseries of thermospheric mass density. This information is then fused with a physics-based, data-assimilative technique to provide calibrated model densities.

1 **Toward Accurate Physics-Based Specifications of**
2 **Neutral Density using GNSS-Enabled Small Satellites**

3 **Eric K. Sutton¹, Jeffrey P. Thayer^{1,2}, Marcin D. Pilinski³, Shaylah M. Mutschler²,**
4 **Thomas E. Berger¹, Vu Nguyen⁴, Dallas Masters⁴**

5 ¹Space Weather Technology, Research and Education Center (SWx TREC), University of
6 Colorado at Boulder.

7 ²Ann and H.J. Smead Aerospace Engineering Sciences, University of Colorado at Boulder.

8 ³Laboratory for Atmospheric and Space Physics (LASP), University of Colorado at Boulder.

9 ⁴Spire Global, Inc., Boulder, CO.

10 Corresponding author: Eric Sutton (eric.sutton@colorado.edu)

11 **Key Points:**

- 12 • GNSS-enabled satellites are capable of monitoring the state of the thermosphere at much
13 higher cadences than current operational datasets
- 14 • We present an initial technique to infer neutral densities from orbit determination
15 products of the Spire CubeSat constellation
- 16 • Densities are used to drive a data-assimilative, physics-based model of the thermosphere
17 and ionosphere during 23 Sept.–9 Dec. 2018

18 **Abstract**

19 Satellite-atmosphere interactions cause large uncertainties in low-Earth orbit determination and
20 prediction. Thus, knowledge of and the ability to predict the space environment, most notably
21 thermospheric mass density, are essential for operating satellites in this domain. Recent progress
22 has been made toward supplanting the existing empirical, operational methods with physics-
23 based data-assimilative models by accounting for the complex relationship between external
24 drivers such as solar irradiance, Joule, and particle heating, and their response in the upper
25 atmosphere. Simultaneously, a new era of CubeSat constellations is set to provide data with
26 which to calibrate our upper-atmosphere models at higher spatial resolution and temporal
27 cadence. With this in mind, we provide an initial method for converting precision orbit
28 determination (POD) solutions from global navigation satellite system (GNSS) enabled CubeSats
29 into timeseries of thermospheric mass density. This information is then fused with a physics-
30 based, data-assimilative technique to provide calibrated model densities.

31 **Plain Language Summary:**

32 Satellites with heights below 1,000 kilometers (or about 600 miles) travel through the upper
33 atmosphere, which influences the path of their orbits. This influence has been monitored, in
34 some capacity, since the first man-made orbiting satellites were launched into space, but
35 predicting the effects is still quite difficult. Now commercial satellite “mega constellations” are
36 being launched into the region at a fast pace, which means that all satellite paths must be known
37 and projected into the future with great accuracy in order to avoid high-speed collisions. Using
38 Global Positioning System (GPS) signals, this work blends information from tracking the
39 position of the mega-constellation satellites themselves with a high-fidelity model of the upper
40 atmosphere, in an attempt to improve our knowledge of where satellites are and where they are
41 going to be.

42 **1 Introduction**

43 Within low-Earth orbit (LEO), a region spanning roughly 100 to 1000 km in altitude for
44 the purposes of this paper, interactions between man-made satellites and the ambient atmosphere
45 cause large uncertainties in the orbit determination and prediction processes (Berger et al., 2020).
46 During episodic periods of moderate to severe space weather activity, such atmospheric drag

47 uncertainties can amplify by a factor of 2–5 in a matter of minutes to hours (Krauss et al., 2015;
48 Sutton et al., 2005). These uncertainties, when combined with the steadily growing launch rate of
49 small satellites and CubeSats and our advancing ability to track smaller and smaller objects, are
50 poised to overwhelm the U.S. Department of Defense infrastructure currently carrying out the
51 Detect–Track–Catalog mission. Products of this mission are pervasive across the Space
52 Situational Awareness (SSA) and Space Traffic Management (STM) enterprises and form a
53 critical infrastructure for nearly all space-based activities. Thus, knowledge and prediction of the
54 space environment, particularly the neutral mass density of the thermosphere and lower
55 exosphere, are an essential part of satellite operations within LEO.

56 One of the major obstacles in predicting orbit trajectories hours to days in advance, and in
57 correlating consecutive or irregular object tracking data with a particular orbiting object, comes
58 from the legacy framework used to model the upper atmosphere’s state and its interaction with
59 satellites and debris. The current model employed by the Combined Space Operations Center
60 (CSpOC) and is the High Accuracy Satellite Drag Model (HASDM) (Storz et al., 2005), an
61 empirical model that self-calibrates by ingesting ground-based tracking data of a select set of
62 orbiting “calibration objects”—i.e., operational and defunct satellites passing through LEO with
63 reasonably stable ballistic coefficients. While this method provides an accurate global-average
64 snapshot of the upper atmosphere, its abilities to capture realistic spatial structure and forecast
65 into the future are limited, particularly ahead of geomagnetic storming that has the largest impact
66 on LEO orbital tracking. Physics-based upper atmosphere simulation approaches offer a vast
67 potential improvement in this regard. Models in this category solve a set of Navier-Stokes fluid
68 equations that have been appropriately tailored for use in the upper atmosphere and are therefore
69 inherently better equipped for simulating a dynamic system response to impulsive energy input
70 from the solar wind and coronal mass ejections. For years the computational cost of these models
71 prohibited their use in an operational setting. However, present-day computing technology is
72 abundantly capable of running an ensemble of such models in near real time. Instead, the
73 primary reason that physics-based methods remain to be adopted by operational centers is the
74 lack of robust data assimilation schemes capable of self-calibrating at levels equal to or better
75 than those currently used in combination with empirical models.

76 Fortunately, significant strides have been made in recent years toward supplanting
77 empirical methods with physics-based data assimilative models of the upper atmosphere. One

78 such advancement has been accomplished by accounting for the complex relationship between
79 external drivers—namely solar flux, Joule, and particle heating—and the response of the upper
80 atmosphere by employing a new least-squares filter called the Iterative Driver Estimation and
81 Assimilation (IDEA) technique (Sutton, 2018). The new filter operates similarly to an unscented
82 Kalman filter (UKF) with the addition of mechanisms to accommodate the lagged response of
83 the upper atmosphere to variations in the external drivers. Using this new technique, notable
84 improvements in neutral density specification—even during a geomagnetic storm—have already
85 been demonstrated (Sutton, 2018), which can help to lower the uncertainty of orbit determination
86 and prediction across the LEO catalog, thereby increasing the efficacy of STM activities,
87 including satellite conjunction assessment and collision avoidance. In addition, the emergence of
88 large constellations of commercial and academic CubeSats over the past 5 years brings with it an
89 excellent opportunity. Most newer SmallSats and CubeSats are equipped with Global Navigation
90 Satellite System (GNSS) devices, making them valuable sources of Precision Orbit
91 Determination (POD) information. Many are also equipped with the ability to monitor their
92 attitude, allowing the construction of an accurate force model. This information can be combined
93 to initialize and constrain models of the upper atmosphere.

