Decentralized Global Satellite Tracking Network: Leveraging Crowd-sourced Astronomical Observations and Machine Learning for Cost Effective Orbital Monitoring

Jay Zhang *

Department of The Thacher School, Ventura, California, America

* Corresponding Author Email: Jayzhang1730@gmail.com

Abstract. With 50,000 current actively tracked objects in orbit and a clear upwards trajectory, especially as launch vehicle technologies improve, orbital density and the amount of assets in space is increasing, making space debris a more and more pressing issue. As active debris removal is difficult to make sustainable, active prevention through precise satellite tracking becomes necessary. While current ground based solutions are limited in update rate and are incredibly expensive making them hard to scale, this paper investigates the feasibility of a decentralized alternative where data gathered from a global network of amateur astronomers, classified using a machine learning model that automatically detects satellite trails in telescope imagery, providing position updates at higher frequency and lower costs than conventional systems. A ResNet-50 convolutional neural network was used for trail detection, trained on more than 11,000 images and achieving an overall accuracy of 98% and F1 score of 0.95 on a validation set demonstrating feasibility of use with a full network. A separate global network simulation using TLE orbital data modelling variations of a global network over a 48 hour period found that performance scaled almost linearly, with the best configuration of 50 stations globally and 5 observers at each station achieving an update rate more than 11x higher than the U.S. Space Force's Space Surveillance Network baseline at a fraction of the cost. The results demonstrate both technical and economic viability of the decentralized network, with the potential to play a very meaningful role in preserving sustainable access to Earth orbit.

Keywords: Decentralized Satellite Tracking Network; Crowd-sourced Astronomical Observations; Machine Learning; Orbital Monitoring; Space Debris.

1. Introduction

Currently, there are around 50,000 actively tracked objects in orbit, a number that will continue to rise dramatically as technologies improve and launch costs decrease. As of now, more than 1.7 million more satellites have already been planned to be launched according to FCC filings [1], almost all of which will be in Low Earth Orbit (LEO). With such a large number of satellites in Earth orbit, collisions between satellites and large debris or between satellites themselves become much more likely, with such likelihood increasing exponentially with the number of satellites due to the rise in orbital density.[2][3] This threatens Kessler's Syndrome, a possible future where a satellite collision produces large amounts of debris that then disperse and hit other satellites, leading to a chain reaction that effectively creates a ceiling of rapidly moving debris that eventually traps us on Earth[4],[5]. While active debris removal, especially for larger objects, is necessary in the long term, the best way and first step to prevent collisions is through precise and accurate satellite tracking data that is accessible to all [6].

Current satellite tracking solutions are expensive and limited, relying on ground radar stations that have high operation costs and are very limited across the world, leading to low update rates of data and decaying tracking accuracy as a result [7]. While alternative solutions like space based observation networks like SpaceX's Stargaze exist [8], all of them lack transparency and are highly centralized, reliant on one source to produce highly sensitive information.

A largely overlooked alternative exists in the global community of amateur astronomers. Tens of thousands of amateur astronomers around the world regularly image the night sky, complaining about satellite trails messing up their otherwise good images. By collecting these observations through a

decentralized network and using machine learning to automatically filter the images that contain satellite trails, it becomes possible to generate position updates for the visible satellites calculated based on their trail. This produces a satellite tracking network that updates far more frequently than traditional radar systems, without needing to build any new dedicated infrastructure. Also, because no single entity controls the network, it would also be inherently more transparent and more resilient than any centralized commercial alternative. This approach is not entirely novel either as precedents like Galaxy Zoo, a crowd sourced project used to categorize millions of newly detected galaxies from NASA's database [9], and other citizen science projects have been proven to be highly successful in the past.

This paper investigates whether this approach is actually viable through two portions: a ResNet-50 machine learning model trained to detect satellite trails in telescope imagery, and the simulation of various configurations of a global observer network to evaluate coverage, update frequency, optimal location distribution, and cost against traditional radar benchmarks. The hypothesis is that a network of 50 or more amateur observers using ML-automated detection can provide position updates at <10% the cost of traditional systems while maintaining adequate update rates for collision avoidance.

2. ML Trail Detection

2.1. Methods

The image dataset was provided by a professional astronomer, consisting of 11,000+ raw telescope images of the night sky of which approximately 24% contained visible satellite trails yielding a naturally imbalanced binary classification dataset. All images were manually annotated using labelImg to produce ground-truth labels for each sample and were then split into 80% training and 20% validation subsets.

ResNet-50, a convolutional neural network (CNN), was used as the base architecture and initialized with weights pretrained on ImageNet. The base model ResNet-50 was also chosen due to its popular use among image classification tasks making it well documented and reliable, and transfer learning was chosen to be able to train a deep network from scratch and produce high quality results with a relatively small dataset. At 50 layers, it is a good balance between depth and computational cost, powerful enough for all trail detection use cases while remaining practical to train on consumer hardware in a reasonable timeframe.

