MOCAT on Temporal Analysis and Quantification for Policies in Space Sustainability

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ABSTRACT

While quantifying policies in space sustainability has been receiving increasing attention, this paper provides the first temporal analysis and quantification for space sustainability on: both the framework integration between traditional economical model and Monte Carlo environment model, and the novel separation of human factors from the environment evolution. We show in detail how economical model can be combined with a Monte Carlo framework, in compliance with existing functionalities in a holistic environment for space population; moreover, we show how policy delay results in economical loss and gain, conveying the implications of temporal policy analysis for space sustainability, while revealing a threshold among options to answer the question "how late is too late" for space environment mitigation action. We present a new concept to quantify human factor based on a mixture of model and historical data, followed by an in-depth analysis with connections that can explain the temporal performance of the LRCI (Learned Reality-Check Index). Furthermore, we show how the LRCI, providing human factor quantification, can be extended into space population prediction, complementing the traditional space population evolution following an assumptious launching model for SR (satellite ratio) evolution. This work updates the charter of how temporal evolution is involved space policy investigation for space sustainability and how temporal information could be employed to not only inform novel insights and trends but also provides interpretability behind space population evolution.

1. INTRODUCTION

The ability to analyze and assess the changing scenes of space population and orbit capacity is foundational for impactful space situational and domain awareness (SSA/SDA). Trustworthy analysis and characterization of the evolution of space population, in particular, are essential in ensuring effective space traffic management (STM) and sustainable space development. Existing analysis [1, 14] has shown the unabated expansion of space population, leading to the infeasible orbit environment in the future. This ominous future leads to the development of debris mitigation techniques and discussion on policy changes. Analysis on these various techniques and policies, ranging from collision avoidance maneuvers, responsible satellite disposal practices, and other proactive measures, despite showing the grand benefits they could bring to the long-term space development, is plagued by the assumption of a prompt implementation of the changes. The hidden question on the timeline of consecutive changes and their effects is largely unexplored (i.e., due to adapting to policy and gradual improvement in technology), along with the analysis on temporal difference for when to initiate such changes. We have adapted and conducted extensive development on MOCAT-MC (MIT Orbital Capacity Assessment Tool - Monte Carlo), enabling robust, trackable, and explainable space population behaviors. The quantification of the temporal analysis, using MOCAT-MC, on possible changes for space sustainability offers a groundbreaking investigation for answering the implementation problems in sustainable space development.

Monte-Carlo-based framework has been widely employed in predicting the future of space population due to its ability to capture the complex space population evolution characterized by the chaotic interaction between space objects, the randomness in debris generation events, and the existence of nonlinear dynamics in circumterrestrial space. The explicit dynamics and trajectory history for a single object in the evolution of the whole space environment, effectively a digital twin of the circumterrestrial space environment, are vital in providing self-evident reasoning behind any Monte Carlo running. Simplification in the dynamics ensures that the propagation of a single space object, the basic component of the system, is efficient while maintaining space population's statistical stability – close-encounters and natural decays are statistically reliable. The temporal evolution of the space population is determined by the sequential interaction between propagation, decaying, new launching, control, debris generation from explosion and collision. Environment parameters that dictate this evolution are typically predetermined throughout the Monte Carlo simulation, representing certain fundamental assumptions. These assumptions include, but are not limited to, simplifications in the dynamics model (such as the oblateness coefficient and atmosphere density) and operational parameters (such as the post-mission disposal rate). MOCAT is developed in such a way that even a single laptop could efficiently run and generate analyses of space population evolution.

The foundational numerical space environment models has seen much improvement in the past years. The growing concerns over space sustainability has driven further research into modeling the space environment. These models are designed to predict future trends in the quantity and distribution of objects in space, encompassing both active payloads and debris. Several space agencies have developed software for this purpose, such as NASA's LEGEND simulator, ESA's DELTA [16], CNES's MEDEE [7], CNSA's SOLEM [19], and JAXA's NEODEEM [12]. There are also models from academia such as MOCAT from MIT and ISOC from Politecnico di Milano. MOCAT serves as the first open-source publicly available software package to evaluate space capacity and predict space environment.

Development of foundational space environment models leads to a growing wave in conducting quantification and monetization of the space economy. This paper adopts the definition in [17, 22], describing the space economy as "the full range of activities and the use of resources that create and provide value and benefits to human beings while exploring, understanding, managing, and utilizing space." Building on this, [2] contributes to the understanding of space activities through a process ecosystem perspective, utilizing open-source data to conduct pattern analysis across different countries. This approach proposes the idea of providing a human-understandable, human-verifiable, and human-explainable AI framework through their employment of statistical analysis under assumptions on a probabilistic system. Additionally, [18] explores the socio-economic impacts of space debris, particularly focusing on the potential consequences of the Kessler syndrome and policy options for enhancing compliance with space debris mitigation measures. Meanwhile, [6] explored the economics of large constellations from a conceptual perspective, partially under their investigation on constellation's impacts on astronomy, another general space sustainability perspective. "The lack of analysis of the collision and debris threats" mentioned in [6] is answered by [1] for mega-constellations using MOCAT-MC, demonstrating how MOCAT-MC could be employed in long-term large-scale numerical study for the space environment. [3] appears as a seminal work in the realm of quantifying and monetizing the cost of orbital debris by being the first work providing data for cost-benefit analysis in a rigorous and wide-reaching manner. Their work is based on NEAT (Number of Encounters Assessment Tool) [5], employing probability-based algorithm to assess the long-term encounter rate between any and all pairs of satellites. There has always be a debate between probability-based approach and deterministic one for assessing encounters in modeling space environment. Their difference lies in that each run in MOCAT-MC or other Monte Carlo way is deterministic and the combination of multiple MC runs represent the final state, providing a clear and straight-forward way of environmental evolution explainability and adaptivity for different development, while the probability-based approach emphasizes more on the speed side. Following the development of the cost model, [15] conducted analysis on the net present value of multiple actions for decision makers to identify an optimal portfolio of actions to reduce risk, and quantitatively analyze policies related to space sustainability. [21, 22] also contributes to the monetization and analysis of different orbital debris mitigation and remediation costs.

Current method of quantification and monetization still takes many assumptions due to a lack of complexity and usability in their environment models. And the environment model development, despite being more and more advanced, needs to be connected with explainable insights. The analysis in [15] covered a series of policies and they showed that the net benefit and cost-benefit ratios associated with changing from a 25-year rule to a lower-year rule. The analysis is conducted with a set implementation time that missing the temporal perspective that would ask the question how far in the future is the limit of implementing those policies. [22] uses sensitivity analysis with alternative inputs to identify uncertainties in the costs of orbital debris and space preservation. The best-fitting method over multiple monte carlo runs is employed to depict the cost of orbital debris. This needs to be improved when the detailed information about the source of orbital debris and different collisions types and costs are included in the more realistic simulation. Similarly, [21] indicates that at a 90% success rate of post-mission disposal (PMD) and an active removal of as few as 5 defunct spacecraft per year are the sufficient and effective space preservation measures if spacefaring communities are in compliance with them sooner rather than later. Notice that the 90% success rate is also for all kinds of satellites, so is ADR, of any purposes, any origins, any technology level, as undifferentiated homogeneous commodities, which is counter-intuitive considering the imbalanced impact of constellations for space environment and their economic gains [1, 6]. In addition, the question of which policy or combination of multiple policies and in what sequence could offer a paradigm-shifting framework for solving the cardinal problem in SSA/SDA and ensuring sustainable use of the congested orbital environment remains unexplored. The quantification of "sooner or later", i.e., how late is too late for a sequence of policies change in space sustainability, is also a rarely asked question. We have developed an extensive set of advanced computational models for simulating the long-term space population around Earth, balancing both stability and computational efficiency. We will show herein how to convert policies and techniques for collision mitigation into temporal model to feed into the MOCAT framework. Subsequently, we will quantitatively evaluate their effectiveness in curbing the growth of space population and mitigating the risk of space debris proliferation. For example, the analysis of an early implementation of active debris removal could likely induce a much lower space population in the long run; but quantifying the extent to which it would be lower compared to implementing it later is crucial for assessing its effectiveness.