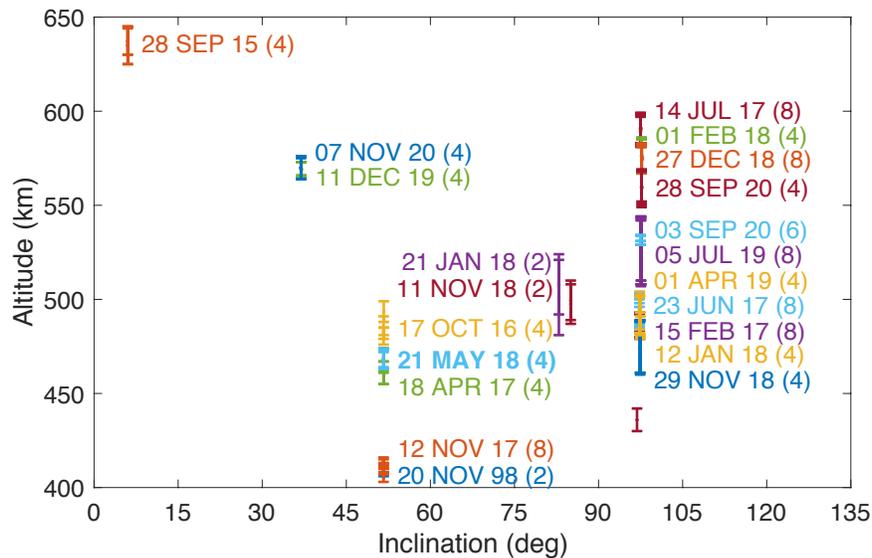
94 In order to track the state of the upper atmosphere with reasonable fidelity, the HASDM
95 model ingests observations from ground-based radar tracks of known objects using a similar
96 technique to the one we present here. However, in order to make strides in specifying and
97 predicting the state of the thermosphere, new data sets with increased spatial resolution, temporal
98 cadence, and global coverage are needed (Bruinsma, Fedrizzi, et al., 2021). Satellite-based
99 GNSS observations are capable of describing the space environment at a much higher spatial
100 resolution and temporal cadence. Whereas the conventional radar-derived, satellite-drag data sets
101 operate on a multi-orbit to multi-day cadence, we will show that the GNSS-derived data sets are
102 capable of operating at a cadence of a single orbital period, i.e., on the order of hours rather than
103 days. Even higher cadences may also be possible but will require further development. The
104 remainder of the paper details our efforts to use the new set of information provided by CubeSats
105 to drive a physics-based, data-assimilative approach to simulating atmospheric densities in LEO.

106 **2 Datasets**

107 2.1 Spire CubeSats

108 Spire operates a constellation of over 100 CubeSats in LEO with altitudes ranging from
 109 400–650 km and inclinations spanning the globe, from equatorial to polar orbits. Figure 1 gives a
 110 snapshot of the distribution of altitude and orbit inclination of Spire CubeSats as of late January
 111 2021.

112



113

114 **Figure 1.** Current coverage of altitude versus inclination for the Spire constellation of CubeSats
 115 (as of 26 January 2021). The error bars show the perigee-to-apogee range of altitudes. CubeSats
 116 are color coded by common launch dates with the total number of CubeSats in each launch group
 117 indicated in parentheses. The 21 May 2018 launch date is emphasized to indicate the launch date
 118 of the three satellites used in this study.

119 The data sets used in this study were provided by Spire Global as part of the NASA
 120 Commercial SmallSat Data Pilot Program and cover the period of 23 Sept.–9 Dec. 2018. For the
 121 purposes of our work, the following data products were utilized:

- 122 • POD solution ephemeris derived from GNSS tracking
- 123 • Satellite pointing in the form of attitude quaternions
- 124 • Satellite geometry model

125 POD solutions were typically available during the duty cycle of the GNSS/Radio
126 Occultation (RO) instrument. For the 2018 dataset, duty cycles were in the range of 30–40% of
127 the time, usually concentrated along 40- to 60-minute segments of an orbit (referred to hereafter
128 as an orbit arc). This efficiency has increased with more recent CubeSat builds such that current
129 duty cycles are beginning to approach 100%. For the current data set, ephemeris from each orbit
130 arc were estimated using the RTOrb software ([https://gps-](https://gps-solutions.com/brochures/GPSS_Brochure_RTOrb_Nov_2011.pdf)
131 [solutions.com/brochures/GPSS_Brochure_RTOrb_Nov_2011.pdf](https://gps-solutions.com/brochures/GPSS_Brochure_RTOrb_Nov_2011.pdf)). This software implements a
132 Kalman filter-based approach to estimate orbit ephemeris. As configured for the current dataset,
133 RTOrb considers Earth’s gravity up to degree and order 120 from the EIGEN-2 model (Reigber
134 et al., 2003), Luni-Solar 3rd body perturbations, atmospheric drag assuming densities from the
135 Mass Spectrometer Incoherent Scatter extension (MSISE-90) model (Hedin, 1991), and solar
136 radiation pressure (SRP) with cylindrical Earth-shadowing effects. The latter two effects use a
137 cannonball approach in which coefficients of drag and reflectivity are estimated within each arc,
138 respectively, along with the orbit ephemeris. The treatment of drag and SRP in the POD process
139 is not to be confused with the force model described later in this section; instead, the parameters
140 estimated here have little bearing on our calculations of orbit energy.

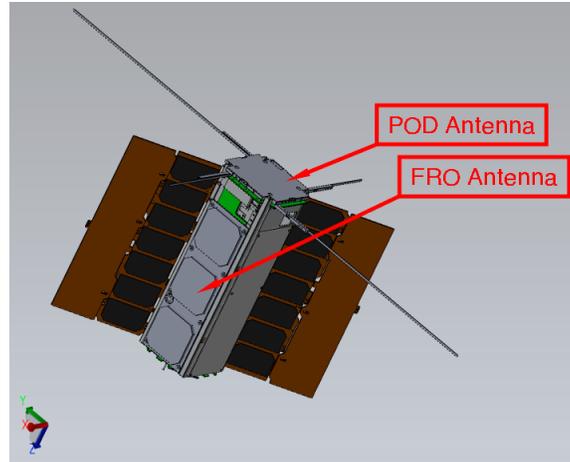
141 The attitude of the Spire CubeSats is represented by a quaternion describing the
142 transformation from the body-fixed coordinate system (see Figure 4 below) to the vehicle
143 velocity/local horizontal (VVLH) orbit-based coordinate system at a given instance in time.
144 These data enable the orientation of the satellite with respect to the final coordinate system
145 introduced in Section 3.2. In the initial phases of the NASA Data Pilot assessment, quaternions
146 were provided at an approximate cadence of 10 seconds during the duty cycle of the GNSS/RO
147 receiver, with nothing available outside of the duty cycle. However, it was realized early on in
148 the project that, due to frequent orientation maneuvers, the accuracy of the retrieved neutral
149 densities would be limited by any breaks in continuity of satellite attitude data (see Section 3.3
150 for further details). The attitude mode of the CubeSats frequently switched between an observing
151 mode aligning GNSS/RO antennas along track and a mode that maximizes the amount of solar
152 flux incident on the solar panels. Because these changes in orientation modify the integrated
153 effect that atmospheric drag has on the orbit parameters, the orientation must be monitored
154 constantly in order to convert orbital energy loss rates to an atmospheric density. Spire has since
155 updated their processing chain for the entire fleet to ensure that a continuous stream of attitude

156 quaternions is available for any datasets originating after 2018. However, for the 2018 data set,
 157 processing was limited to a small subset of three CubeSats from Spire Global’s constellation for
 158 which attitude data had been continuously downlinked and archived. These satellites, which will
 159 be used throughout the remainder of the paper, are referred to by Spire’s internal satellite ID
 160 numbers: 83, 84, and 85. These three CubeSats trace back to a common launch on 21 May 2018
 161 into a 51.6° inclination orbit. During the time period of interest these satellites orbited between
 162 the altitudes of 467–492 km and remained within 800–2100 km (or 2–4.5 minutes) of one
 163 another along the orbit track. Additional properties and designations of these CubeSats can be
 164 found in Table 1.

165 **Table 1.** Properties of Spire CubeSats used in this study. Note: the last three columns apply to all
 166 three satellites

Spire ID	NORAD ID	COSPAR ID	Perigee/Apogee Altitude (km)	Inclination (degrees)	S/C Mass (g)
83	43560	2018-046G			
84	43559	2018-046F	467–492	51.6	4933 ± 4
85	43558	2018-046E			

167 Figure 2 shows the geometry for the three Spire CubeSats. The GNSS/POD antenna
 168 nominally points in the zenith direction while the front radio occultation (FRO) antenna
 169 generally points along the in-track or anti-in-track directions when the satellite is recording RO
 170 data. When the RO instrument is cycled off, the satellite reorients in such a way as to maximize
 171 illumination of the solar panels.



172

173 **Figure 2.** Computer model of Spire's version 3.3 Lemur CubeSat.