Because the majority of images did not contain trails, a weighted cross-entropy loss function was used to assign a higher penalty for missed images that contained trails in them, as a 'dumb' model guessing 'no trail' for all images would have still produced a 76% overall accuracy. The model was trained for approximately 100 epochs using PyTorch with data augmentation in the form of horizontal and vertical flips as well as random rotation being applied during training to improve generalization.

2.2. Model Evaluation

The ResNet-50 trail detection model achieved a strong overall performance on the separate validation set of 3,941 images. Overall accuracy was 98%, with a precision of 95%, recall of 95%, and an F1-score of 0.95. The confusion matrix recorded 826 true positives, 2909 true negatives, 47 false positives, and 43 false negatives, showing how the model was able to produce near equal error rates across both classes rather than simply defaulting to the majority class, proving the effectiveness of the weighted cross entropy loss function in counteracting the 24% positive-class prevalence in the dataset as shown in Figure 1.

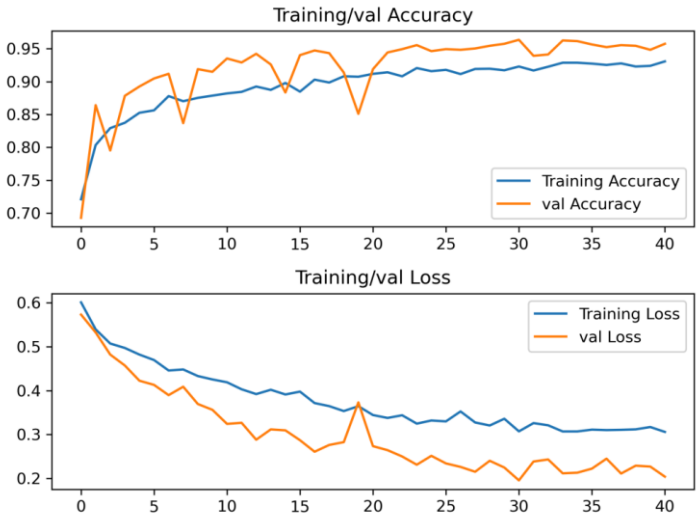


Figure 1. A graph depicting loss and accuracy of the satellite trail detecting model throughout the training epochs.

3. Network Simulation

3.1. Methods

Using the newest TLE data from public US Space Force data with more than 30,000 actively tracked objects, variations of the proposed network of observers was tested over a 48hr period, with Skyfield, a python library built for astronomy, being used to simulate the motion of each satellite from the TLE dataset as shown in Figure 2. Four different variations of the network were tested, one with 10 stations globally and 1 observer at each, one with 10 stations globally but 5 observers each, one with 50 stations globally each with 1 observer, and one with 50 stations globally each with 5 observers. The location of each station was chosen by city, optimized for even geographical distribution and population density, as more populated areas would have better odds of having astronomy communities.

Simulation of the network occurred in two major steps: the detection of all satellites that transited each station, and the calculation of which of those satellites were actually seen by a simulated observer. First, every satellite that came into view at each station was recorded, with satellites being considered in view if they were sunlit, if it was night time at the station, and if they had risen above 20° in altitude to simulate the realistic viewing conditions. Due to the sheer volume of calculations necessary for this step, optimizations were used to decrease run time. To begin with, of the 48hr experimentation range, calculations were limited to when it was considered night time at each station, more than halving the amount of redundant calculations. Then, satellites were filtered based on their orbital inclination, removing each one that could not pass over a station due to orbital mechanics. Of the remaining satellites, their location was checked at an interval of 5 minutes to quickly filter through the remaining satellites, with what was left finally being checked at an interval of 1 minute to record all satellites that passed above a station. These optimizations ultimately decreased the runtime from what would have lasted more than a week to just over a day.

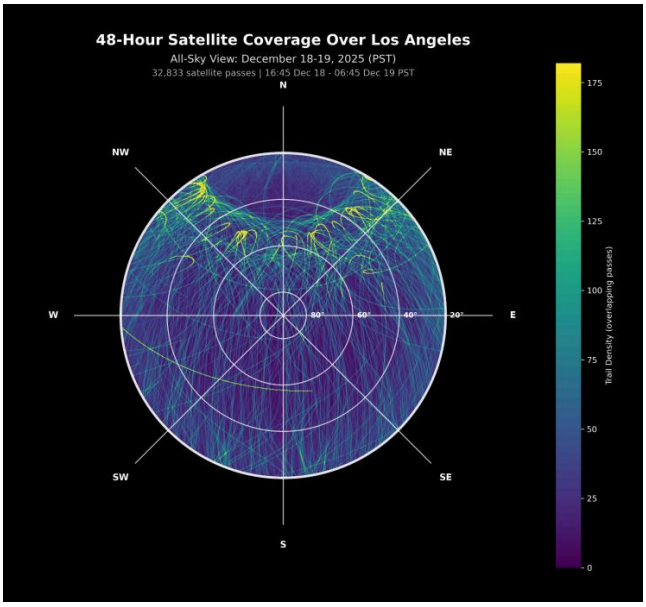


Figure 2. A density graph showing all visible satellites over Los Angeles over the 48 hour test period, a visualization of the results generated by step one of the network simulations.