Temporal analysis on space environment is receiving increasing attention. Most current methods for modeling space traffic project historical launch patterns into the future. This approach is utilized in published analyses of MEDEE, NASA's ORDEM software, and SOLEM, all of which rely on repeating eight years of launch data over several decades. [20] describes a parameterized way to model future launching activities, ppoinging out that launches are a significant source of uncertainty for the evolution of the space environment. It is developed for the purpose of scenario investigation, tuning the parameters in their launch model, people could investigate different launching performance and their impact on the space environment. This provides a convenient tool for policy makers to understand the different scenarios and the necessity for responsible launching performance. While providing parameter space for different scenarios, it still faces the problem of choosing the parameters to reflect the realistic prediction and future evaluation for launching model. In addition, the parameterized model faces the question of defining the physical meaning of each parameters. There are also papers working on the more specific configuration for quantifying the future space environment with very specific numbers of objects and plans. In a study on debris mitigation measures, [13] includes a theoretical mega-constellation of 1000 satellites. With the FCC and ITU filings for future megaconstellation, MOCAT is able to run scenario of megaconstellations and for the first time reaches the level of millions of space objects in [1, 10]. Most of the research focuses on the temporal launching performance yet the scenario and discussion needs to extend to other aspects of space environment evolution. This paper investigated the temporal analysis on policy implementation and the associated results of those temporal scenario on space environment.

Temporal analysis also includes another aspect - quantification the change in the time series. Specifically under the space sustainability, that is to quantify the influence of human factor on a given period of time. Human factor includes launching activities, controlling active satellites, and conducting post-mission disposal and extends beyond that to include more abstract perspective such as policy making, economical performance, and could also include geopolitical actions and as well as global health. There is complicated intrinsic connection between human factors and how they create a combined effort on space environment. The no-launch scenario represents the closest to realistic scenario in a simulated environment. When launching is involved, automatically the dimension of uncertainty would increase and down goes the environment prediction accuracy. Yet, the no-launch scenario is not well-used in many tools and they would only serve as a comparison baseline. This quantification on human factor from space environment evolution is proposed for the first time in this work.

The following of the paper is arranged in the following format. First, we present the temporal analysis on different timeline for policy changing and their impact on space environment, specifically for PMD in megaconstellation satellites. We explain how the concept on cost from [3] can be adopted by a Monte Carlo model, using MOCAT-MC as an example. Monte Carlo simulation and their associated economic cost evolution are combined to create the evolution of collision cost density distribution to represent the evolution of the collision risk. We then propose a method to expand the discrete sampling of the approach cost to an estimation of the continuous case. Providing the first Monte Carlo economic model for policy investigation, we further investigate the first temporal analysis on the first type-based policy investigation. We analyzed the economical gains and loss of multiple delays of increasing megaconsteallation PMD and also found the critical threshold among the investigated delays. Then, we discussed the temporal quantification of human factors by proposing LRCI (learned reality-check index). The analysis from LRCI evolution is detailed and some conclusions from the temporal performance difference are drawn to support finding explanation and connection with real world events. Afterwards, we discuss about how to implement LRCI extrapolation into conducting future prediction. Finally, we conclude the paper with our core findings and methods.

2. TEMPORAL POLICY COST FRAMEWORK

2.1 Improvements to Megaconstellation PMD

In this section, the improvement to successful PMD (post mission disposal) of constellation satellites is analyzed. A successful PMD refers to a successful deorbiting of an active satellite that has reached the end of its mission, whereas a failure to PMD results in the payload becoming derelict in its original orbit. The historical constellation PMD rate of 90% is used [8], and an improvement of the PMD rate to 99% is modeled with varying delay in such improvement. The very high PMD [1, 6] is essential to avoid the worst environmental impacts - the long-horizon Kessler syndrome, the case of not a single debris generation event rendering the space environment unusable but the irreversible gradual encroachment on usable space environment. This comparison shows the consequences of delaying PMD improvement, whether through policy adherence or through technological improvement. Notice that PMD could involve both internal disposal as well external one, i.e. active debris removal, as it is critical to provide redundancy and robustness to PMD [6]. The MOCAT-MC model [11] is used to simulate the megaconstellation launch model described in [9], with the simulations starting in March 1, 2023. Fig. 1 depicts several typical evolution of both the total space objects population (upper panel) and the derelict numbers (lower panel) for the policy of delaying PMD change implementation for 2 years (in 2025), 5 years (in 2028), 10 years (in 2033), 20 years (in 2043), and 30 years (in 2053) using 5 MC runs for each scenario. The lower panel in Fig. 1 shows the total population difference between the scenarios for objects larger than 10 cm. Scenarios where 99% PMD is used show a marked improvement in keeping the total object count low by reducing collisions and thereby debris. The upper panel in Fig. 1 shows the difference in the population of derelict objects for the various adoption delays, ranging from immediate improvement to PMD to no such improvement taking place. The variation in the number of derelict objects is clearly seen. It is clear that the reduction of derelict objects through greater adherence to PMD will be crucial in addressing the space debris problem. In a future where the modeled megaconstellations are launched, PMD of greater than 90% will be advisable.

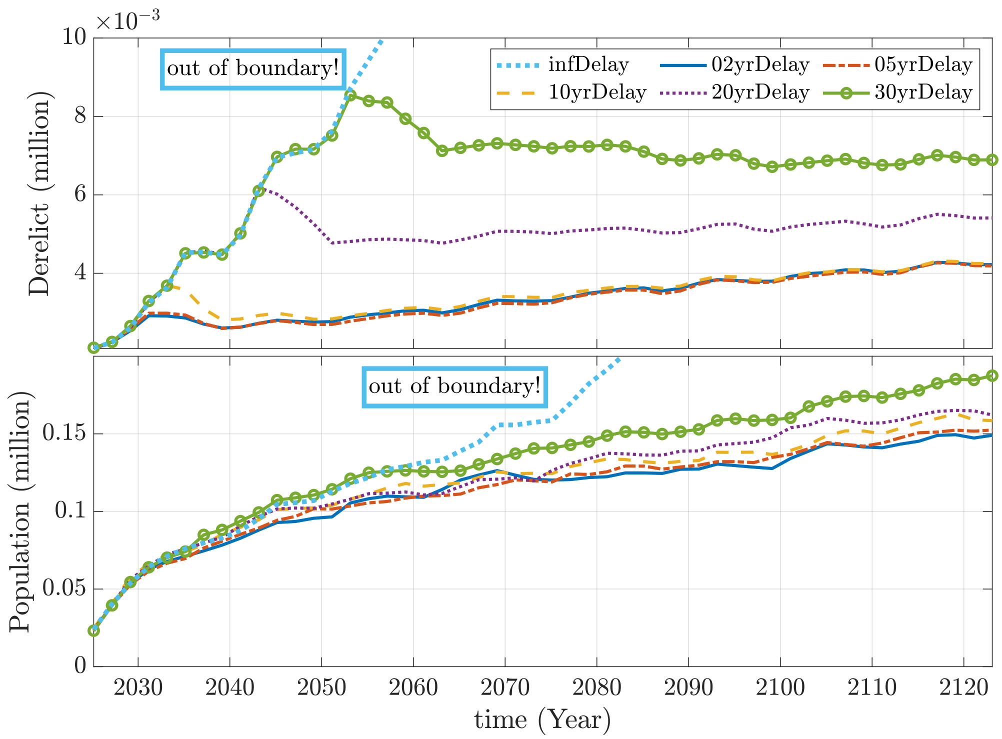

Fig. 1: Comparison of derelict (top) and total population (bottom) across scenarios of various delay in PMD improvement. The case of keeping the same PMD is noted as infDelay and its growth quickly goes out of boundary for the cases comparing to the the rest.

2.2 Collision Cost

Collision cost comes directly from counting the number of active satellites (either being part of a constellation or not) involved in the appearance of catastrophic collisions throughout the evolution of the environment. Collision cost of different types of objects comes from Table 1. Beside referring the raw cost data from [4], Operator Class is also defined in [4]. The definition of Commercial Large Constellation is Starlink and OneWeb. These objects are considered megaconstellation and are assigned a constellation flag in MOCAT-MC. Commercial Medium Constellation in [4] involves Globalstar and Iridium which are labeled as satellite in MOCAT-MC. Those satellites tend to be humongous thus we use a weight threshold of 1000kg to classify them. Commercial Small Constellation in [4] involves HawkEye 360, Planet SkySat, Blacksky Global, etc.. They are labeled as satellite in MOCAT-MC as well. Those satellites weight typically more than 100kg so we use a criteria of between 100kg and 1000kg to define similar satellite in MOCAT-MC. The last but the least class in [4] is CubeSat/SmallSat. We assign a satellite to be in this class when its weight is less than 100kg. The classification and association are not referring to NORAD ID in this work as, although NORAD ID could be used to refer satellites in known scenarios, when future launching is involved, it would loss its validation. And as our simulation focuses on the policy impact on the future space environment, it is of more advantage if we choose the criteria described to investigate future collisions as the weight is typically associated with their investment and satellites' cost. But further study on making correlation on determining a collision cost could be one of the future directions.

