MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÃO
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS

Studying missions that could benefit from small satellite constellations.

- **Número do processo Institucional: 444327/2018-5**
- **Número do processo Individual: 317961/2021-7**
- **Bolsista: Safwan Aljbaae**
- **Supervisor: Antonio Fernando Bertachini de Almeida Prado**
- **Área: Engenharia e Tecnologias para o Setor Espacial**
- **Vigncia original: 01/11/2021 a 31/01/2022**
- **Vigncia excecutada da bolsa: 01/11/2021 a 31/01/2022**
- **Modalidade: PCI-DB**
- **Natureza da obra: Relatório PCI**

INPE
São José dos Campos
2022

Abstract

Recently (2000-2021), human-space activities are increasing faster than ever. More than 36000 objects, greater than 10 cm, in orbit around the Earth, are tracked by the European Space Agency (ESA)[1]. Around 70% of all cataloged objects are in Low-Earth Orbit (LEO). Aerodynamic drag provides one of the main sources of perturbations in this last population, gradually decreasing the semi-major axis and period of the LEO satellites. Usually, a empirical atmosphere model as a function of solar radio flux and geomagnetic data is used to calculate the orbital decay and life-times of LEO satellites. In this respect, a good forecast for the space weather data could be a key tool to study the drag perturbation on LEO Satellites. In this work, we propose using Time Series Forecasting Model to predict the future behavior of the solar flux and calculate the atmospheric density, in order to improve the analytical models and reduce the uncertainty of the drag.

keywords: methods: data analysis – celestial mechanics – atmospheric effects – space vehicles – gravitation

List of Figures

List of Tables

1 Introduction

During the last years, an exponential increase in the population of objects in orbit around our planet is being observed, especially in LEO. That reduces the available operational orbits and, also increases the probability of collisions, which in case of happening results in clouds of debris propagated around the orbits, for example in the case of the Iridium 33 and Kosmos 2251. Moreover, recent activities, such as the multiple tests of Anti Satellite Weapons (ASAT) and the new Large Scale Constellations could increase exponentially the population of objects around the Earth in the next few years. If these activities are not controlled and/or regulated, one possible catastrophic scenario is known as the Kessler effect, limiting the space activities and access to orbit for a long period (Kessler, 1991).

The natural environment of the LEO influence naturally the mitigation of artificial objects in orbit, due to the loss of orbit mechanical energy, influenced by the atmospheric-satellite interaction, mathematically modeled as the perturbation due to drag. Usually, a simplified model for satellites in LEO is used to reduce the computational cost during the propagations, the main forces that influence the motion are the Keplerian gravity field of the Earth, the perturbation due to the non-sphericity of the central body (J2 and J4 terms of the gravitational perturbation) and the atmospheric drag. Other perturbations like Third-body from the Moon and Sun, Solar Radiation Pressure, tides, and albedo could be negligible at altitudes lower than 400 km (Vallado, 2007; Dell'Elce et al., 2015). With the previous considerations, the equation of motion of the satellite moving in LEO in an inertial system, located at the Earth´s center of mass, is written as:

$$\ddot{\vec{r}} = -\vec{g_{4\times 4}} + \vec{a}_D \tag{1}$$

[1] https://www.esa.int/Safety_Security/Space_Debris/Space_debris_by_the_numbers

where, $g_{4\times4}$ represents the Earth´s Gravitational Model (EGM-08) of order 4×4, r is the inertial acceleration vector, and, a_D is the drag acceleration vector, which is acting in the opposite direction of the airflow vector $\vec{V}_\infty$. The airflow is the difference between the inertial velocity vectors and the atmospheric velocity due to the Earth´s rotation, including the winds. Several models of drag have been applied to determine the atmosphere-satellite interaction and reduce the uncertainty (Mostaza Prieto et al., 2014). The basic drag acceleration model is described as follows

$$\vec{a}_D = -\rho\left(\frac{C_D A}{2m}\right)V_\infty \vec{V}_\infty \tag{2}$$

where, A is the satellite's mean area normal to its velocity vector, which is a difficult parameter to estimate. C_D is the coefficient of drag, which is a dimensionless quantity that indicates the satellite's susceptibility to drag forces. and m is the satellite's mass. The quantity m/AC_D is Usually called the ballistic coefficient. A satellite with a low ballistic coefficient will be considerably affected by the drag forces. ρ is atmospheric density, which is a very difficult parameter to determine, it is a function of the solar activity, local time, altitude and geographic coordinates. For more details about modelling the aerodynamic drag, we refer the readers to (Vallado, 2007; Vallado and Finkleman, 2014; Zhejun and Hu, 2017).