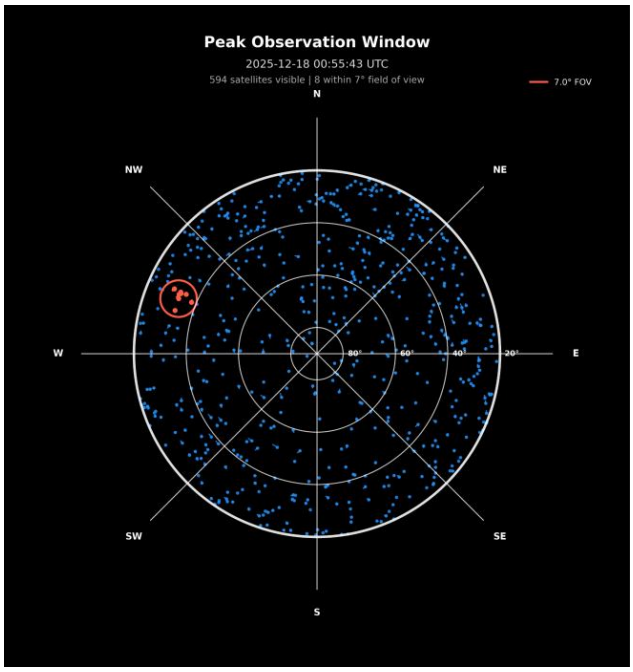


Figure 3. A 2 second snapshot of the entire visible area over Los Angeles from the entire 48 hour period, with the simulated visible area of an astronomer highlighted alongside the satellites inside it, a visualization of one moment during step 2.

Then, using the data generated by the first step, a series of random pointings within the field of view occurring every 2 seconds was generated to simulate the use of the telescope by each astronomer, with each satellite being checked to to see if it was within a 7º field of view, a common size among amateur astronomers. Similarly, due to the large amount of calculations required, optimizations were made such as reading all satellite files once at the beginning of the script and storing it in cache as well as calculating if a satellite would be in each pointing's field of view by satellite instead of by station, greatly reducing the total amount of I/O operations which was a bottleneck for the program, Decreasing run times from 3-4 days down to 7-8 hours. The main metrics collected from this simulation for each configuration of the network include detection probability per telescope pointing, mean amount of satellites observed per pointing, total number of individual satellites observed per station, total observations made per station, and update frequency.

3.2. Results

Results for each individual station were promising. The probability to detect at least one satellite during a pointing was about 87.4% and about 69.8% to detect more than 2 satellites in one pointing. About 3.5 satellites were seen during each pointing on average, and a median of about 5,149 unique satellites being seen by each station. Full statistics can be seen in Table 1.