Classification in MOCAT-MC	Operator Class in [4]	Cost Per Collision
Satellite weight $>$ 1000kg	Commercial Medium Constellation	\$20,000,000
100kg $\leqslant$ Satellite weight $\leqslant$ 1000kg	Commercial Small Constellation	\$3,000,000
Constellation Satellite	Commercial Large Constellation	\$1,000,000
Satellite weight $\leqslant$ 100kg	CubeSat / SmallSat	\$300,000

Table 1: Cost per collision definition in MOCAT-MC. Constellation Satellite has its own unique flag in MOCAT-MC and it is equivelant to commercial large constellation. MOCAT-MC consider the rest as satellite even tho they appear to be considered as both constellation and cubesat/smallsat in [4]. Weight criteria is used to assign object types in those cases.

We use multiple MOCAT-MC simulations and their difference to capture the chaotic nature of space environment prediction. We show the case of a 10-year delay in PMD policy implementation in Fig. 2. Despite the general trend of increasing collisions, which has been the case in numerous simulation in [10], the evolution and the number of collision from each scenario are different. We count the number of accumulated collisions in each scenario. Then by using Table 1, the cost of collision $C_{\otimes}$ are found from Eq. 1.

$$C_{\otimes}(t) = \sum_{i=1}^{i_{max}} \sum_{p=1}^{p_{max}} \otimes_{i,p}(t) C_{\otimes,i}. \tag{1}$$

$C_{\otimes}$ ((read as C O-cross)) is the total cost of collision; $\otimes_{i,p}$ for $i_{max} = 4$ represents the number of type-1, -2, -3, or -4 objects (the types corresponds to the four types listed in Table 1) for one of the objects involved in a collision; we use $p_{max} = 2$, assuming a simultaneous collision among 3 objects or more does not happen. $C_{\otimes,i}$ represents the cost of catastrophic colliding of the specified type-i object.

A single MC run is deterministic, however the realistic prediction over the evolution of the space environment could only happen with multiple MC runs considering the chaotic nature of the interaction among space objects. Involvement of multiple MC run is important and so is the combining of the cost from multiple MC runs. The probability of each scenario happening in our simulation is calculated by the histogram distribution shown in Fig. 2. This distribution is calculated with a bin size of 10 over the final accumulated number of collision. Risk is defined as the cost times the probability of the scenario happening by Eq. 2.

$$Risk(t) = C_{\otimes}(t) P(i), \tag{2}$$

where $P(i)$ is the probability of a single scenario, we use the probability of the final population to represent the probability of a single scenario in multiple MC runs, $C_{\otimes}$ is the cost of collision. From the risks of different scenario, using a normal distribution kernel, we compute the cost density distribution (*Risk*) shown in Fig. 3.

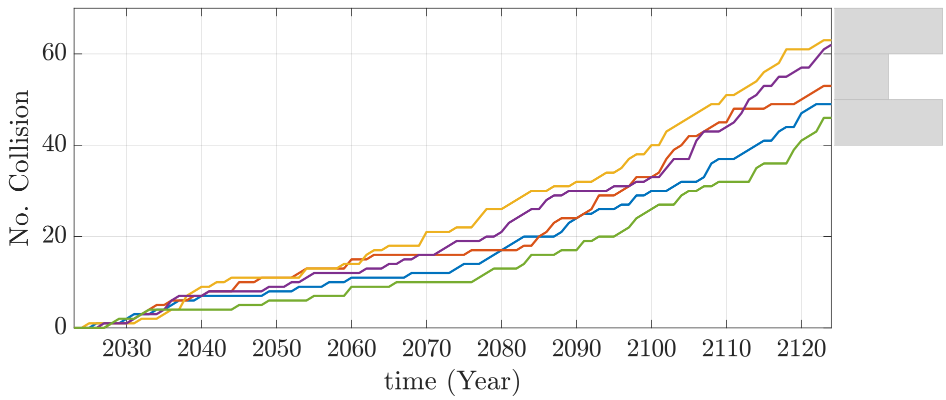

Fig. 2: Multiple runs of the 10-year delay in PMD policy change. 5 evolutions starting from the same initial conditions are shown. The final objects are used to create a histogram distribution of the multiple runs to represent the probability of different final population and different scenarios.

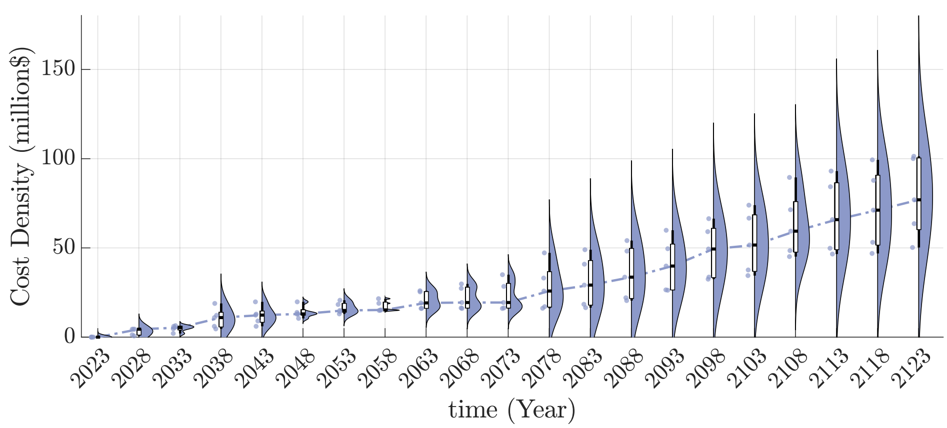

Fig. 3: Cost density distribution evolution in the 100 year horizon. Cost density is calculated from counting all the risks from different evolutions. The policy implemented is a 10-year PMD change delay.

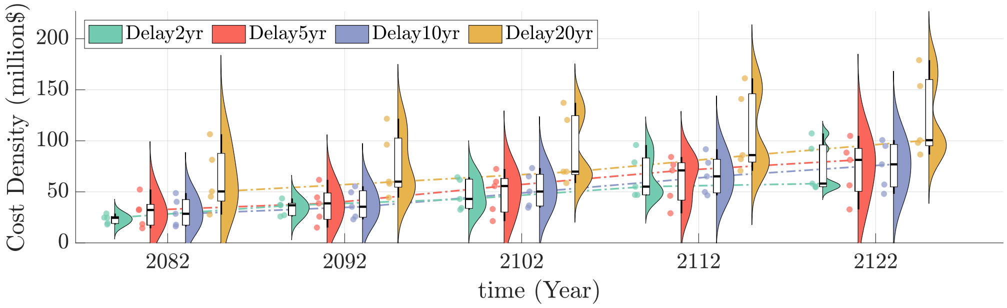

Fig. 4: Collision cost density distribution evolution in the 100 year horizon. The policies implemented are for 2-year, 5-year, 10-year, and 20-year delay policies. Cost density is calculated from counting all the risks from different evolutions under each policy.

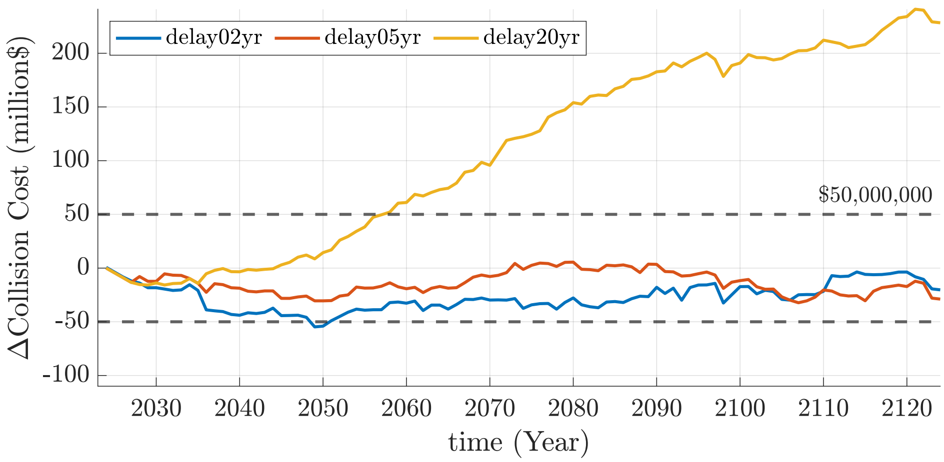

Fig. 5: Difference in the collision cost for different policies comparing to the baseline of 10-year delay in PMD change. A value above 0 means more expensive while a lower one means a gaining if the policy is implemented.