$$\vec{a}_D = -\rho\left(\frac{C_D A}{2m}\right)V_\infty \vec{V}_\infty \tag{3}$$

where, A is the satellite's mean area normal to its velocity vector, which is a difficult parameter to estimate. C_D is the coefficient of drag, which is a dimensionless quantity that indicates the satellite's susceptibility to drag forces. and m is the satellite's mass. The quantity m/AC_D is Usually called the ballistic coefficient. A satellite with a low ballistic coefficient will be considerably affected by the drag forces. ρ is atmospheric density, which is a very difficult parameter to determine, it is a function of the solar activity, local time, altitude and geographic coordinates. For more details about modelling the aerodynamic drag, we refer the readers to (Vallado, 2007; Vallado and Finkleman, 2014; Zhejun and Hu, 2017).

Due to the satellite geometry, materials, and uncertainly of the attitude, the C_D is approximated to a mean value, reported in the scientific literature as 2.2 for satellites in the upper atmosphere in Free Molecular Flow (FMF) (Vallado, 2007). With the information of the satellite geometry, attitude, and materials it is possible to implement a high fidelity model of the drag for FMF and/or Rarefied Flow, as was presented in Mostaza Prieto et al. (2014); Rafano Carná and Bevilacqua (2019); Tewari (2009), however, this is out of the scope of this present research. In fact, the main problem for orbital determination and propagation in LEO is the accuracy of the drag perturbation. As shown in Eq. 3, the drag model is a function of the atmospheric density, and at the same time, it is a function of the space weather, which is a stochastic model due to the multiple uncertainties such as the atmospheric conditions due to the solar and magnetic activity or the atmospheric density estimations due to the use of empirical models and the atmospheric dynamics (including winds). In this context, predicting the future behavior of the weather data with reasonable confidence is of particular interest. This challenging task is already addressed by several authors, for instance, Lean et al. (2009) used a linear Autoregressive algorithm with lags based on the autocorrelation function. The highest correlations of each day is used to forecast the next one, this is similar to the simple naively forecasting method that we will use later in this work. Henney et al. (2012) used the global solar magnetic field to forecast the solar 10.7 cm (2.8 GHz) radio flux. A simple forecasting model is applied in Warren et al. (2017), using a linear combination of the previous 81 observations to forecast the solar flux from 1 to 45 days. In this work, we will apply Deep Learning methods for Time-Series forecasting, using historical data of solar activity (Since 1/10/1957 to 1/11/2021), available in the EOP and Space Weather Data[2], to predict the behavior of the weather data and calculate the atmospheric density.

[2]https://celestrak.com/SpaceData/, accessed on November 2021.

2 Methodology and Results

Daily data, since 1/10/1957, for the Solar Radio Flux (**F10.7 OBS**) is available in the EOP and Space Weather Data, It is a univariate series we are interested to, presented in the top panel of Fig. 1. Observing this plot, we can notice that kind of seasonality probably exists. Centered 81-day arithmetic average of the solar flux (**F10.7 OBS CENTER81**, middel panel of Fig. 1) is often used in density calculations. This parameter is simply calculated from the daily obdervations also available in the EOP and Space Weather Data. Daily planetary amplitude (**AP AVG**), is also available as an average of the 8 geomagnetic planetary amplitude, shown in the bottom panel of Fig. 1. This parameter has integer values from 0 to 280, only 102 observations with value grater that 100.