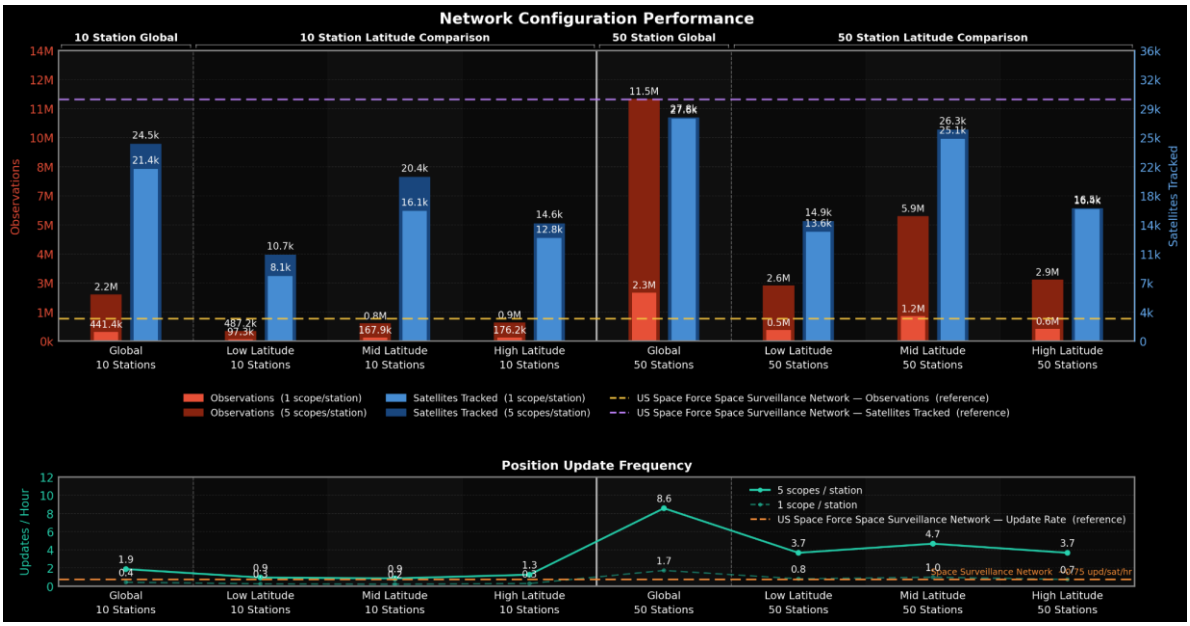


Figure 4. A bar chart and a line graph comparing the observation count, unique satellites observed, and update rate of various configurations of the satellite tracking network

As a whole, the network's performance vastly outperformed the baseline of the SSN. For the configuration of 10 stations globally each with 1 observer, about 441,400 observations were made during the 48 hour period, with 21,400 individual satellites being tracked and an update rate of 0.43 updates per satellite per hour, the only configuration that underperformed in comparison to the SSN. However, the 10 station configuration, each with 5 observers, made a total of 2.21 million observations, tracking 24,500 total satellites during the test period and reaching an update rate of 1.88 updates per satellite per hour, a 150.4% increase in comparison to that of the SSN. The 50 stations configuration each with 1 observer, made 2.29M observations and tracked 21,400 individual satellites during the test period, reaching an update rate of 1.73 updates per satellite per hour, a 130.6% increase in comparison to the SSN. By far the best performing configuration, 50 stations each with 5 observers, made 11.45M observations and tracked 27,800 individual satellites out of the 30,000 that was provided for simulation. It reached an update rate of 8.60 updates per satellite per hour, less than 7 minutes in between each update and a 1046.3% increase in comparison to the SSN, statistics visualized by figure 3 and seen in full table 2. Performance scaled almost linearly with size. Total observations scaled by 5.18x by increasing from 10 stations globally to 50 stations globally and update rate similarly scaled by 4.58x.

Comparing stations from all three latitude ranges, in all configurations, high latitude stations had the highest number of unique satellites detected, followed by mid latitude and low latitude in all configurations. In a cross comparison of 3 stations each from high, mid, and low latitude regions, high latitude polar locations had the highest total detection counts due to polar orbit convergence though the amount of unique satellites was low. Reykjavik, a high latitude station at 64.1º N, made 10,534 unique satellite observations at a median inclination of 89.0º . By contrast, Singapore, a low latitude station at 1.3° N identified the fewest number of unique satellites at 5,450. Los Angeles, a mid latitude station at 34.1° N, captured 6,090 unique satellites as shown in Figure 5. This data is useful for reference for the planning of observer locations during the implementation of the network,

though accounting for the inclinations of future satellite constellations is more important. This data is visualized in figure 4 and can be seen in full in table 3.

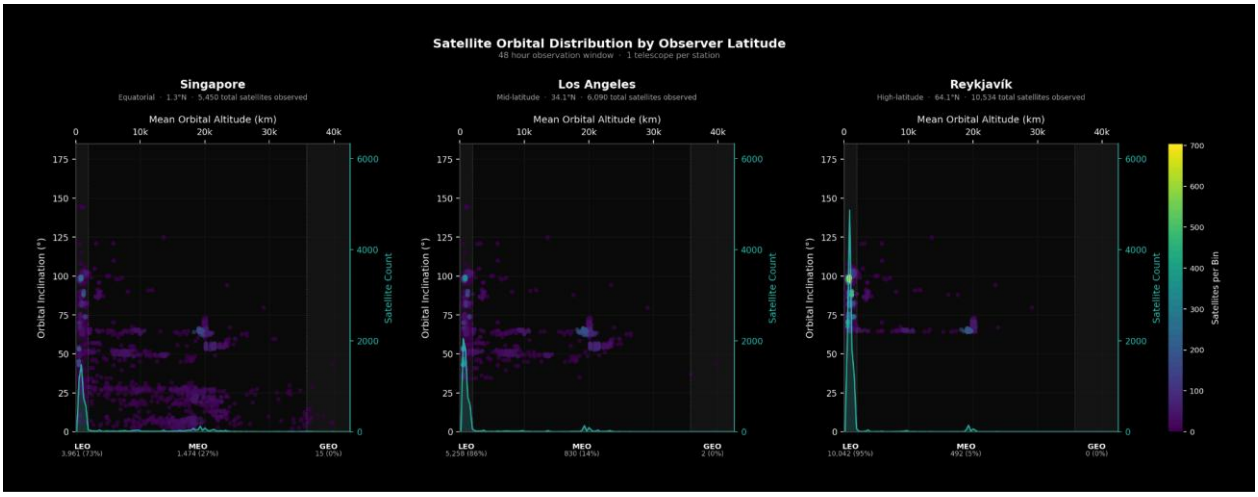


Figure 5. A scatter plot and an overlaid line graph displaying the orbital distribution of all detected satellites over each station location, comparing the detection results of Singapore, Los Angeles, and Reykjavik; low, medium and high latitude stations respectively.