174 2.2 Swarm Satellite Mission

175 As an independent data source, neutral densities from the Swarm satellite mission (Friis-
176 Christensen et al., 2008) are used to compare with the assimilated model density output at
177 locations that differ from the Spire dataset. Anomalies in the Swarm accelerometer data were
178 noticed early in the mission (Siemes et al., 2016), preventing their use for neutral density
179 determination using established methods (e.g., Bruinsma et al., 2004; Doornbos et al., 2010;
180 Sutton et al., 2007). Instead, GNSS tracking data are used to produce POD solutions of neutral
181 density for the Swarm satellites at a temporal resolution of about 20 minutes, which is then used
182 to constrain the uncertainties in the accelerometer measurements (van den IJssel et al., 2020).

183 The Swarm mission consists of three satellites: Swarm-A, -B, and -C. Swarm-A and -C
184 reside in essentially the same near-polar orbit, while the orbit of Swarm-B is higher in altitude
185 and slightly lower in inclination. Of the three satellites, accelerometer data is only currently
186 available from Swarm-C. This data, referred to as Swarm-C ACC, spans the altitude range of
187 437–468 km during the 2018 period of interest. During this period, anomalies in the data can
188 cause the densities to attain non-physical values; these are removed from data prior to
189 performing any comparison. In addition, orbital averages of the Swarm-C densities are taken and
190 compared with a corresponding orbital average of model densities in order to mitigate any
191 spurious errors in the accelerometer data. The orbital plane of Swarm-C precesses 12 hours with
192 respect to local time approximately every 133 days of the mission. Because the lower-inclination
193 Spire CubeSats precess much faster (i.e., 12 hours of local-time precession every 31.25 days),

194 Swarm-C data allows us to assess the accuracy of the assimilation model for local times and
 195 locations far away from the ingested Spire data over the 2018 period of interest.

196 **3 Methods**

197 **3.1 Orbital Energy Determination**

198 To drive our data assimilative process, we use information from GNSS measurements
 199 taken aboard CubeSats. There are several methods available to infer neutral densities from orbit
 200 positioning information. For instance, this can be done by estimating a scaling correction for a
 201 density model within a POD solution using two-line element (TLE, e.g., Brandt et al., 2020) sets
 202 or GNSS tracking (e.g., van den IJssel & Visser, 2007) . We choose instead to employ a model-
 203 agnostic energy tracking method that uses the existing POD solutions routinely obtained by
 204 Spire. The first step is to calculate the orbital energy at each available ephemeris data point and
 205 track the change in this quantity between subsequent orbits. For an Earth-orbiting satellite, this
 206 energy can be approximated in the following way:

$$207 \quad \xi = \frac{v^2}{2} - \omega_{Earth}^2 \frac{x^2+y^2}{2} - \frac{\mu}{r} - U_{nonSpherical} \quad (1)$$

208 where $r = \sqrt{x^2 + y^2 + z^2}$ and v are the satellite's respective position and velocity in an Earth-
 209 centered Earth-fixed (ECEF) coordinate frame, ω_{Earth} is the rotation rate of the Earth, μ is the
 210 gravitational parameter for the Earth, and $U_{nonSpherical}$ is a potential function describing
 211 deviations in Earth's gravitational field from the purely spherical (i.e., $-\mu/r$) term. $U_{nonSpherical}$
 212 is most commonly expressed as a spherical harmonic expansion of degree, n , and order, m . In
 213 the absence of nonconservative forces (e.g., atmospheric drag or solar radiation pressure) or any
 214 additional perturbing conservative forces not accounted for in Equation 1 (e.g., 3rd body
 215 attraction, solid Earth tides, ocean tides, atmospheric tides, etc.), ξ is a conserved quantity along
 216 the orbit of a satellite.

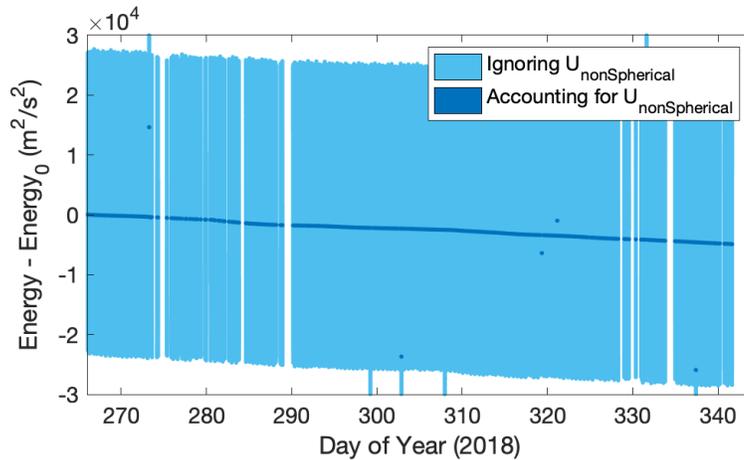
217 We have found that the choice of Earth-fixed coordinates becomes important when
 218 considering the non-spherical gravity terms in the energy equation (i.e., Equation 1), particularly
 219 any non-zonal terms (i.e., $m > 0$), which depend on longitude. In ECEF coordinates,
 220 $U_{nonSpherical}$ is clearly a function of position alone. The alternate formulation of the energy
 221 equation in an inertial coordinate frame, however, would require $U_{nonSpherical}$ to be a function

222 of both position and time, violating the assumptions underlying a potential function and its use in
 223 the energy equation. As a result, the formulation of energy in an inertial coordinate frame does
 224 not remain constant along an orbit when considering non-zonal terms—even in the absence of
 225 nonconservative forces—and leads to twice-daily oscillations of approximately ± 130 – 140 J/kg/s
 226 or m^2/s^3 for the orbits analyzed in this paper, or equivalently, about ± 30 – 35 m in the semi-major
 227 axis. Much of this can be directly attributed to the $n = m = 2$ gravitational potential term, which
 228 is the largest non-zonal term in $U_{nonSpherical}$. The 3rd body attraction from the sun and moon
 229 depend on time in both Earth-fixed or inertial coordinates, although much less so in the latter.
 230 While fairly minor, the work done by 3rd body attraction on a satellite’s orbit can be taken into
 231 account over time using the following equation:

$$232 \quad \Delta\xi_{3B} = \int_{t_0}^{t_1} \vec{a}_{3B}(\vec{r}, t) \cdot \vec{v} dt \quad (2)$$

233 where $\Delta\xi_{3B}$ is the difference in orbital energy due to 3rd body acceleration between times t_0 and
 234 t_1 ; \vec{r} and \vec{v} are the position and velocity vectors in ECEF coordinates; and \vec{a}_{3B} is the acceleration
 235 vector of the satellite caused by the gravitational attraction from the sun and moon, also
 236 expressed in the ECEF reference frame. In contrast to Equation 1, continuous knowledge of the
 237 satellite ephemeris is required in order to carry out the integral calculation of Equation 2. While
 238 this is not available directly from the GNSS measurements due to duty cycling, it can be
 239 obtained at sufficient precision using Two-Line Element (TLE) sets along with the Simplified
 240 General Perturbations (SGP4) satellite propagator, both available at <https://space-track.org>. The
 241 continuous position of the sun and moon were obtained from JPL’s planetary and lunar
 242 ephemeris product (Park et al., 2021 and references therein).