As the first step for a more complete study, we used one-step time-series forecasting to predict the value of the three parameters already mentioned, **F10.7 OBS**, **F10.7 OBS CENTER81**, and **AP AVG**. The last 365 time steps (one year) are used as a test set to evaluate a very simple naively forecasting method, fitted on all the remaining observations. This strategy of forecasting teaks simply the previous period and apply it to the actual one. The walk-forward validation method is used to measure the performance of the model, where we applied one separate one-step forecast of each of the test observations, the true data was then added to the training set for the next forecast. We used the Mean absolute percentage error regression loss (MSE) to compare our results with the real test set, Our results are presented in Fig. 2, where we can notice a good performance for **F10.7 OBS** and **F10.7 OBS CENTER81** with an MSE of 0.025% and 0.001%, and a relative error less than 0.15 and 0.005, respectively. Week performance identified for the **AP AVG** with MSE of 0.7%, which is expected with respect to the chaotic behavior for this parameter as shown in the bottom panel of Fig. 1.

In the next, We tried to develop a deep learning models to make one-week forecasts. For that purpose, we first attempt to use a simple naively method then we applied a Convolutional Neural Network (CNN). In the whole weather data, We have 23406 days, giving 3343 full weeks. We split the data into 3008 weeks as a train set and 335 as a test set. Here, We also used a walk-forward validation method to evaluate the models, where the model is used to predict one week, then the real data of this week is added to the training set. The process is repeated for all the weeks in the training set. Our results are presented in Fig. 3, where we can notice a relativly week performance with an MSE of 0.231%, 0.005%, and 1.745% and a relative error less than 0.3. 0.0125, and 6 for the selected parameters, **F10.7 OBS**, **F10.7 OBS CENTER81**, and **AP AVG**, respectively.

To ameliorate our results, we used a more sophisticated CNN method. CNN was originally created for image data (Pugliatti and Topputo, 2020; Pasqualetto Cassinis et al., 2019; Song et al., 2022), However, several CNN models can be adapted to time-series prediction tasks. In this work, we used a CNN model with two convolutional layers with the Rectified Linear Unit activation function (ReLU) defined to returm the positive part of the input. In Each layer, a convolutional operation will read the tested week 3 times (kernel size of 3) and the process will be performed 32 times (32 filters), then a poolin layer is added to select the maximum value over a window of size 2. The connected layers that interprets the features is then increased to 300 nodes. We fitted the model exposeing the model 100 times to the whole training dataset (100 epochs). The weights of the model are updated each epoch for each 12 samples (batch size of 12). For more details abour our prociss, we refere the reader to Brownlee (2020). Our results are presented in Fig. 4, we notice that we CNN can considerably reduce the MSE for the solar flux (**F10.7 OBS** and **F10.7 OBS CENTER81**) parameters to 0.041% and 0.003% and a relative error less than 0.1 and 0.008, respectively. However, the simple naive model privide better performance that the CNN model.

3 Conclusion

In this project, we initiated a new approach to use Machine Learning to predict the influence of Drag in Satellites. This is still ongoing work with promising preliminary results that could proceed to publication to support an application on constellations of CubeSats. We plan to continuing this