4. Discussion

4.1. ML Results

The overall accuracy of 98% and an F1-score of 0.95 demonstrated the effectiveness of the ML model and its viability for use in the satellite tracking pipeline, with precision and recall values being near identical, further demonstrating its robustness. Satellite detection probabilities for each telescope were similarly encouraging, proving the viability in using the unused data from pointings made by astronomers instead of needing for the use of specifically planned observation paths.

4.2. Network Simulation and Station Distribution

Of all the results, that of the network simulation was most encouraging, with all tested configurations of the network, except for the one with only 10 stations globally and 1 observer at each, vastly outperforming the US Space Force's Space Surveillance Network (SSN). The best configuration with 50 stations globally, each with 5 observers vastly outperformed the SSN, achieving an update rate of 8.59 times per satellite per hour, or less than 7 minutes in between every update, a rate that is roughly 11.5 times higher than the SSN despite being a fraction of the cost.

Simulation results showed that network performance scaled nearly linearly as the global number of stations increased, though during early stages of network implementation, per station density is slightly more important than total station count, with the 10 station 5 observer configuration achieving near identical observation numbers as that of the 50 station 1 observer configuration, though update rates were slightly higher in that of the 10 station 5 observer configuration. This finding is especially encouraging because the scaling of the network will be easier when existing social and community structures within the amateur astronomy community can be leveraged, where a single regional contact can organically recruit multiple local observers through established networks, making high per-station observer density a naturally occurring characteristic.

From station comparison results, we are able to recognize the optimal distribution of stations across the world to maximize for total satellite detections and total satellites detected. High latitude locations are excellent for detection of high inclination orbits, yielding high observation numbers as a result. Mid latitude stations also had high observation numbers, though their number of unique satellites that were detected were higher than that of higher latitude locations due to the large amount of mid-inclination orbits in satellite constellations, especially that of LEO, making it especially useful for our

network. Low latitude equatorial stations had the lowest performance among the latitude ranges both in terms of the number of total detections and the number of unique satellites, though they are still a necessary component of our network for the detection of low inclination and geosynchronous orbits, though their total numbers can be less than that of mid and high latitude stations. However, recognizing current patterns is insufficient. The network should also plan ahead for future satellite constellations. For example, of the 1 million satellites for space based data centers that SpaceX plans to have, what will make up a large majority of satellites in LEO, their orbits will be distributed among a 30 degree inclination orbit and others will be among a Sun Synchronous Orbit (SSO) [10], a highly polar orbit, necessitating higher numbers of low mid latitude and high latitude stations.

4.3. Costs

According to U.S. Space Force's 18th Space Defense Squadron, the US Space Force's Space Surveillance Network (SSN), by far the largest ground based satellite and orbital debris tracking network globally, makes hundreds of thousands of observations daily, tracking roughly 30,000 satellites, equating to an update rate of about 0.75 updates per satellite per hour, a metric that is achieved through a global network made mostly of mechanical and phased array radars and amounting to an estimate of several billion dollars in infrastructure and millions more in annual costs. However, by leveraging the unused data of astronomers globally who already have their own equipment, we are able to achieve even higher update rates without additional equipment costs, and the only running cost being that of cloud computing which would only cost $3000-4000 annually.

4.4. Limitations

The only limitations of the proposed system include the limited viewing range of the optical systems, and the reliance on amateur astronomers. Due to the use of optical equipment, visible objects are limited to larger objects like satellites and large debris like fairings in Low Earth Orbit (LEO) and maybe Medium Earth Orbit (MEO) depending on visibility. This isn't particularly problematic though, because most satellite constellations (current and planned) are in LEO, with inter satellite collisions or collisions between large debris having the greatest consequences. Another limitation is the reliance on amateur astronomers that may have irregular telescope use patterns and may be affected by weather, as well as the risk of tampered data. However, almost all of the problems mentioned previously are solved by the redundancy of observers. By having a broad distribution of observers globally, if one observer is unable to produce quality data whether that is due to weather, technical issues, or intentional sabotage, other observers are able to compensate for this loss and produce marginal detriments, with the system being able to recognize the anomaly if all other observers produce data that is in agreement with each other but contradicting that of one specific station. Finally, if an observer has no plans for viewing on a specific day, a script can be provided to produce the optimal satellite tracking path able to be taken by the telescope, nonetheless contributing to the global observer network.