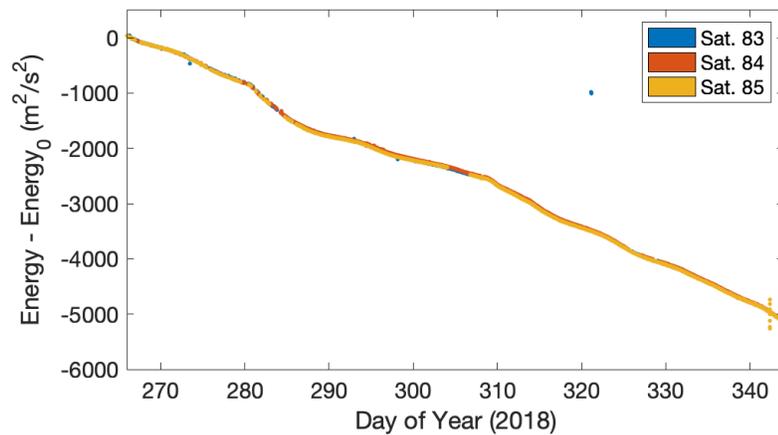
243 If we describe the Earth’s gravity field using the two-body approximation—ignoring for a
 244 moment the non-spherical and 3rd body contributions—the energy dissipation due to atmospheric
 245 drag remains obscured by the large variations in energy due to Earth’s J_2 oblateness term (i.e.,
 246 $n = 2, m = 0$) and higher-order gravitational terms. The light blue data points in Figure 3 show
 247 this simplified calculation of orbital energy for a single CubeSat from Spire Global’s
 248 constellation (satellite 83) during the period spanning 23 Sept.–9 Dec. 2018. However, when we
 249 account for a spherical harmonic gravity field up to degree and order 36 and 3rd body effects, the
 250 change in energy caused by atmospheric drag is more readily isolated from variations in the
 251 gravity field as depicted by the dark blue curve.



252

253 **Figure 3.** Keplerian orbital energy (light blue curve, i.e., ignoring the $U_{nonSpherical}$ term from
 254 Equation 1) and total orbital energy (dark blue curve, i.e., including the $U_{nonSpherical}$ term from
 255 Equation 1) for Spire CubeSat 83 during the period of 23 Sept.–9 Dec. 2018.

256 Figure 4 depicts the orbital energy of all three CubeSats over the same time span as
 257 Figure 3 but zoomed in to reveal variations in the rate of decay. To conform with the POD
 258 solutions, we have used the non-spherical terms specified by the EIGEN-2 gravity model
 259 (Reigber et al., 2003). We found that, for our purposes, including terms of degree or order higher
 260 than 36 yielded diminishing returns.



261

262 **Figure 4.** Orbital energy (i.e., including the $U_{nonSpherical}$ term from Equation 1) for Spire
 263 CubeSats 83, 84, and 85 during the period of 23 Sept.–9 Dec. 2018. The three timeseries lie
 264 approximately on top of one another, given that they reside in nearly the same orbit and therefore
 265 experience very similar accelerations.

266 During this period of time, the energy curves track one another quite well due, in part, to
 267 the fact that all three CubeSats occupy essentially the same orbital plane, with separations along
 268 the orbit track in the range of 800–2100 km (or 2–4.5 minutes). Changes in energy were on the
 269 order of 5000 m²/s² over the entire period of analysis, or about 65 m²/s² per day. This is
 270 equivalent to a change in the semi-major axis of 1.2 km total, or about 15 meters per day. These
 271 magnitudes are specific to the size, shape and ballistic coefficients of the satellites, as well as the
 272 altitude and prevailing geophysical conditions sampled during the time period of interest. After
 273 applying a simple filter to reject erroneous arcs (note the obvious outliers on day 273, 320, and
 274 342 in Figure 4), the noise level of these timeseries of orbital energy becomes low enough to
 275 derive an effective energy dissipation rate between subsequent orbit arcs.

276 3.2 Satellite Force Model

277 To interpret the timeseries of energy from Figure 4 in terms of the behavior of the upper
 278 atmosphere, it is necessary to understand how the satellite drag interaction depends on
 279 atmospheric density. The rate at which energy is lost from a satellite's orbit to the atmosphere
 280 via the drag force, or the energy dissipation rate (EDR), can be related to atmospheric mass
 281 density through the following equation:

$$EDR \equiv -\frac{d\xi}{dt} = \frac{1}{2m} C_D A_{ref} \rho v^3 \quad (3)$$

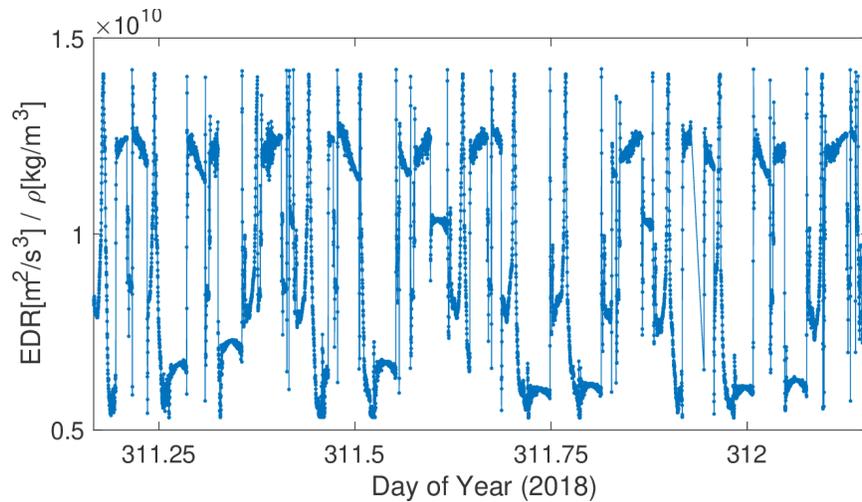
where C_D is the satellite's coefficient of drag, A_{ref} is the cross-sectional area of the satellite projected in the direction of v , the velocity of the satellite in the ECEF coordinate frame, m is the satellite mass, ρ is the mass density. Winds are neglected in this equation, however, the co-rotation of the atmosphere with the Earth is automatically considered through the use of ECEF coordinates. The force model of Sutton (2009) is used to compute the coefficient of drag. From their Equation 7, we consider the transfer of momentum between incoming atmospheric particles and the satellite surface assuming that particles are accommodated to the approximate surface temperature of the satellite using an accommodation coefficient of $\alpha = 0.93$. While the accommodation coefficient is kept constant, both C_D and A_{ref} can vary significantly over the course of an orbit due to changes in the attitude of the satellite.

In order to compare two subsequent observations of orbital energy ξ_0 and ξ_1 calculated by Equations 1 and 2 at their respective epochs t_0 and t_1 , Equation 3 can be integrated to find the dependence on atmospheric density:

$$\xi_1 - \xi_0 = -\frac{1}{2m} \int_{t_0}^{t_1} C_D A_{ref} \rho v^3 dt = -\frac{1}{2m} \rho_{eff} \int_{t_0}^{t_1} C_D A_{ref} v^3 dt \quad (4)$$

Solving for ρ_{eff} , similar in theme to the work of Picone (2005), gives an effective mass density between t_0 and t_1 along the orbit of the satellite.

Figure 5 shows the simulated change in orbital energy normalized by neutral density (EDR/ρ) as given by Equation 3 for one of Spire Global's CubeSats according to its orientation over the course of a single day. This parameter, which we can refer to simply as the force model, is the conversion factor between the observed energy dissipation rate and atmospheric density. The periodic shift between pointing modes—one optimized for RO sensing and the other for solar panel illumination—can be clearly seen in Figure 5. Accounting for the large variations in the force model becomes crucial because a satellite can dwell in a given pointing mode for a significant fraction of an orbit, and this dwell time is not necessarily consistent between orbits. If neglected, these approximate factor-of-two variations in the force model have the potential of causing errors of similar magnitude in the density retrievals.



309

310 **Figure 5.** Force model for Spire CubeSat 83 for a single day starting early on 7 Nov. The force
 311 model is the conversion factor between the observed energy dissipation rate and atmospheric
 312 density.