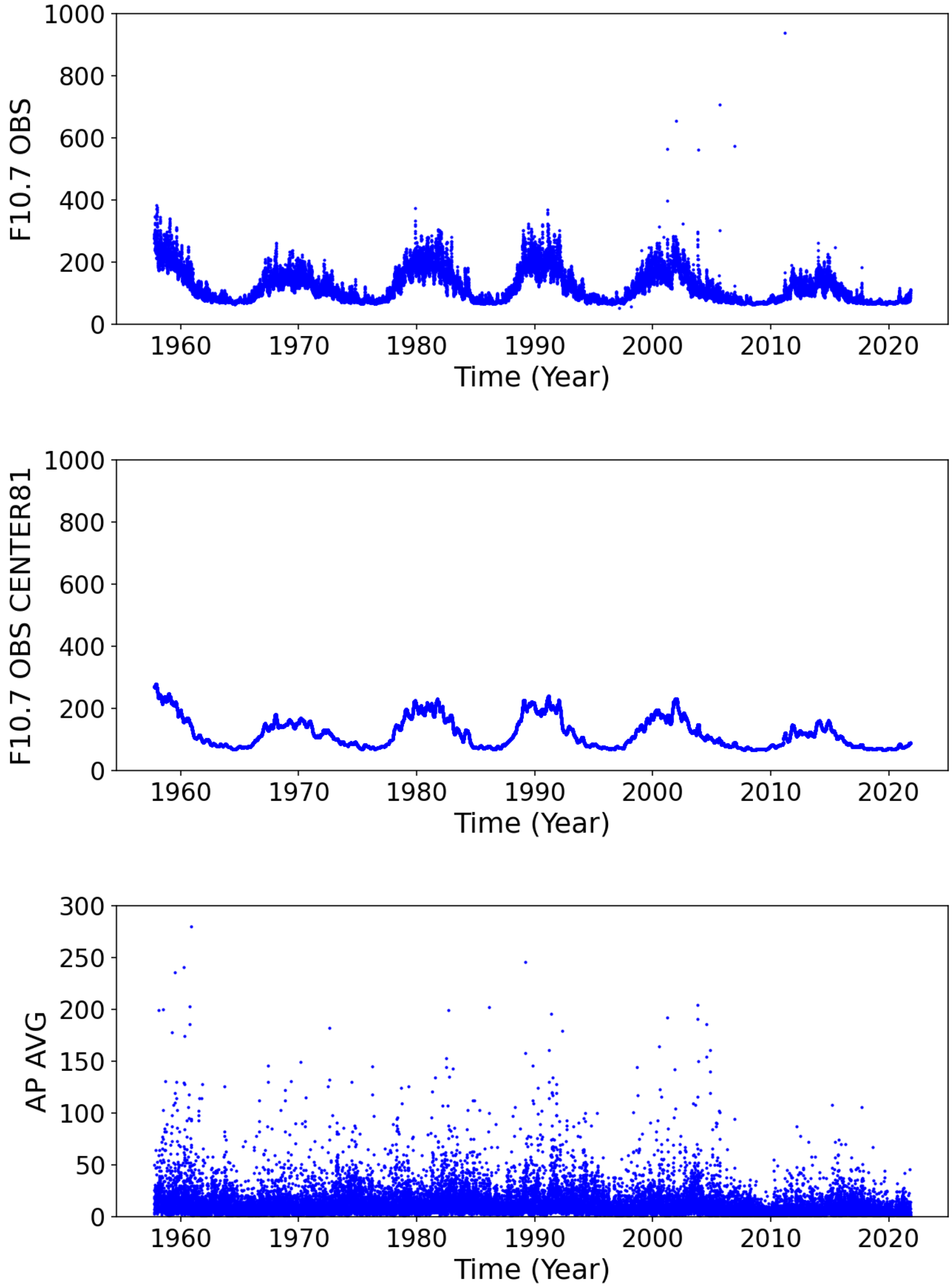

Figure 1: Space weather data vs. timestep from the EOP and Space Weather Data

line with close cooperation with **Dr. LEONARDO BARBOSA TORRES DOS SANTOS** how will continue this fellowship

References

J. Brownlee. *Deep Learning for Time Series Forecasting. Ed. Machine Learning Mastery, San Juan, PR, USA.* 2020.

Lamberto Dell'Elce, Maarten Arnst, and Gaëtan Kerschen. Probabilistic Assessment of the Life-