When different policies are implemented such as a 2-year delay, a 5-year delay, and a 20-year delay in PMD change, the different cost distributions in the later part of the evolution are shown in Fig. 4. Different policy not only give a general difference in the magnitude but also different performance in terms of diverging evolutions. The 2-year delay has a clear diverging performance towards the end of the evolution and the 20-year delay has a similar diverging performance but a general larger distribution overall. The 5-year delay and 10-year delay are generally more centered. Besides, the cost density of 2-year delay locates almost relatively always at the lowest, following by a 5-year delay, 10-year delay, and 20-year delay. These corresponds to a reduced derelicts in the total evolution.

The total cost of collision for each scenario is the summation of all the cost density from different scenarios in a single policy implemented case. When we use 10-year delay as the baseline, we can get the difference of cost between different policies as shown in Fig. 5. The 20-year policy results in a more expensive value for the total collision cost. This means comparing to a 10-year policy delay, a 20-year policy delay would result in a much more expensive collision scenario in the evolution. In the meantime, both 2-year and 5-year collision cost evolutions are actually cheaper than the 10-year one. This means if the policy change in PMD can be made earlier, benefits would be brought to the overall space collision cases. We also notice that although those scenarios are cheaper comparing to the baseline, the difference is roughly within $50 million. This means if the $50 million collision costs is acceptable, it would not harm too much by delaying the PMD change by 10-year. But delaying it to 20-year would largely harm the space environment and brings a large loss to the space economy. So within the scenario tested here: a 2-year, 5-year, 10-year, and 20-year delay in PMD change from 0.9 to 0.99, we can conclude that 10-year delay would be the last affordable timeline given a $50 million affordable buffer for collision cost.

2.3 Approach Cost

Approach cost are calculated by the combination of the warning cost and operation cost. We used the same threshold for different approach classification as in [4]. A warning is defined as an approach that comes within 3 km of another object. Then a conjunction data message indicating a warning will prompt the spacecraft operator involved in the message to perform some sort of actions that likely requires some amount of labor time while likely assisted by algorithms, thus resulting in an averaged cost of $3. A maneuver is defined as an approach within 1 km happens and this will prompt the spacecraft operator to perform an avoidance maneuver. As defined in [4], such scenario will result in a combination of labor and operation loss, thus resulting in $696 per approach. These values are also used as the default distances used by the NEAT tool [5] and appear to be reasonable approximations as indicated by [4].

Approach Action Type	Approach Action Threshold	Cost Per Approach
Warning	Approach Distance < 3km	$3
Maneuver	Approach Distance < 1km	$696

Table 2: Cost per approach definition in MOCAT-MC.

Cube method is employed in MOCAT-MC for approach and collision determination [11]. It combines probabilistic collision with deterministic values. With a $10 \times 10 \times 10$ km^3 cube size, when cube method and MOCAT-MC gives a counting of 1 for a close-approach, it means, from the thresholds given in Table 2, we are at a combined state of 1/1000 chance of taking maneuver action and $3^3/1000 = 27/1000$ chance of taking warning action. So the approach cost in MOCAT-MC is generalized as Eq. 3.

$$C_{\varnothing}(t) = \varnothing(t) \sum_{i=1}^{i_{max}} \frac{D_i^3}{r_{cube}^3} C_{\varnothing,i}. \tag{3}$$

$C_{\varnothing}$ represents the total cost of approach; $\varnothing$ is the number of approach in MOCAT-MC environment; D_i for $i_{max} = 2$ represents the distance threshold for first kind approach (Warning) or second kind approach (Maneuver) in Table 2; $C_{\varnothing,i}$ for $i_{max} = 2$ represents the cost per first kind approach (Warning) or second kind approach (Maneuver) in Table 2; and r_{cube} is the cube resolution in MOCAT-MC's cube method.

MOCAT-MC records the discrete snapshots of the space environment and record the corresponding approaches at those moments. To estimate an infinitely small discrete snapshots and the corresponding approaches we need an infinitely small discrete time step for realistically propagation and counting. However that will be both computational infeasible and unnecessary. Here, the approach cost are extrapolated from 5-day snapshot, 10-day snapshot, 15-day snapshot, 20-day snapshot, 25-day snapshot, and 30-day snapshot as shown in Fig. 6. The policy implemented is the 10-year PMD delay. We validate the extrapolation technique by testing on the 10-day snapshot extrapolation and showing that it could get the correct values relatively accurate. Comparing to collision cost, the absolute value in approach cost is not as high.

When we use 10-year delay as the baseline, we can find the difference in the total cost in those difference in delaying 2, 5, 20 years. The difference in the total approach cost is shown in Fig. 7. We could find that most of the difference stay relatively close to 0. 5-year delay in policy implementation sticks out probably due to the randominess involved in the process. If we use a buffer amount of $5000, we could see that the different delay policies are generally within the buffer. So to answer the “how late is too late” question in the approach cost, we could likely find the answer to be not too amusing that delaying PMD would not necessarily result in a lot difference in the approach cost.

3. LRCI (LEARNED REALITY-CHECK INDEX)

Modeling future space environment evolution requires the involvement of human factors. Speculation on specific human actions into the future are highly unrealistic. The expected action may or may not happen in the first place. Then, in the case of the action happening, the exact time may not be at the expected time. In addition, there are multiple aspects of human factors on space environment. The intrinsic connection within the human factors would make predicting specific human actions highly chaotic and unpredictable in large. Predicting future space environment

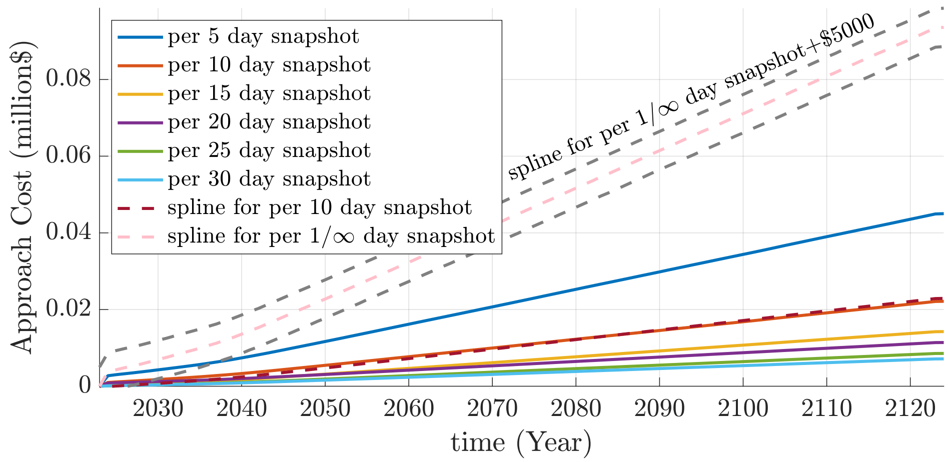

Fig. 6: Difference in the collision cost for different policies comparing to the baseline of 10-year delay in PMD change. A value above 0 means more expensive while a lower one means a gaining if the policy is implemented.