313 3.3 Data Assimilation

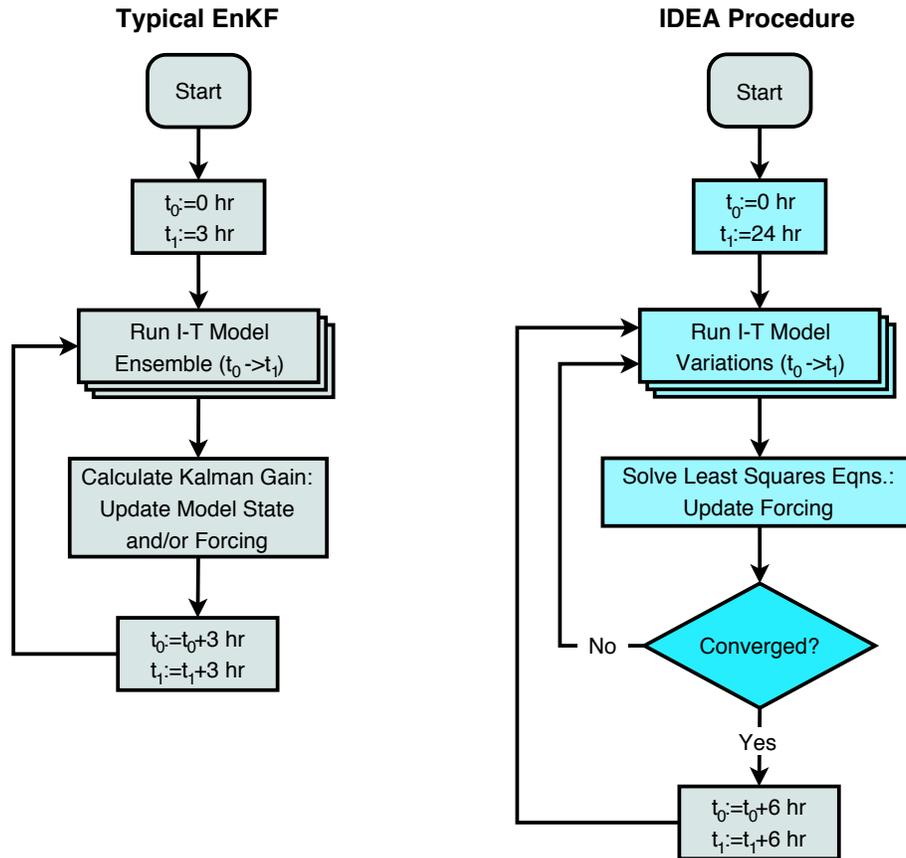
314 After processing the GNSS measurements and applying the force model described above,
 315 the final step in our process is to ingest these observations into a data assimilative framework to
 316 correct the global upper atmospheric density. Here we briefly describe the Iterative Driver
 317 Estimation and Assimilation (IDEA) technique, based on the method of Sutton (2018). This
 318 method accounts for the complex relationship between external drivers—namely solar flux and
 319 geomagnetic heating—and the resulting response of the upper atmosphere. In general, these
 320 drivers are poorly monitored and often rely on proxies that only very approximately represent the
 321 physical mechanisms that heat and energize the upper atmosphere. To represent the absorption of
 322 solar extreme and far ultraviolet (EUV/FUV) irradiance, the solar radio flux at 10.7 cm
 323 wavelength ($F_{10.7}$) is often used as a proxy. In terms of the solar wind–magnetosphere–
 324 ionosphere–thermosphere interaction, the geomagnetic Kp index is often used to characterize
 325 heating and momentum exchange at high latitudes. Empirical formulas, such as the Heelis et al.
 326 (1982) convection electric field model, are then used to help convert these proxies into
 327 atmospheric heating, incurring further uncertainty into the overall modeling process. The
 328 reliance on these proxies and their empirical coupling functions leads to large uncertainties when
 329 driving a model of the thermosphere.

330 IDEA estimates corrections to the external forcing parameters and their empirical
331 coupling functions in order to bring a physics-based model into better agreement with direct
332 observations of the thermosphere. The discrepancies between model output and observations are
333 minimized by employing a least-squares filter similar in nature to an unscented Kalman filter
334 (UKF). Figure 6 compares the IDEA process (right) to that of a typical ensemble Kalman filter
335 (EnKF) configured for ionosphere/thermosphere modeling. IDEA runs several versions of the
336 thermosphere model, each experiencing slightly different external driving conditions.

337 In the current implementation of IDEA, the Thermosphere–Ionosphere–Electrodynamics
338 General Circulation Model (TIEGCM) (Qian et al., 2014; Richmond et al., 1992; Sutton et al.,
339 2015) is used as the physics-based environment model. TIEGCM is a finite-difference solution to
340 the conservation equations of momentum, mass, and energy describing the upper atmosphere in
341 the presence of momentum and energy sources. TIEGCM accounts for the dominant features in
342 the upper atmosphere of molecular diffusion and circulation, solar heating in the EUV and FUV
343 bands, and high-latitude auroral heating. TIEGCM also has the ability to simulate the ionosphere
344 and associated electrodynamic coupling between the neutral and plasma environment in a self-
345 consistent manner at middle and low latitudes. The model spans from 97 km at its lower
346 boundary to between 450 and 700 km at its upper boundary, mostly depending on the level of
347 solar flux. Migrating diurnal and semi-diurnal tides are specified at the lower boundary in a
348 climatological sense. Other dynamic features of the lower and middle atmosphere are ignored,
349 which could lead to uncertainty when estimating corrections to the external forcing.

350 In terms of data assimilation, additional measures must be taken to deal with the lagged
351 response of the upper atmosphere to variations in the external drivers. It is well known that the
352 response of the thermosphere can take on a large range of timescales depending on several
353 factors, height being among the largest contributors. In order for an estimated correction of the
354 external forcing parameters to have a timely effect on the model, the time-lagged response must
355 be accounted for. IDEA abandons the sequential filtering techniques typically used for
356 ionosphere/thermosphere applications (e.g., M. V. Codrescu et al., 2004, 2021; S. M. Codrescu
357 et al., 2018; Fuller-Rowell et al., 2004; Godinez et al., 2015; Matsuo et al., 2012, 2013; Minter et
358 al., 2004; Morozov et al., 2013; Murray et al., 2015). Instead, an iterative approach is adopted so
359 that estimated forcing parameters can be re-applied to a simulation over the course of a day so

360 that the model can respond to forcing (refer to the additional feedback loop on the right side of
 361 Figure 6).



362

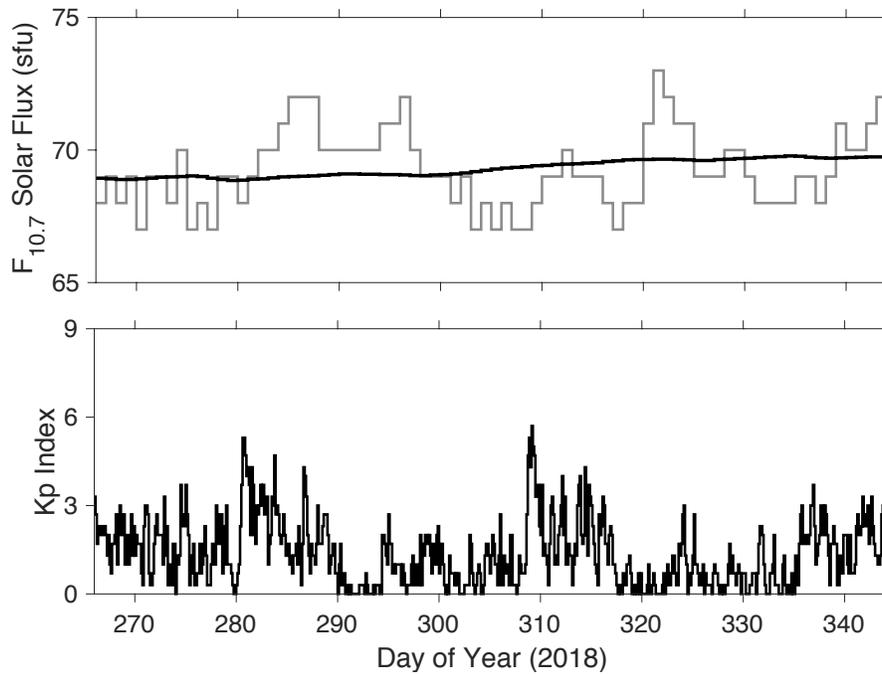
363 **Figure 6.** Comparison of a typical Ensemble Kalman Filter as configured for use with a time-
 364 dependent thermospheric model (left) with the IDEA technique (right; features in color differ
 365 from their counterparts in the EnKF flow chart on the left), where t_0 and t_1 are the respective start
 366 and end times of the model runs during a given data assimilation cycle (adapted from Sutton,
 367 2018).