5. Conclusion

This project sets out to answer whether data collected from a global, decentralized network of amateur astronomers, filtered using a machine learning algorithm, could realistically compete with existing radar based satellite tracking solutions in terms of performance while dramatically undercutting it in cost. Based on the results of both machine learning and network simulation components of this research, the answer is yes, and more.

The ResNet-50 trail detection model was able to achieve a 98% overall accuracy and a 0.95 F1 score on the validation set, demonstrating its feasibility for use in classifying images captured by a global amateur astronomer network. The global network simulation showed that the network's performance scaled almost linearly with size increase, with the best configuration of 50 stations globally and 5 observers at each location achieving an update rate of about once every 7 minutes for

every satellite, 11 times the baseline of the U.S. Space Force's Space Surveillance Network, at less than a millionth of all their infrastructure cost. These results not only confirm the hypothesis but far exceed any preliminary expectations.

Due to time constraints, only the validation phase of the project was completed, so future work would entail the implementation of the trail-to-satellite matching algorithm and the collision risk calculator and alert system which would allow for true high frequency position updates for satellites and make the system truly ready for full implementation.

However, the broader significance of this work extends beyond the technical results. As launch frequencies increase and orbital density grows, especially in LEO, the limitations of expensive, centralized tracking infrastructure become increasingly evident and dangerous. A crowdsourced optical network does not need to and will not replace radar entirely, with radar excelling in other areas such as the detection of smaller objects, but it will complement it, filling coverage gaps and increasing update frequency at a scale that no traditional system can realistically match, significantly improving orbital safety and reducing collision risks. This project shows that the infrastructure already exists in the hands of amateur astronomers worldwide, and that connecting it through an automated network is not only viable but also worth seriously pursuing to ensure a safe and space faring future for all mankind.

6. Appendix

Table 1. Satellite detection statistics for all 55 stations that were simulated (original data).

Station	Lat (°)	Lon (°)	P(≥1 Sat) (%)	P(≥2 Sats) (%)	Mean Det/ Pointing	Max Det (Single)	Unique Sats	Successful Pointings
Melbourne	-37.8	144.9	95.62	85.74	4.4422	21	8,839	31,753 / 33,207
Christchurch	-43.5	172.6	96.51	88.34	4.8949	28	8,111	29,827 / 30,906
Sydney	-33.9	151.2	93.91	81.08	3.9648	23	8,001	32,440 / 34,544
Cape Town	-33.9	18.4	91.54	77.04	3.7003	21	7,961	31,596 / 34,516
Buenos Aires	-34.6	-58.4	93.56	81.05	3.9726	22	7,932	32,079 / 34,286
Santiago	-33.4	-70.7	93.17	79.75	3.8969	25	7,781	32,305 / 34,675
Perth	-31.9	115.9	93.00	78.68	3.7160	25	7,326	32,713 / 35,175
Salt Lake City	40.8	-111.9	86.83	68.63	3.2782	25	6,991	46,135 / 53,134
Beijing	39.9	116.4	87.42	69.81	3.4168	21	6,960	46,160 / 52,803
Athens	38.0	23.7	81.29	62.02	2.9271	26	6,731	42,345 / 52,094
Denver	39.7	-104.9	86.67	68.21	3.2522	21	6,699	45,676 / 52,702
Tokyo	35.7	139.7	85.32	65.76	3.0914	25	6,530	43,818 / 51,358
Vancouver	49.3	-123.1	87.49	70.98	3.5525	25	6,476	49,834 / 56,959
Tehran	35.7	51.4	80.58	60.52	2.8104	25	6,427	41,361 / 51,326
Ulaanbaatar	47.9	106.9	87.80	71.47	3.5972	24	6,425	49,339 / 56,196
London	51.5	-0.1	83.71	67.36	3.4924	23	6,424	48,717 / 58,196
Winnipeg	49.9	-97.1	86.54	69.66	3.4948	23	6,421	49,560 / 57,266
Brisbane	-27.5	153.0	91.61	75.59	3.4283	19	6,293	33,400 / 36,457
Berlin	52.5	13.4	83.44	67.02	3.4734	24	6,241	49,080 / 58,822
Los Angeles	34.1	-118.2	83.51	62.91	2.8860	21	6,226	42,468 / 50,851
Warsaw	52.2	21.0	82.98	66.62	3.4199	23	6,186	48,651 / 58,630
Irkutsk	52.3	104.3	86.40	69.89	3.5921	23	6,144	50,706 / 58,690
Johannesburg	-26.2	28.0	88.31	71.30	3.2685	19	6,010	32,483 / 36,783
Almaty	43.2	76.9	85.51	67.55	3.2406	25	5,762	46,223 / 54,054
Vladivostok	43.1	131.9	87.61	69.89	3.4235	20	5,700	47,347 / 54,046
Sapporo	43.1	141.4	87.36	69.65	3.3820	26	5,690	47,212 / 54,045
Shanghai	31.2	121.5	82.76	61.32	2.8097	22	5,589	41,375 / 49,991
Cairo	30.0	31.2	77.44	56.93	2.5311	21	5,287	38,425 / 49,618
Punta Arenas	-53.2	-70.9	95.80	86.81	4.7818	26	5,149	24,278 / 25,343
Murmansk	68.9	33.1	79.61	65.75	3.8935	42	5,129	68,781 / 86,400