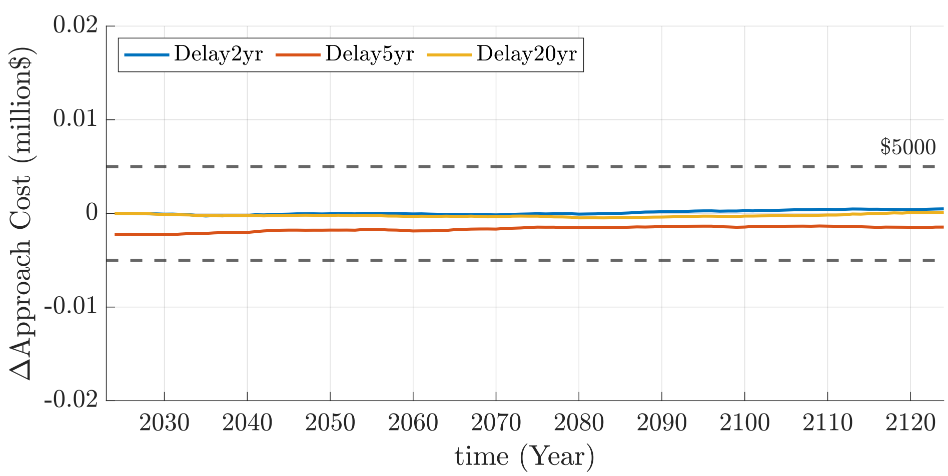

Fig. 7: Difference in the approach cost for different policies comparing to the baseline of 10-year delay in PMD change. A value above 0 means more expensive while a lower one means a gaining if the policy is implemented.

could take another perspective on involving human factors. Following an assumption that human factor is not random, we could extract it directly from the real data. Given an initial state of the space environment, the nature evolution of space environment without human interaction could be simplified as a go-as-planned propagation following the physical laws. At the end of the propagation, the propagated state is a state that would have zero human impact during the propagation time period. The real state, when available, could be extracted as a reality-check. The real state is a state that would contains the human impact during the propagation time period. The difference between the real state and the propagated no-launch state, i.e. the reality-check, results from the accumulation of the human factors during the propagation period. Taking a simplified linear growth modeling, the human factor for the reality-check is the traingle area created by the initial state, the no-launch propagated state, and the real state, shown in Fig. 8.

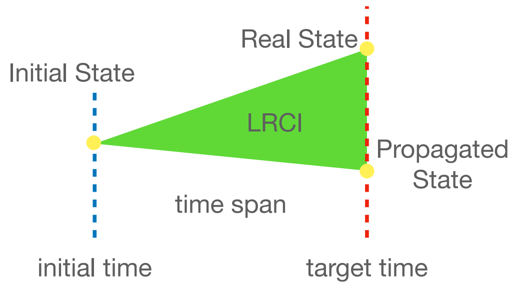

Fig. 8: LRCI concept.

If SR ratio defined as in Eq. 4 is of interest, LRCI can be calculated by Eq. 5. LRCI can be both positive and negative. A positive LRCI indicates a positive effect on SR. A negative one indicates a decreasing effect on SR. LRCI is a general framework index and it extends beyond SR. Any difference between real state and propagated state together initial state could be used to form an LRCI, giving the assumption that the triangle approximation for the diverging effects of the initial state is reasonable. Notice that we should not constrain the evolution to be linear between target time and initial time.

SR represents the utility versus the total consumption of the space environment so we choose to demonstrate LRCI with SR. A SR value of 1 means that every space object in space is a human active satellite; and 0 means that no active human satellite exists in the space environment, the ultimate silence. SR value should have a natural trend of going down. Because if we stop launching space objects right now, SR value should go to 0 in the future.

$$\mathrm{SR} = \frac{S}{T}, \tag{4}$$

where S represents the number of active satellites; T represents the total number of space objects.

$$LRCI = \frac{1}{2}(\mathrm{SR}_r - \mathrm{SR}_p)\Delta t, \tag{5}$$

where SR_r represents the real SR state at the target time; SR_p represents the propagated SR state at target time from the initial state; and Δt is the time span between initial state and propagated state.

3.1 Analysis on the historical LRCI time series

Monthly information based on TLE are extracted from SpaceTrack to create the real state SR to check with the propagated state SR. Four horizons are considered: 1-year, 2-year, 3-year, and 5-year. The time horizon is counted from the start of an initial state. The propagation time span is the length of the horizon. LRCI value is associated with the initial time. Monte Carlo running is conducted in the no-launch scenario with a different 10 MC runs and 30 MC runs. The LRCI for the starting time year 2000 is shown in Fig. 9. With different horizons, the length of LRCI time series will differ with the same final time. In Fig. 9, the monthly TLE information ranges from January 2000 to June 2024. With June 2024 being the latest real information, a 1-year horizon LRCI time series yields a time series from January 2000 to Jul 2023; 2-year horizon LRCI time series ranges from Janauray 2000 to June 2022; 3-year to June 2021; and 5-year to June 2019. This corresponds to the different length of time series for different horizons shown in Fig. 9. When multiple MC runs are implemented, the median values from the multiple corresponding LRCI values are picked. There are little difference in the 10-MC LRCI time series of various horizons and the 30-MC cases.

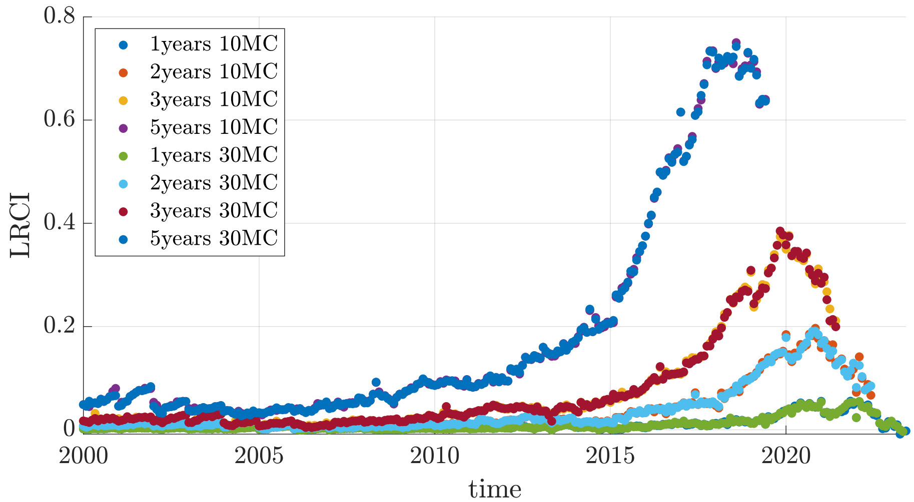

Fig. 9: Multi-scale LRCI timeseries from MOCAT-MC and TLE + DISCOS data.

The absolute values of LRCI count for the accumulation of the human factor in different timespans. The absolute scale shown in the multi-scale LRCI time series in Fig. 9 can be directly applied to conduct multi-scale prediction and mixture. A normalization taking into account the time span difference between multiple horizons is necessary to compare the extracted information. Area of Similar Triangles Theorem is implemented to normalize LRCI into a single unit year scale. According to the theorem, if two triangles are similar, then the ratio of their areas is equal to the square of the ratio of their corresponding side lengths. This means for a x-year LRCI, to normalize it to a unit year LRCI, the following calculation Fig. 6 needs to happen. A normalized LRCI represents a linearly scaled human factor according to time. And the situation of constant human factor should yield a rather constant normalized LRCI. While a change in the human's influence on the space environment would yield a difference. The normalized LRCI time series is shown in Fig. 10 with the normalization operating denoted by $\mathscr{N}(\cdot)$.

$$\mathscr{N}(LRCI) = LRCI \times \frac{1}{x^2} \tag{6}$$

For the normalized LRCI evolution shown in Fig. 10, before 2015, LRCI from different timescales match with each other. Diverging of the 5-year LRCI and the rest starts at around year 2015. This indicates some action in the 5-year horizon at those dates but out of the 3-year horizon from the same dates are making a significant difference. Similarly, diverging of the 3-year LRCI and the rest starts at around 2018. This indicates a similar case as in the 5-year LRCI divergence scenario: a significant pattern change has happened comparing to the 1-year and 2-year horizon versions. Another pattern difference exists after year 2020. The 3-year time series locates below 2-year and 1-year time horizons. This indicates a continuous pattern change in the more recent years. More importantly, Fig. 10 shows that human factor has peaked in the years between 2020 to 2023 and is decreasing. It is even possibly becoming negative.

The physical meaning of the divergence is straight-forward. The bump in around 2015 in the 5-year horizon means at year 2015, if a prediction is made about future active satellite in a the 5-year horizon, i.e. for year 2020, using 1-year, 2-year, or 3-year horizon will result in an underestimation. In general, if the normalized longer-horizon LRCI locates above a normalized shorter-horizon LRCI, it means during the time difference between the two horizons, a intensifying human factor on space environment takes place. On the contrary, if a normalized longer-horizon is below a normalized shorter-horizon, there is a mitigating human factor on space environment during the difference horizon difference. Notice that, as LRCI represents an accumulated human factor over the time span, the normalization is essential for the conclusions to be made.