368 In Sutton (2018), satellite-borne accelerometer observations of thermosphere density
 369 were used to calibrate the external forcing parameters driving the TIEGCM. Here we use EDRs
 370 based on POD ephemeris derived from GNSS measurements from 3 satellites from Spire
 371 Global's constellation of CubeSats. A forward model, based on output from the TIEGCM, the
 372 satellite geometry model shown in Figure 2, and the force model of Sutton (2009), is used to
 373 synthesize orbital energy dissipation for each satellite according to Equation 4. Accelerometer
 374 instruments operate at high cadence (0.1–1 Hz) equating to a resolution of 7–70 km along the

375 satellite's orbit. The GNSS/POD data set yields a measurement of density more on the order of
376 once per orbit arc (possibly higher with additional development). This difference in information
377 content between data sets necessitates additional consideration when designing a thermospheric
378 estimation filter. In this case, we found that the observability of IDEA was limited to estimation
379 of the most recent daily $F_{10.7}$ value and the most recent 6-hourly effective K_p value for each
380 assimilation cycle. The configuration used in this study iterates 3 times per assimilation cycle
381 and uses five 48-core nodes of a high-performance computer (HPC) to advance by 6 hours to the
382 next assimilation cycle in less than 3 minutes (i.e., $>120x$ realtime). For comparison, Sutton
383 (2018) found it possible to estimate the most recent daily $F_{10.7}$ value and the three most recent 3-
384 hourly K_p values for each assimilation cycle when using the high-resolution accelerometer-
385 derived density data set. However, it is expected that improvements in observability will be
386 enabled through the use of more CubeSats in the estimation process. And considering the greater
387 coverage of CubeSats in altitude and local time, accuracy could very well exceed accelerometer-
388 based density model corrections.

389 **4 Results and Discussion**

390 The period spanning 23 Sept.–9 Dec. 2018 (days 266–343) of our study was marked with
391 very low activity in terms of the magnitude and variation of solar EUV and FUV, as
392 approximated by measurements of the 10.7 cm solar radio flux ($F_{10.7}$; top panel of Figure 7).
393 Note that $F_{10.7}$ has an approximate lower bound of 66 solar flux units (sfu) at solar minimum and
394 attains values above 200 during solar maximum. During the latter, 27-day solar rotational
395 modulation can also produce large swings in $F_{10.7}$, causing large signals in the thermospheric
396 density. Because the available data for this study falls firmly within solar minimum, the
397 variations seen here are quite small. In terms of geomagnetic activity, however, there were two
398 minor-to-moderate disturbances on 7 Oct. (day 280) and 4 Nov. (day 308) as shown by the 3-
399 hourly K_p geomagnetic index (lower panel of Figure 7).

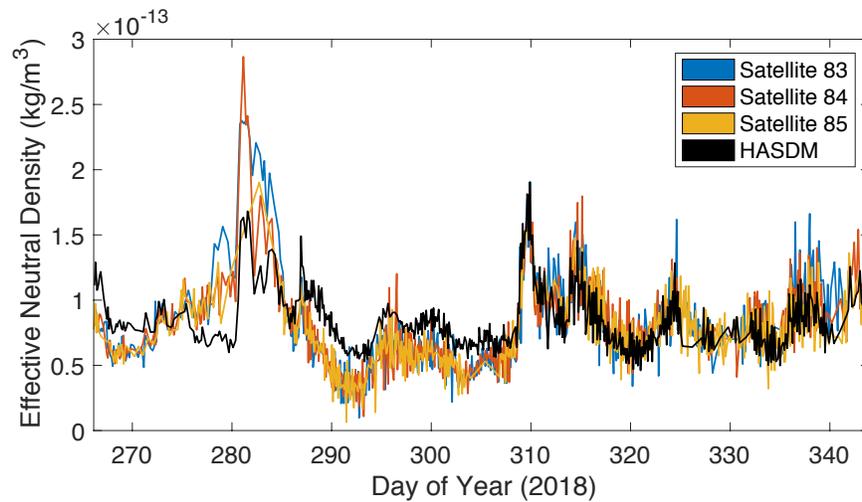


400

401

402 **Figure 7.** Top: observed solar $F_{10.7}$ radio flux. The grey curve is the daily measured value from
 403 the Ottawa observatory normalized to 1 AU sun-earth distance; the black curve is an 81-day (~ 3
 404 solar rotation) centered average. Bottom: the 3-hourly planetary magnetic index Kp. Both panels
 405 span the period of interest 23 Sept.–9 Dec. 2018.

406 Given observations of orbital variations and an appropriate force model as discussed in
 407 the previous section, an effective atmospheric mass density can be inferred between consecutive
 408 orbit arcs. Figure 8 shows such neutral mass densities derived from the three CubeSats (blue, red
 409 and yellow curves) of Spire’s constellation. The cadence of these densities is approximately one
 410 measurement for each consecutive set of orbit arcs. For the time period studied, this equates to a
 411 cadence of about 2–2.5 hours on average. This cadence depends on the instrument duty cycle,
 412 which has steadily improved since 2018. A higher cadence may be possible in the future as duty
 413 cycle improves, however, the exact allowable cadence will also depend on the altitude of the
 414 satellite and the noise errors of the GNSS measurements. HASDM output is also shown with the
 415 black curve for reference. This empirical model is calibrated by ground-based radar tracking
 416 observations of approximately 70–90 orbiting objects. Because the individual tracking
 417 observations are sparse—relative to those available from GNSS—densities derived from this
 418 technique have an effective cadence of several hours to several days (Storz et al., 2005).



419

420 **Figure 8.** Neutral mass densities derived from Spire CubeSats 83–85. Also shown is output from
 421 HASDM as sampled on the orbit of satellite 84. The values plotted are the effective densities
 422 (see the right-hand side of Equation 4) between subsequent orbit arcs.

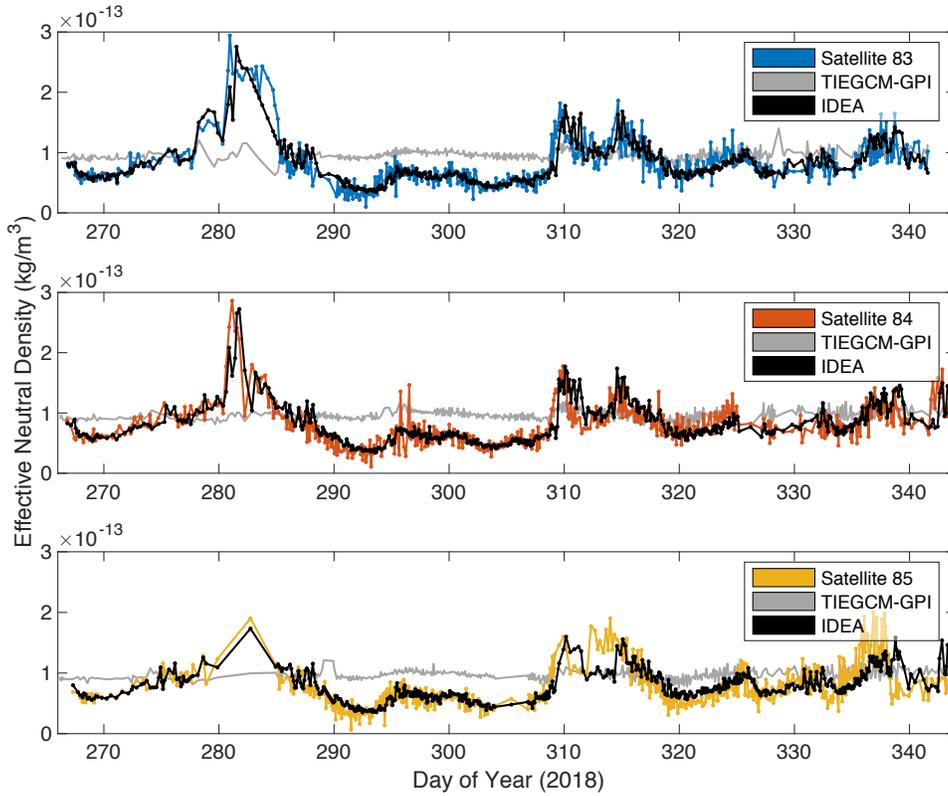
423 The CubeSat-derived densities maintain good agreement with one another, given the
 424 close proximity of all three spire satellites within 800–2100 km (or 2–4.5 minutes) along the
 425 orbit track. Agreement with HASDM is also reasonable during this time period. As Figure 7
 426 shows, there are several minor to moderate variations in K_p over the time interval. The
 427 signatures of these disturbances are also seen in the neutral densities of Figure 8. There are
 428 several deviations between data and model though, most notably around days 270, 290, and 300,
 429 where CubeSat-derived densities are significantly lower than HASDM. We have not yet
 430 concluded whether model or data are in error during these intervals, since very little ground-truth
 431 data exists during this period for validation. Another period of discrepancy exists around the
 432 geomagnetic disturbance on day 280, where CubeSat-derived densities experience a much larger
 433 storm-time increase. While it is possible that the higher cadence GNSS densities are capturing
 434 actual storm dynamics better than HASDM, we note that POD data were less frequent during this
 435 particular event than during other times. Additionally, attitude data was unavailable for satellite
 436 83 over much of the disturbance, particularly days 282–285. The discrepancy in amplitude
 437 during this event could also be a function of the higher cadence of the CubeSat POD data fit
 438 spans (5–6 hours during this event) relative to that of the HASDM data fit spans (~ 1 day or
 439 more), in which case, the CubeSat-derived densities would be expected to more accurately
 440 resolve the storm-time disturbance.