Station	Lat (°)	Lon (°)	P(≥1 Sat) (%)	P(≥2 Sats) (%)	Mean Det/ Pointing	Max Det (Single)	Unique Sats	Successful Pointings
New Delhi	28.6	77.2	80.68	58.20	2.6155	23	5,096	39,719 / 49,233
Tromsø	69.6	18.9	80.26	66.37	4.0065	44	5,085	69,345 / 86,400
Brasilia	-15.8	-47.9	92.40	78.54	3.6579	21	4,878	36,358 / 39,350
Taipei	25.0	121.6	87.61	67.78	3.0042	23	4,806	42,334 / 48,321
Miami	25.8	-80.2	87.26	66.48	2.8486	19	4,787	42,318 / 48,496
Riyadh	24.7	46.7	82.75	62.79	2.7766	22	4,745	39,898 / 48,213
Fairbanks	64.8	-147.7	82.61	66.44	3.6181	31	4,671	60,289 / 72,977
Reykjavik	64.1	-21.9	83.42	68.13	3.8417	34	4,651	59,584 / 71,427
Nairobi	-1.3	36.8	90.40	78.19	4.2645	28	4,581	38,401 / 42,481
Hawaii	19.8	-155.5	89.32	70.97	3.1757	18	4,494	42,028 / 47,054
Lima	-12.0	-77.0	92.81	79.47	3.8894	26	4,457	37,314 / 40,204
Mexico City	19.4	-99.1	90.22	72.49	3.2651	19	4,453	42,365 / 46,960
Jakarta	-6.2	106.8	94.39	82.86	4.3929	27	4,447	39,154 / 41,483
Mumbai	19.1	72.9	88.32	70.58	3.1577	19	4,370	41,389 / 46,860
Anchorage	61.2	-149.9	86.96	72.07	4.0542	32	4,360	58,041 / 66,741
Singapore	1.3	103.8	94.77	84.16	4.7488	29	4,333	40,802 / 43,052
Khartoum	15.6	32.5	86.31	70.16	3.2334	24	4,294	39,758 / 46,065
Lagos	6.5	3.5	89.87	76.37	3.7885	26	4,260	39,639 / 44,106
Bangkok	13.8	100.5	92.78	78.11	3.6446	25	4,258	42,398 / 45,698
Manila	14.6	121.0	91.60	76.22	3.5389	23	4,256	42,020 / 45,874
Saint Petersburg	59.9	30.3	83.39	67.76	3.7264	31	4,205	54,298 / 65,114
Oslo	59.9	10.8	83.03	67.46	3.7195	36	4,198	54,066 / 65,116
Svalbard	78.2	15.6	90.30	78.40	4.9070	49	3,961	78,023 / 86,400
Moscow	55.8	37.6	82.11	65.45	3.3313	25	3,687	50,250 / 61,196
Novosibirsk	55.0	82.9	84.74	67.14	3.4043	26	3,571	51,327 / 60,568

Table 2. Comprehensive overview of network simulation results of all configurations (original data).

Configuration	Scopes /Station	Observations	Δ vs SSN	Satellites Tracked	Δ vs SSN	Update Rate (upd/s at/hr)	Δ vs SSN
10-Station Network — Global							
Global — 10 Stations	1	441.4k	−59.1%	21.4k	−28.7%	0.4302	−42.6%
Global — 10 Stations	5	2.21M	+104.5%	24.5k	−18.3%	1.8779	+150.4%
10-Station Network — Latitude Subsets							
Low Latitude	1	97.3k	−91.0%	8.1k	−73.1%	0.2507	−66.6%
Low Latitude	5	487.2k	−54.9%	10.7k	−64.3%	0.9472	+26.3%
Mid Latitude	1	167.9k	−84.5%	16.1k	−46.2%	0.2167	−71.1%
Mid Latitude	5	838.4k	−22.4%	20.4k	−32.1%	0.8570	+14.3%
High Latitude	1	176.2k	−83.7%	12.8k	−57.3%	0.2866	−61.8%
High Latitude	5	883.4k	−18.2%	14.6k	−51.2%	1.2583	+67.8%
50-Station Network — Global							
Global — 50 Stations	1	2.29M	+112.1%	27.6k	−8.0%	1.7296	+130.6%
Global — 50 Stations	5	11.45M	+960.4%	27.8k	−7.5%	8.5975	+1046.3%
50-Station Network — Latitude Subsets							
Low Latitude	1	526.4k	−51.3%	13.6k	−54.7%	0.8071	+7.6%
Low Latitude	5	2.63M	+143.8%	14.9k	−50.3%	3.6766	+390.2%
Mid Latitude	1	1.18M	+9.5%	25.1k	−16.3%	0.9818	+30.9%
Mid Latitude	5	5.91M	+446.9%	26.3k	−12.4%	4.6839	+524.5%
High Latitude	1	581.6k	−46.1%	16.4k	−45.5%	0.7408	−1.2%
High Latitude	5	2.91M	+169.7%	16.5k	−45.0%	3.6751	+390.0%