As such, during 2020 to 2023, the decreasing ranking of 1-year, 2-year, and 3-year horizon time series indicates, for example, at year 2021, if a prediction is made about the future active satellite ratio in the 3-year horizon, i.e. for year

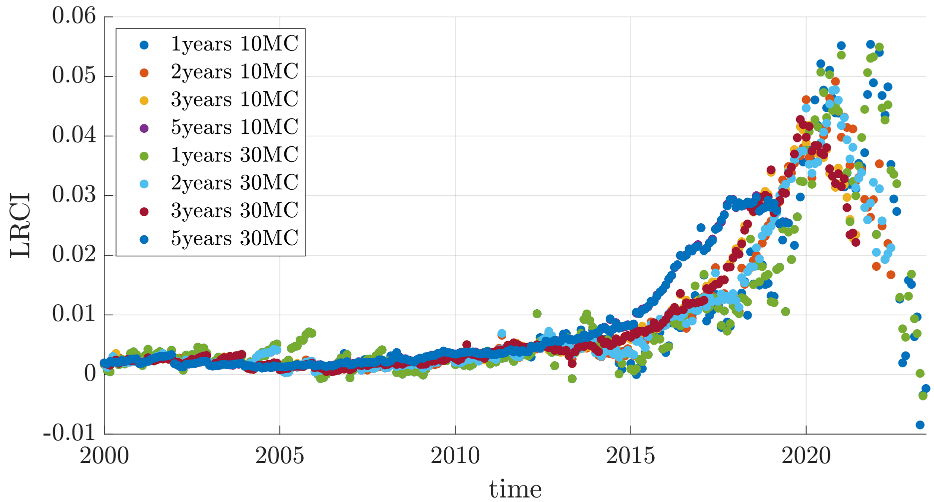

Fig. 10: Multi-scale normalized LRCI timeseries from MOCAT-MC and TLE+DISCOS data.

2024, using 2-year will result in an overestimation, and using 1-year will result in an even larger overestimation. The decreasing ranking of the normalized 1-year, 2-year, and 3-year horizons indicate a continuously decreasing "speed" on the increasing SR ratio.

Moreover, the peaking and decreasing in the time series in the recent years is of great significance. Besides directly indicating a continuous decreasing "speed" in the time evolution of SR, the trend and some data points indicate a possible negative "speed" for SR. However, the meaning of a negative "speed" does not equal to superior human performance. It only means a non-positive human factor on SR. As this comes from the definition of SR, the increasing creation of debris in the denominator could also drag down SR value and show as a negative LRCI. The case of Kessler syndrom would corresponds to a negative LRCI as in the assumption of Kessler syndrom, no more active satellites are launched and creation of debris from collision will continue to increase denominator in SR.

The causal factors for the two LRCI divergences around year 2015 and 2020 mentioned above could be complicated. The actually correlation would be impossible to single out considering the changing scenarios of launching actions and space sustainability movement. To identify specific activities contributing in the pattern shift, from the definition of LRCI and their corresponding timespan, the following conditions should be satisfied.

1. **Within the 5-year horizon of 2015 but outside the 3-year horizon.**
2. **Within the 3-year horizon of 2018 but roughly outside the 1-year and 2-year horizon.**

The following programs are highlighted with their correlation with the two requirements that would suffice to be influential for the two divergence.

- **SpaceX Starlink Program**: The first 60 Starlink satellites launched on May 23, 2019, aboard a SpaceX Falcon 9 rocket. By the end of 2021, SpaceX had launched over 1,800 Starlink satellites. **May 23, 2019 is within the 5-year horizon of 2015 but out of the 3-year horizon. More over, it is within the 3-year horizon of 2018 and roughly out of the boundaries of the 1-year and 2-year horizon.**
- **OneWeb Satellite Constellation**: OneWeb started launching its constellation of broadband internet satellites. They launched their first batch in February 2019 and continued with several launches through 2020. **February 2019 also satisfies the two conditions mentioned.**
- **Amazon's Project Kuiper**: Amazon announced plans for Project Kuiper, aiming to deploy a constellation of 3,236 satellites. Kuiper's launching did not happen until late 2023. Yet, we do not have enough data to find a pattern to significantly single out its influence yet.

Note that LRCI indicates a combined human factor for space environment directly learned from the data. The mentioned programs indicate a change in launching performance in the latest space development, but the human factor influence change exceeds only launching performance. The raising awareness of space sustainability, space congestion, and intentional communication between satellite operators and space surveillance providers are all well within the boundary of contributing to the change in the LRCI. The combined factor results in the divergence in the growing trend of LRCI, and to list a few:

- **Long-Term Sustainability Guidelines**: In June 2016, the UNOOSA (United Nations Office of Outer Space Affairs) Committee agreed to a first set of guidelines for the long-term sustainability of outer space activities.
- **Space Policy Directive-3**: Officially issued in June 2018, preparatory work and discussions in the preceding years (2016-2017) laid the groundwork for this directive. It focuses on enhancing space situational awareness (SSA) and improving data sharing for collision avoidance.
- **Space Situational Awareness (SSA) Program**: ESA's SSA program aimed to enhance Europe's capabilities in tracking space debris and predicting potential collisions. The programme included efforts to increase data sharing and cooperation with other spacefaring entities. In 2016, ESA expanded its SSA program to improve the tracking and prediction of space debris. This included initiatives to share data with other spacefaring nations and commercial entities to enhance collision avoidance capabilities.
- **OneWeb's Transparency Commitment (2016)**: OneWeb, in preparation for its large satellite constellation, committed to sharing its orbital data with other satellite operators and regulatory bodies to enhance transparency and collision avoidance efforts.
- **SpaceX's Licensing Agreements (2017)**: SpaceX worked with regulatory bodies like the Federal Communications Commission (FCC) to ensure compliance with space debris mitigation guidelines, including transparency in reporting satellite positions and maneuvers.

The investigation over the decreasing speed in the time evolution of SR indicated by the decreasing ranking of the normalized 1-year, 2-year, and 3-year horizon LRCI time series involve looking into the recent years' commitment and activities. The connection, as mentioned above, would be at best a conceptually causal one due to the complicated intrinsic connections. Some important cases are listed here just for reference including not only technical but also political and economical in a global sense.

- **OneWeb Bankruptcy (2020)**: OneWeb's financial troubles and subsequent bankruptcy delayed the launch of its satellite constellation, affecting the overall growth rate of satellite deployments.
- **FCC Rule Changes (2020)**: The FCC implemented new rules requiring satellite operators to provide more detailed plans for debris mitigation, increasing the complexity and length of the licensing process.
- **Global Factors**: Sanctions imposed on Russia affected the availability of Russian launch vehicles for international customers, leading to delays and cancellations of planned satellite launches. Besides, the COVID-19 pandemic led to widespread disruptions in manufacturing and supply chains, affecting the production and launch schedules of satellites.

4. SPACE ENVIRONMENT SR PREDICTION

To apply LRCI in SR prediction, we illustrate the concept here with three examples of different target dates. With a target date specified, a 1-year, 2-year, 3-year, or 5-year look-back horizon is determined to apply the corresponding multi-scale LRCI. A determined look-back horizon corresponds to a different initial time. The initial time decides both the initial SR value and the initial condition for MOCAT-MC to propagate as no-launch scenario like in Fig. 8. The SR values at the end of the propagation are calculated. According to the LRCI and the corresponding look-back horizon, the increase on top of the SR values are determined.

The random performances of the no-launch scenario result in different final states and SR values. With the same LRCI corresponds to the initial state and time span, multiple SR values for a given look-back horizon are calculated for a target time. For each of the time span, i.e. 1-year, 2-year, 3-year, and 5-year, different initial states and time spans are selected to propagate to the same target date. Figs. 11 to 13 illustrate the prediction of three different target dates' SR values. Multiple triangles similar to the conceptual triangle in Fig. 8 are shown on the left of Figs. 11 to 13. The triangles starting from the same initial state represents the different Monte Carlo runs of the no-launch scenario. And the triangles at different initial times use LRCI values of different time spans. The final SR values, always shown on the right of Figs. 11 to 13, from different initial states and time spans are all for the specified target time. There are overlapping and concentrations on those different SR values of different time spans. The variance in the SR values represents the varying possible future to the nature of statistically predictive future that space environment has.