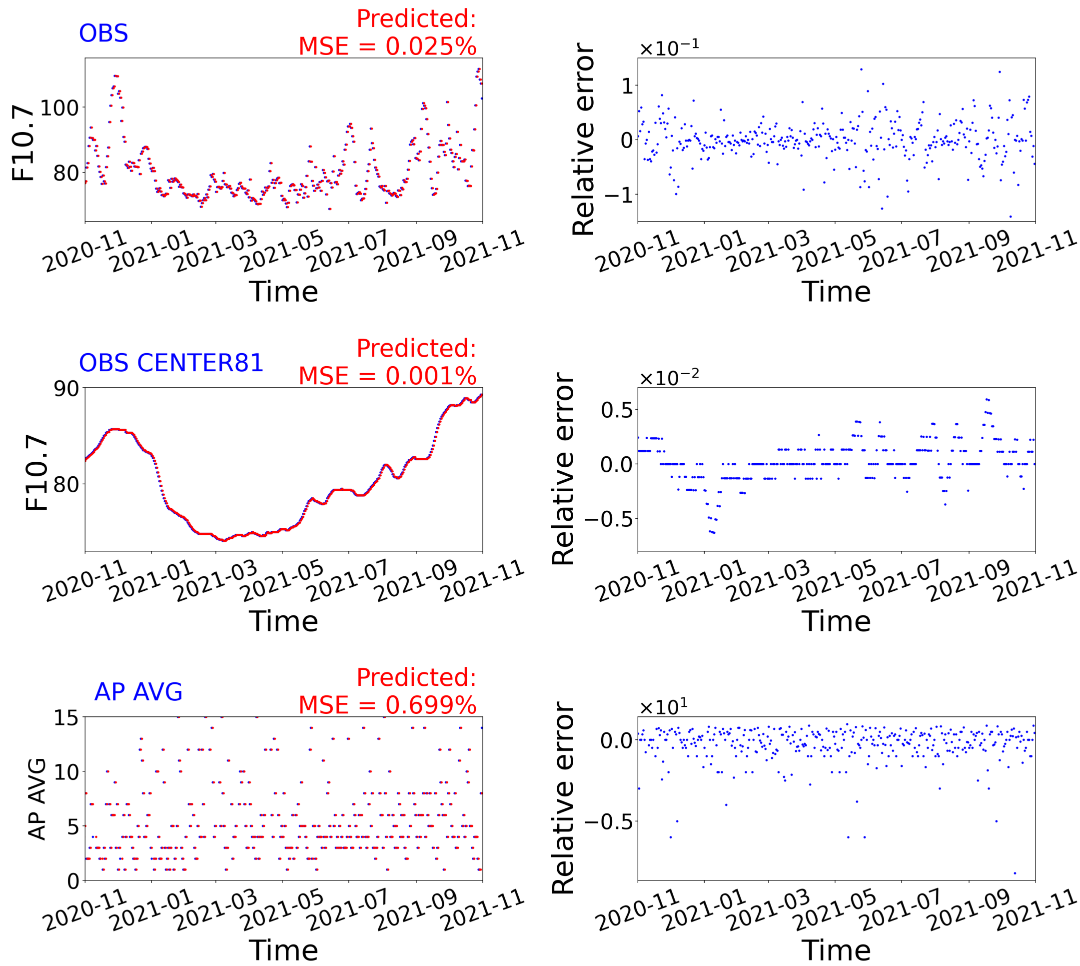

Figure 2: Naive one-step time series forecasting

time of Low-Earth-Orbit Spacecraft: Uncertainty Characterization. *Journal of Guidance Control Dynamics*, 38(5):900–912, May 2015. doi: 10.2514/1.G000148.

C. J. Henney, W. A. Toussaint, S. M. White, and C. N. Arge. Forecasting f10.7 with solar magnetic flux transport modeling. *Space Weather*, 10(2), 2012. doi: https://doi.org/10.1029/2011SW000748. URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011SW000748.

Donald J. Kessler. Collisional cascading: The limits of population growth in low earth orbit. *Advances in Space Research*, 11(12):63–66, January 1991. doi: 10.1016/0273-1177(91)90543-S.

J. L. Lean, J. M. Picone, and J. T. Emmert. Quantitative forecasting of near-term solar activity and upper atmospheric density. *Journal of Geophysical Research: Space Physics*, 114(A7), 2009. doi: https://doi.org/10.1029/2009JA014285. URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2009JA014285.

David Mostaza Prieto, Benjamin P. Graziano, and Peter C.E. Roberts. Spacecraft drag modelling. *Progress in Aerospace Sciences*, 64:56–65, 2014. ISSN 0376-0421. doi: https://doi.org/10.1016/j.paerosci.2013.09.001. URL https://www.sciencedirect.com/science/article/pii/S0376042113000754.