Table 3. Observed satellite orbital distribution comparison across stations from high, mid and low latitude ranges (original data).

Metric	Singapore (Equatorial, 1 3°N)	Los Angeles (Mid-Latitude, 34 1°N)	Reykjavík (High-Latitude, 64 1°N)
Observation Metrics			
Unique Satellites Identified	5,450	6,090	10,534
Total Satellite Detections	51,462	33,142	61,171
Detections per Unique Satellite	9.4	5.4	5.8
Orbital Parameters			
Altitude Range — Mean Alt (km)	302 – 39,720	239 – 39,720	220 – 29,112
Inclination Range (°)	0.1 – 144.6	34.2 – 144.6	64.1 – 124.8
Median Altitude (km)	1,121	859	894
Median Inclination (°)	71.0	72.0	89.0
Peak Density Altitude (km)	885	531	885
Orbital Regime Breakdown			
LEO (<2,000 km)	3,961 (72.7%)	5,258 (86.3%)	10,042 (95.3%)
MEO (2,000–35,786 km)	1,474 (27.0%)	830 (13.6%)	492 (4.7%)
GEO (>35,786 km)	15 (0.3%)	2 (0.0%)	0 (0.0%)
LEO Detail			
Sun-Synchronous Proxy (96–100°)	1,103 (20.2%)	1,390 (22.8%)	3,921 (37.2%)
LEO Median Inclination (°)	82.7	74.1	89.4
GEO Median Inclination (°)	8.8	40.6	N/A

References

[1] Borlaff, A. S., Marcum, P. M., & Howell, S. B. (2025). Satellite megaconstellations will threaten space-based astronomy. Nature, 648(8092), 51–57. https://doi.org/10.1038/s41586-025-09759-5

[2] Federal Communications Commission. (2026, February 4). Space Bureau accepts for filing SpaceX's application for orbital data centers (DA 26-113). https://docs.fcc.gov/public/attachments/DA-26-113A1.pdf.

[3] Kessler, D. J., & Cour-Palais, B. G. (1978). Collision frequency of artificial satellites: The creation of a debris belt. Journal of Geophysical Research: Space Physics, 83(A6), 2637–2646. https://doi.org/10.1029/JA083iA06p02637

[4] Lawrence, A., Rawls, M. L., Jah, M., Boley, A., Di Vruno, F., Garrington, S., Kramer, M., Lawler, S., Lowenthal, J., McDowell, J., & McCaughrean, M. (2022). The case for spaceenvironmentalism. Nature Astronomy, 6, 428–435.https://doi.org/10.1038/s41550-022-01655-6

[5] Ly, D., Lucken, R., & Giolito, D. (2020). Correcting TLEs at epoch: Application to the GPS constellation. Journal of Space Safety Engineering, 7(3), 302–306. https://doi.org/10.1016/j.jsse.2020.07.032

[6] Morin, J. (2019, March 7). Four steps to global management of space traffic. Nature, 567, 25–27.https://doi.org/10.1038/d41586-019-00732-7

[7] National Aeronautics and Space Administration, Orbital Debris Program Office (Ostrom, C. L., Manis, A. P., Matney, M., & Liou, J.). (2025, September 1). Orbital Debris Quarterly News (Vol. 29, Issue 3). NASA.https://orbitaldebris.jsc.nasa.gov/quarterly-news/pdfs/ODQNv29i3.pdf

[8] SpaceX. (2026, January 30). Stargaze: SpaceX's Space Situational Awareness System. Starlink. https://starlink.com/updates/stargaze

[9] Witze, A. (2025, March 18). Swarms of satellites are harming astronomy. Here's how researchers are fighting back. Nature, 639, 564–566. https://doi.org/10.1038/d41586-025-00792-y

[10] Zooniverse. (n.d.). Research. Galaxy Zoo. https://www.zooniverse.org/projects/zookeeper/galaxy-zoo/about/research