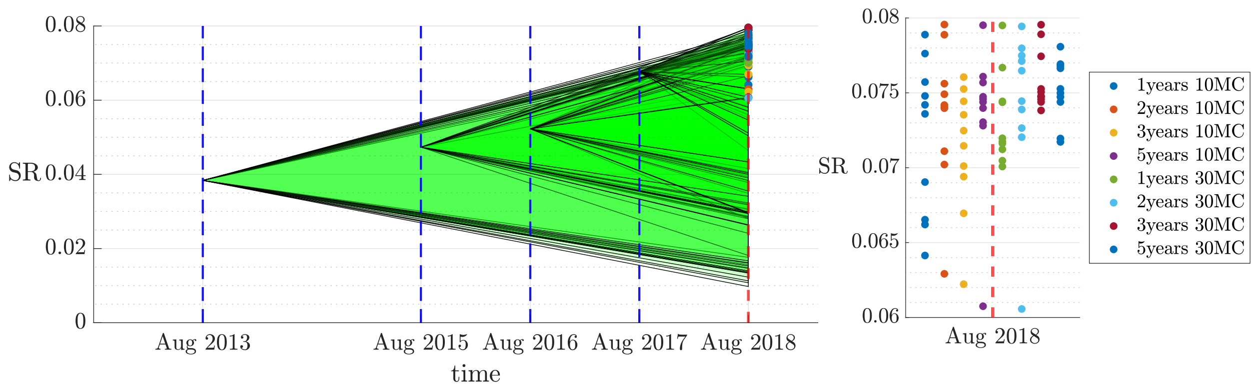

Fig. 11: Multi-scale SR prediction of target date 2018-08-01.

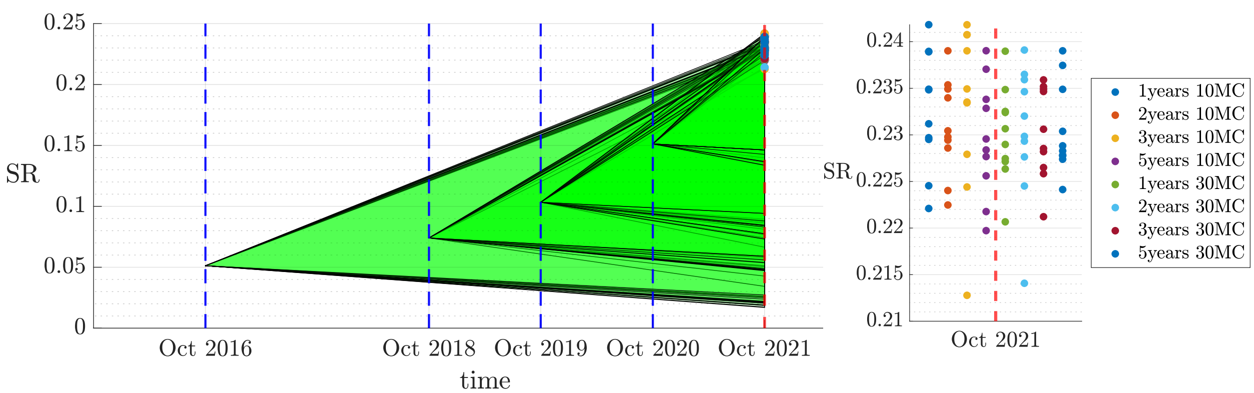

Fig. 12: Multi-scale SR prediction of target date 2021-10-01.

The way to extend the SR prediction from a single target date to the future SR time series prediction requires a integration of the time series extrapolation. Given a LRCI time series, the unknown future LRCI values need to be extrapolated based on the previous LRCI evolution. Two extrapolation are implemented here. One is to fit an logistic-exponential (LogExponential) curve to the time evolution. The LogExponential function is used in modeling space launch activities in [20]. The LogExponential curve follows Eq. 7. t_0 is the start time of the time series and (n, A, b, c, d) are the free variables.

$$LRCI(t) = n + \frac{A \cdot \exp(d(t-t_0))}{b + \exp(-c(t-t_0))}. \tag{7}$$

The second case is to fit a 7th-order Gaussian curve, which can be expressed in Eq. 8. t_0 is the start time of the time series, and a_i, b_i, and c_i are the amplitude, mean, and standard deviation parameters of each Gaussian component, respectively.

$$LRCI(t) = \sum_{i=0}^{7} a_i \exp\left(-\frac{(t-t_0-b_i)^2}{2c_i^2}\right). \tag{8}$$

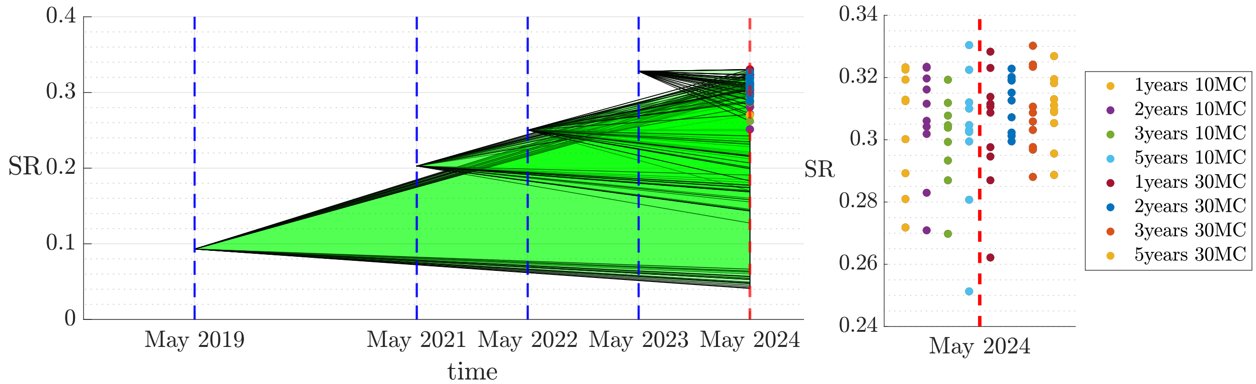

Fig. 13: Multi-scale SR prediction of target date 2024-05-01.

Time series extrapolation would yield future LRCI values for the same time span. Similar to the cases shown in Figs. 11 to 13, for each given target time in the predicted series, the SR values could be calculated from Monte Carlo simulation. The complete data extrapolation of one year into the future at an assumed end of the time series and future SR value predictions are shown in Figs. 14 and 15.

The first case of predicting future SR time series between May 2022 to April 2023 assumes the last LRCI data is from April 2022. The upper panels in Fig. 14 shows the LogExponential extrapolation (left) and 7-order Gaussian extrapolation (right) and the true LRCI. Notice that we are conducting this case as a test to understand the prediction mechanism for LRCI. We could see, from the lower panel of Fig. 14 that the multi-scale time span prediction of LRCI time series would yield a distributional SR result similar to the single target date case. And more importantly, the true evolution of SR locates in between the predicted SR distributions. This is caused by that the real LRCI is in between the two extrapolation. To great interest, we also notice that the LogExponential prediction produces an underestimation and 7-order Gaussian prediction produces an over estimation. These two predictions conveniently put the real LRCI evolution in the middle resulting in that the real SR time series is between the two distributional time series created by the two extrapolated LRCI time series.

The second case predicts the SR time series between May 2024 and April 2025. Almost one year ahead of future when the paper is created and June 2024 data is the last one the authors could get. Following the same procedure done in case one, the two extrapolations are shown in the two upper panels in Fig. 15. The prediction of distributional SR values are shown in the lower panel in Fig. 15. When putting the real SR values from May 2024 and June 2024 onto the predicted distribution, we could see that they do land within the distributional SR values.

The future SR time series prediction shows an increasing range for the distribution and an upper lifting trend in general. This means that future active satellite will likely take increasing ratio in the total number of space objects. The human factor on space environment is increasing the intensity of space environment, with the uncertainty represented by the distribution.