441 In general, some error in the observations and modeled output is expected, of
442 instrumental, data sampling, and geophysical origins. Part of this error is caused by variations in
443 sampling location for a given data point. In other words, the data points presented in Figure 8 do
444 not represent the density averaged over a complete orbit; instead, each data point can be sampled
445 over a very different part of the globe than the previous. The resulting error can be seen in the
446 HASDM model, which if plotted as an average over full orbits, would appear much more
447 smooth. Another important source of error in the density timeseries comes directly from
448 uncertainties in the POD solutions themselves. Because the POD solutions were not designed
449 with a thermospheric application in mind, we expect that some of the estimation parameters may
450 have been overfit. And finally, there is certainly an amount of geophysical variability seen in the
451 observed density timeseries that is not captured by the HASDM model. While an in-depth error
452 analysis is beyond the scope of the present work, we will continue to investigate techniques to
453 minimize these sources of error, including improving the underlying POD solutions and
454 combining timeseries from additional satellites.

455 A central goal of this work is to ingest multiple data sources into a physics-based,
456 assimilative thermosphere model to combine information and mitigate the uncertainty of any one
457 dataset. Figure 9 shows the baseline TIEGCM simulation without any assimilation (grey curve)
458 driven externally by the observed geophysical indices (GPI) of K_p and $F_{10.7}$; the POD-based
459 densities derived using the techniques described in the previous Section (blue, red, and yellow
460 curves); and the IDEA output over the interval spanning 23 Sept.–9 Dec. 2018 (solid black
461 curves).

462 The baseline TIEGCM-GPI simulation shows muted response to the K_p and $F_{10.7}$ inputs
463 during this solar-minimum interval, when compared with the IDEA output (or with the HASDM
464 output in Figure 8). CubeSat densities and IDEA output agree very well over the interval. There
465 are, however, several short periods when POD data from a single satellite becomes sparse, such
466 as the period around day 304–306 for satellite 85 (yellow curve), or when attitude data becomes
467 unavailable, such as the period around day 282–285 for satellite 83 (blue curve). There are also
468 several periods during which data from a single satellite becomes spurious, not agreeing with the
469 data from the other two satellites, such as the period around 335–340 for satellite 85 (yellow
470 curve). In these cases, the other two data sets tend to compensate for missing or spurious data
471 from the third satellite. This leads us to believe that adding data from additional satellites and

472 constellations should improve performance and increase the "signal-to-noise ratio" of the data
 473 assimilation process.



474

475 **Figure 9.** Comparison of observations with model output. CubeSat-derived densities are given
 476 by the colored curves for satellites 83 (top), 84 (middle), and 85 (bottom). Also shown is the
 477 output from the baseline thermosphere model driven by measured geophysical indices
 478 (TIEGCM-GPI, grey curves) $F_{10.7}$ and K_p . The data assimilation IDEA output is given along
 479 each of the CubeSat orbits by the black curves.

480 The performance of these models with respect to the CubeSat-derived densities are
 481 assessed using the metrics of Sutton (2018) and Bruinsma, Boniface, et al. (2021). These consist
 482 of the mean (μ), standard deviation (σ), and root mean square error ($RMSE$) of the ratio of model
 483 density to observed density, all computed in logarithmic space:

$$484 \quad \mu(m/o) = \exp\left(\frac{1}{N} \sum_{i=1}^N \ln \frac{\rho_{m,i}}{\rho_{o,i}}\right) \quad (5)$$

$$485 \quad \sigma(m/o) = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\ln \frac{\rho_{m,i}}{\rho_{o,i}} - \ln \mu(m/o) \right)^2} \quad (6)$$

$$486 \quad RMSe(m/o) = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\ln \frac{\rho_{m,i}}{\rho_{o,i}} \right)^2} \quad (7)$$

487 As mentioned in Sutton (2018), these metrics have several properties that are desirable
 488 when working with the ratio of two quantities that vary exponentially, such as neutral densities.
 489 The $RMSe(m/o)$ and $\sigma(m/o)$ quantities are best interpreted as a percentage in the following
 490 way: $\% = 100 \times (\exp \sigma(m/o) - 1)$. The $RMSe(m/o)$ is a combination of $\mu(m/o)$ and
 491 $\sigma(m/o)$, as can be see through the following relation: $RMSe(m/o)^2 = (\ln \mu(m/o))^2 +$
 492 $\sigma(m/o)^2$. The $RMSe(m/o)$ is therefore a good indicator of total model errors. However, if the
 493 intent is to drive a POD process using the density model, it may be more informative to use the
 494 $\sigma(m/o)$ metric, since a ballistic coefficient is typically estimated per satellite. In practice, this
 495 estimated ballistic coefficient will soak up errors not only in the assumed coefficient of drag, but
 496 also in the mean bias of the density model. Table 2 shows the overall performance of the three
 497 models, TIEGCM-GPI, HASDM, and IDEA at re-creating the energy dissipation rates observed
 498 by the Spire CubeSats' GNSS data. Table 2 also shows the performance of the three models in
 499 synthesizing the independent data set of orbit-averaged neutral densities from the Swarm-C
 500 satellite.

501 During the period of interest, the IDEA method outperforms HASDM in all three metrics
 502 with respect to the assimilated Spire data. This is true of both the prior and posterior IDEA
 503 estimates of density. The 'posterior' IDEA estimate is the fully assimilated nowcast solution,
 504 whereas the 'prior' IDEA estimate is a 6-hour forward simulation (i.e., forecast) by the TIEGCM
 505 based on the initial conditions and estimated drivers from the previous posterior assimilation
 506 cycle. The prior mean is expected to remain close to the posterior mean if no major changes in
 507 the actual geophysical conditions occur during this 6-hour span. Minor fluctuations in the actual
 508 conditions could cause upward or downward trends over a given 6-hour span, resulting in density
 509 variations that tend to average out of $\mu(m/o)$ while slightly increasing the $\sigma(m/o)$ metric for
 510 the prior IDEA estimates relative to the posterior. It should be noted, however, that IDEA has a
 511 clear advantage in this comparison over the other two models, since IDEA assimilates the very

512 data that it is now being compared against. This comparison confirms that the IDEA technique,
513 as an estimation filter, has the requisite control authority to sufficiently adjust the model to the
514 assimilated data set.