Lorenzo Pasqualetto Cassinis, Robert Fonod, and Eberhard Gill. Review of the robustness and applicability of monocular pose estimation systems for relative navigation with an uncooperative

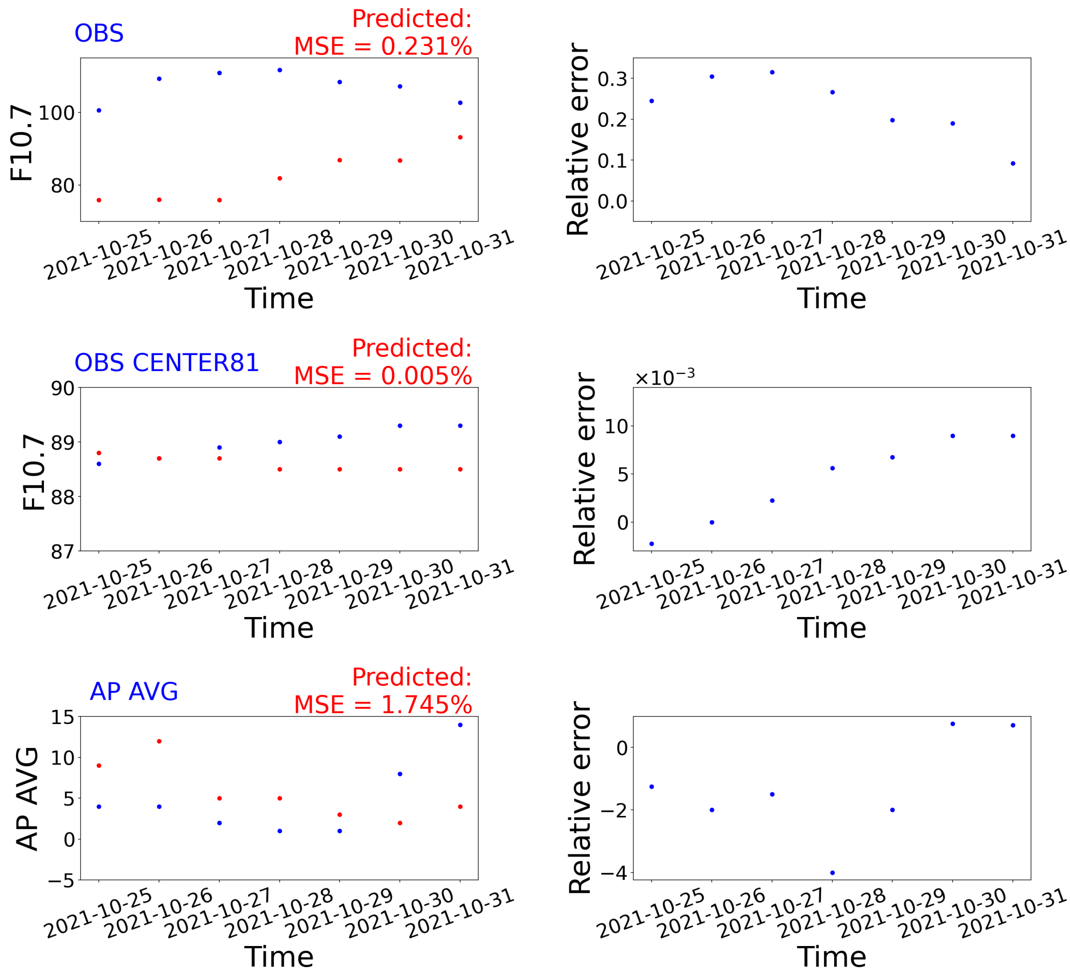

Figure 3: Naive One-week weather data Forecasting

spacecraft. *Progress in Aerospace Sciences*, 110:100548, October 2019. doi: 10.1016/j.paerosci.2019.05.008.

M. Pugliatti and F. Topputo. Small-body shape recognition with convolutional neural network and comparison with explicit features based methods. *AAS/AIAA Astrodynamics Specialist Conference*, 09 2020.

S. F. Rafano Carná and R. Bevilacqua. High fidelity model for the atmospheric re-entry of CubeSats equipped with the Drag De-Orbit Device. *Acta Astronautica*, 156:134–156, March 2019. doi: 10.1016/j.actaastro.2018.05.049.