5. CONCLUSION

This paper provides the first full-scale temporal analysis framework on policy scenario and also proposed LRCI (learned reality-check index), an abstract index for human factor quantification in a given period of time. The cost framework is provided in terms of collisions and approach. The stochastic nature of space environment evolution is integrated in the cost framework. We implemented the framework with MOCAT-MC which provides Monte Carlo simulation of the space environment. In addition, we propose a method to approximate the true approach cost ($1/\infty$-day continuous snapshot) from computational feasible discrete snapshot of the approach cost. Moreover, we provide the workflow of evaluating policies of different temporal implementation. The analysis is conducted in terms of the cost of time delay of implementing PMD policy and providing the first clear answer between several choices on the question of *how late is too late* for space policy to take in forms and shapes, together with the reasoning behind their corresponding cost of the delay in implementation. On the other hand, we propose the general index LRCI on quantifying human factor from a temporal evolution perspective. Working with satellite ratio (SR), we provide the first

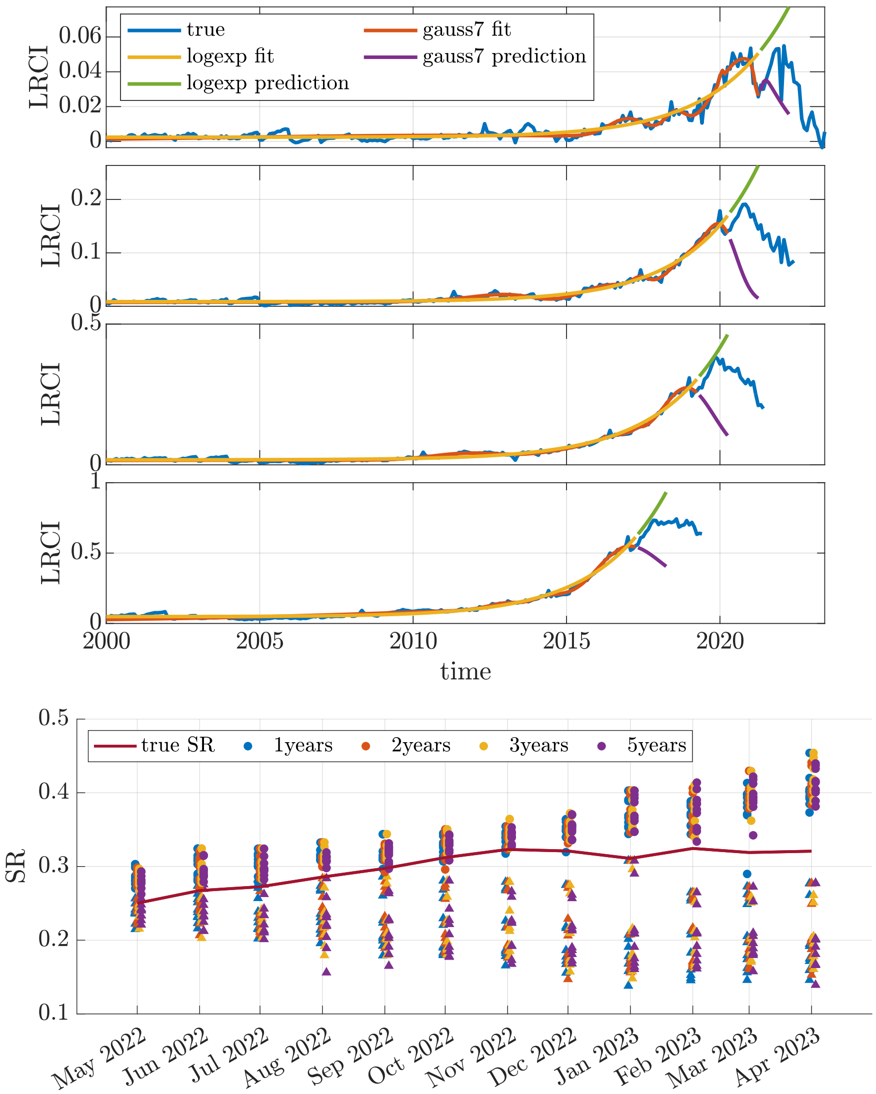

Fig. 14: Monthly SR prediction (lower panel) from LogExponential extrapolation and 7-order Gaussian extrapolation (upper panel) for one year starting from May, 2022. LogExponential and Gaussian extrapolations for each LRCI evolution, 1-, 2-, 3-, and 5-year from top to bottom, are independently implemented. SR prediction from LogExponential extrapolation is marked by circle and from Gaussian by triangle. Since the one-year time span from May, 2022 is also known, the real SR time series from TLE data are shown as well.

evaluation of human factor in space environment as a whole. We use LRCI to find the pattern shifts in the past evolution of space environment. And further we indicate some well-known facts that could contribute to the pattern shift in the process. Then, we provide a method to use the quantified human factor to predict the future of space environment. The method is verified by past evolution and we also use this method to provide prediction into the future.

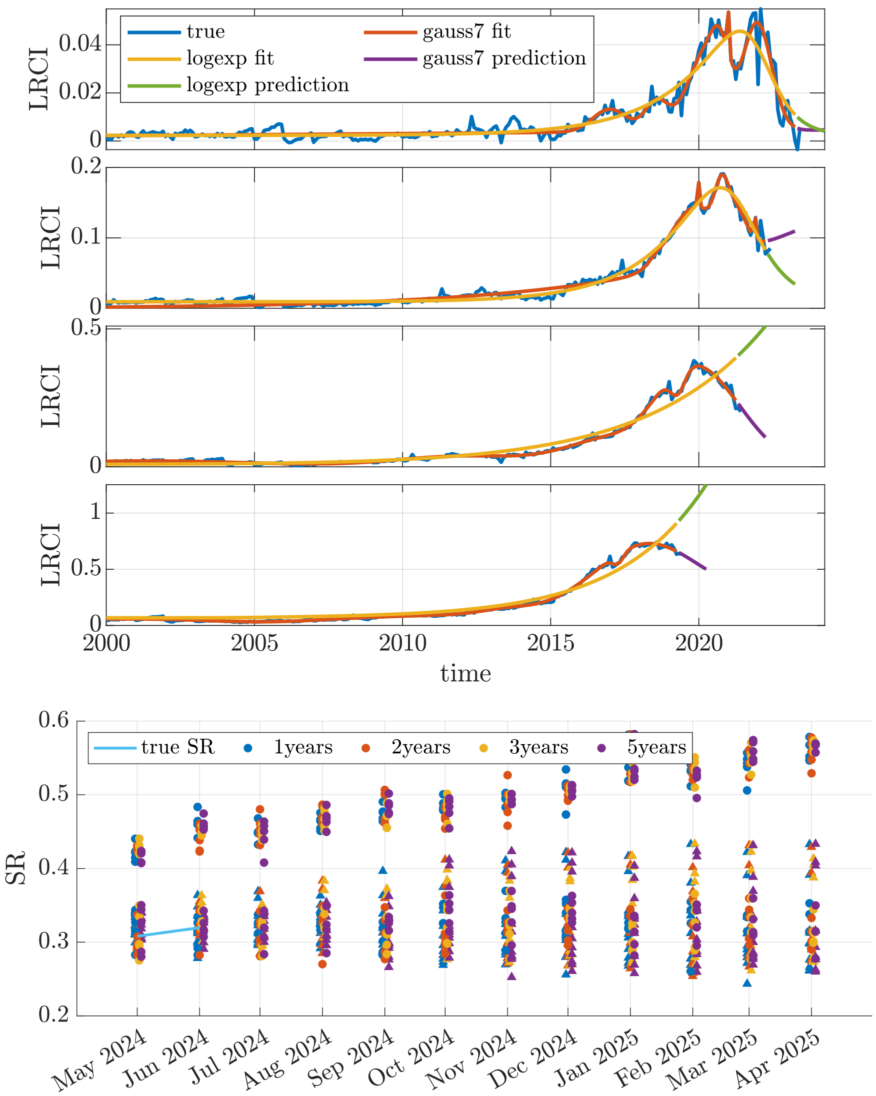

Fig. 15: Monthly SR prediction (lower panel) from LogExponential extrapolation and 7-order Gaussian extrapolation (upper panel) for one year starting from May, 2024. LogExponential and Gaussian extrapolations for each LRCI evolution, 1-, 2-, 3-, and 5-year from top to bottom, are independently implemented. SR prediction from LogExponential extrapolation is marked by circle and from Gaussian by triangle. Since only partial time span from May, 2024 is known (May and June SRs are available when the experiment is conducted.), the partial real SR time series from TLE data are shown as well.

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