515 To go a step further, the Swarm-C ACC data is used as an independent data source to
516 assess the performance of IDEA in locations outside the vicinity of assimilated data. Due to the
517 differences in precession rates between the Spire CubeSats and the Swarm-C satellite, the local
518 times of their orbital planes align approximately once every 41 days. This alignment occurs
519 twice during the 23 Sept.–9 Dec. 2018 time period, on 10 Oct. (day 283) and 20 Nov. (day 324).
520 Aside from these brief alignment periods lasting only a few days, Spire and Swarm data sets are
521 sampling vastly different sectors of the globe. Table 2 shows that IDEA succeeds in reducing the
522 $\mu(m/o)$ and overall $RMSe(m/o)$ with respect to the free-running TIEGCM-GPI simulation but
523 at the expense of an increased $\sigma(m/o)$. In the comparison with Swarm-C data, HASDM
524 performs the best in all three metrics. However, it should be noted that HASDM has a clear
525 advantage in this comparison over the other models because HASDM assimilates data from ~ 75
526 satellites from across the globe while IDEA only assimilates within a single orbit.

527 Sutton (2018) used accelerometer-derived neutral densities from a single satellite to drive
528 the IDEA technique. In the previous study, the technique showed high proficiency for estimating
529 neutral densities in local times away from where the assimilated data resided. In the current
530 work, using effective neutral densities from a single orbit plane at an approximate 2–2.5 hour
531 cadence per satellite, the comparison with data from other local times deteriorates. While this is
532 not all that surprising, it does provide some insight into the specificity required to apply adequate
533 corrections to the external drivers. The observability of these corrections depends on features of
534 the observations, including the global coverage, spatial resolution, temporal cadence,
535 measurement error, and measurement type (e.g., mass density from accelerometers vs. chemical
536 composition from a mass spectrometer). In essence, the impact that each external driver has on
537 the observation must be distinguishable from the impact caused by other drivers. With
538 accelerometer data, this is satisfied to some extent because measurements are of high cadence
539 and sample two distinct local time and all latitudes over the course of an orbit. Any change in
540 geomagnetic activity will first impact high-latitude thermosphere before influencing lower
541 latitudes, while changes in solar flux affect the thermosphere in a much less localized manner.
542 Likewise, the model's day-to-night ratio of density will decrease as geomagnetic activity

543 increases yet is only slightly affected by variations in solar flux (Waldron, 2020). Both of these
 544 signals can be discerned with accelerometer data but not with orbit-averaged data. Several
 545 questions remain: Can this issue of observability with POD-inferred densities be overcome by
 546 including data from multiple local-time orbital planes and/or with reduced averaging? And in
 547 terms of assimilation, which characteristic of a density data set is more valuable, spatial
 548 resolution in the latitudinal direction or sampling of multiple local time planes?

549 **Table 2.** Performance metrics of each model with respect to the assimilated Spire Global
 550 CubeSat data and independent Swarm-C ACC data, calculated over the entire interval spanning
 551 days 266–343, 2018. Orbital averages of the Swarm-C data (as well as the corresponding model
 552 output) have been taken to minimize the effect of spurious errors in the accelerometer data.

	TIEGCM-GPI	HASDM	IDEA	
			Prior	Posterior
Assimilated Spire CubeSat POD Data				
$\mu(m/o)$	1.33	1.10	1.04	1.04
$\sigma(m/o)$	48.7%	40.6%	34.6%	30.7%
$RMSe(m/o)$	62.7%	42.6%	34.9%	31.1%
Independent Swarm-C ACC Orbit-Averaged Data				
$\mu(m/o)$	1.40	1.12	1.20	1.19
$\sigma(m/o)$	24.9%	8.2%	37.2%	32.4%
$RMSe(m/o)$	49.6%	15.2%	43.8%	39.4%

553 **5 Summary and Conclusions**

554 The increases in satellite and debris populations in LEO necessitates improvements in
 555 how we detect, track, and catalog orbiting objects. Additionally, if we are to avoid catastrophic
 556 collisions in LEO, we must also be able to reliably predict the trajectories of satellites multiple
 557 days in advance, giving satellite operators sufficient lead time to plan safe and effective
 558 maneuvers. With the variability of the space environment, particularly thermospheric mass
 559 density, being the largest uncertainty in the orbit prediction chain, this study investigates new
 560 ways to monitor the upper atmosphere. In this notoriously data-starved region, the
 561 instrumentation commonly carried on recently launched LEO SmallSats and CubeSats,

562 particularly GNSS receivers, can be used to improve the accuracy of physics-based neutral
563 density specifications. Notably, the amount of data available from this new category of
564 observation should continue to scale with the crowdedness of LEO, whereas the current ground-
565 based tracking database remains limited in quantity and resolution.

566 In the current work, we have applied a post-processing method to the timeseries of POD
567 ephemeris from three CubeSats in Spire's constellation. This has allowed us to track the time
568 evolution of orbital energy of each CubeSat over an orbit arc. Further application of a satellite-
569 surface force model converts this information into a timeseries of *in situ* atmospheric mass
570 density. By analyzing 78 days' worth of data from late 2018, we were able to observe the impact
571 of minor and moderate fluctuations in geomagnetic activity during the prevailing solar minimum
572 conditions. We also found good agreement with HASDM, one of the only sources of
573 thermospheric data currently available for comparison. While the resulting timeseries from a
574 single satellite may be prone to errors, identified here simply as a discrepancy between density
575 timeseries derived from co-orbiting CubeSats, this can be mitigated by assimilating timeseries
576 from multiple data sets into a physics-based model of the thermosphere.

577 Additionally, with more advanced processing methods, it may be possible to lower the
578 error for timeseries of individual CubeSats. The POD solutions used here were not specifically
579 tailored to the application of measuring density. One potential complication is that overfitting of
580 parameters or insufficient arc size may have led to significant noise in the inferred densities.
581 Future work will focus on improving the POD solutions to reduce error and finding the optimal
582 size of the POD fitting window as a function of altitude, phase of the solar cycle, satellite
583 geometry characteristics, and GNSS instrument precision and errors. With these improvements
584 in place, it may even be possible to attain higher cadences than a single data point per orbit. This
585 has been demonstrated when using a state-of-the-art geodetic GNSS receiver (van den IJssel &
586 Visser, 2007), but extending this technique to GNSS-equipped SmallSat constellations would
587 provide much needed global coverage of thermospheric observations. When paired with a
588 suitable assimilative, physics-based models of the thermosphere, there is great potential to lower
589 the uncertainty of orbit predictions across the LEO catalog, improve the accuracy of conjunction
590 assessments, and increase the efficacy of STM activities.

591 Acknowledgments

592 EKS, JPT, and TEB acknowledge the generous support of the University of Colorado at
593 Boulder Grand Challenge Grant: Space Weather Technology, Research, and Education Center
594 (SWx TREC). EKS gratefully acknowledges support from the NASA Operations-to-Research
595 (O2R) program under grant number 80NSSC20K1399. Support for SMM has been provided by
596 the National Defense Science and Engineering Graduate (NDSEG) Fellowship program. Data
597 from the Spire constellation used in this study may be requested and downloaded from the
598 NASA Commercial SmallSat Data Acquisition Program (CSDAP) website at
599 <https://earthdata.nasa.gov/esds/csdap>. The TIEGCM is developed and maintained by the National
600 Center for Atmospheric Research's High Altitude Observatory (HAO) and is available at
601 <https://www.hao.ucar.edu/modeling/tgcm/tie.php>. The HASDM density data are provided for
602 scientific use courtesy of Space Environment Technologies (SET) and can be downloaded from
603 <https://spacewx.com/hasdm/>. Swarm-C ACC data is available from ESA at [https://swarm-](https://swarm-diss.eo.esa.int/#swarm/Level2daily/Entire_mission_data/DNS/ACC/Sat_C)
604 [diss.eo.esa.int/#swarm/Level2daily/Entire_mission_data/DNS/ACC/Sat_C](https://swarm-diss.eo.esa.int/#swarm/Level2daily/Entire_mission_data/DNS/ACC/Sat_C). The TLE sets and the
605 SGP4 satellite propagator are available at <https://space-track.org>. Planetary and lunar ephemeris
606 are available from the JPL Solar System Dynamics website at <https://ssd.jpl.nasa.gov/>.

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