Jianing Song, Duarte Rondao, and Nabil Aouf. Deep learning-based spacecraft relative navigation methods: A survey. *Acta Astronautica*, 191:22–40, February 2022. doi: 10.1016/j.actaastro.2021.10.025.

Ashish Tewari. Entry Trajectory Model with Thermomechanical Breakup. *Journal of Spacecraft and Rockets*, 46(2):299–306, March 2009. doi: 10.2514/1.39651.

D. A. Vallado. *Fundamentals of Astrodynamics and Applications*. 2007.

David A. Vallado and David Finkleman. A critical assessment of satellite drag and atmospheric density modeling. *Acta Astronautica*, 95:141–165, February 2014. doi: 10.1016/j.actaastro.2013.10.005.

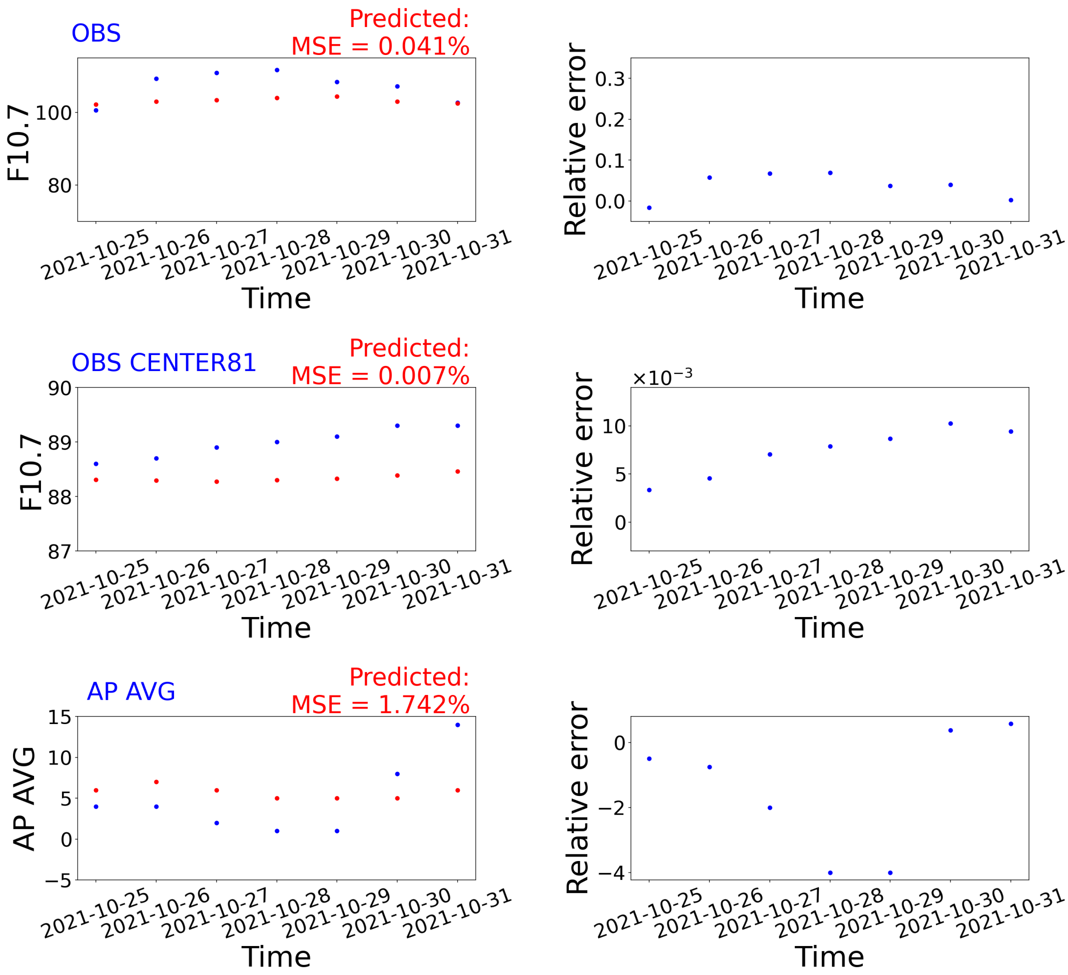

Figure 4: CNNs One-week weather data Forecasting

Harry P. Warren, John T. Emmert, and Nicholas A. Crump. Linear forecasting of the f10.7 proxy for solar activity. *Space Weather*, 15(8):1039–1051, 2017. doi: https://doi.org/10.1002/2017SW001637. URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017SW001637.

Lu Zhejun and Weidong Hu. Estimation of ballistic coefficients of space debris using the ratios between different objects. *Chinese Journal of Aeronautics*, 30, 04 2017. doi: 10.1016/j.cja.2017.03.009.

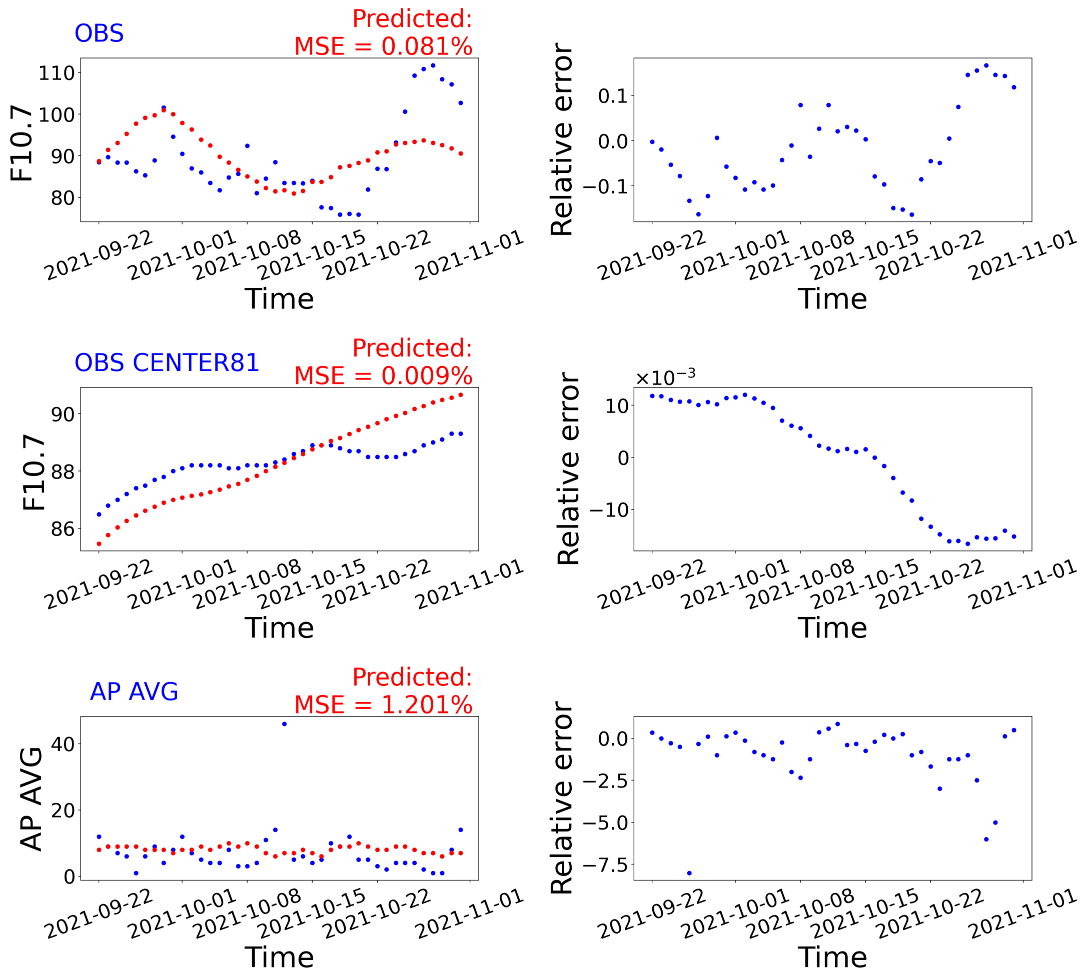

Figure 5: CNNs 40-days weather data Forecasting