

Relationship Between Earth-Moon Distance and Tides

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Abstract. For residents and fishermen in coastal cities, tidal phenomena are a dangerous existence, and for tidal power stations, tidal phenomena will bring clean energy to them. For the formation of tidal phenomena, the most closely related is the distance between the Earth and the Moon. Therefore, this paper collects the tides and Earth-Moon records in New York in 2022, and performs data visualization operations on the data, and uses STL (Seasonal Decomposition of Time Series), MSTL (Multiple Seasonal-Trend Decomposition using Loess) models to predict, so as to explore the concern between the Earth-Moon distance and tides. Monthly seasonality is found from our analysis as well as the general trend which follows the research results regarding to earth moon distance variation. The results show that when the Earth is close enough in the Moon, the tides are more pronounced.

Keywords: SLT; MSTL; Matplotlib; Prediction.

1. Introduction

Tides, the periodic rise and fall of sea levels, have been a subject of scientific curiosity and study for centuries. These natural phenomena are primarily driven by the interplay of the Earth, Moon, and Sun's gravitational fields. The intricate dance of these celestial bodies, combined with Earth's rotation, results in the complex tidal patterns observed along coastlines worldwide [1]. The Moon, being our closest celestial neighbor, plays a pivotal role in generating tides. As the Moon orbits the Earth, its gravitational pull causes the oceans to bulge outwards, creating a high tide. Conversely, areas positioned away from this bulge experience a low tide. This gravitational interaction is not constant, due to the variable distance between the Earth and the Moon. The Moon's orbit around the Earth is elliptical, leading to variations in the Earth-Moon distance. When the Moon is closest to the Earth, a position known as perigee, its gravitational influence is stronger, leading to higher tides. Conversely, when the Moon is at its farthest point, or apogee, the tides are generally lower [2].

There are several types of tidal patterns, each influenced by the relative positions of the Earth, Moon, and Sun. The most common is the semidiurnal tide, observed in many coastal areas, especially those at mid-latitudes. Every lunar day (24 hours and 50 minutes), there are two high tides and two low tides according to this schedule. The two high tides and the two low tides are approximately of the same height [3]. Some regions, such as the Gulf of Mexico, experience a diurnal tide pattern, characterized by one high tide and one low tide each lunar day. Yet other areas, like the U.S. West Coast, witness mixed tides, which are intermediate between semidiurnal and diurnal, resulting in two unequal high tides and two unequal low tides each lunar day. Furthermore, the alignment of the Earth, Moon, and Sun leads to variations in tidal amplitude [4].

Tides have many effects on the environment and human activities. For example, tides can cause flooding in low-lying areas that can damage homes and businesses and cause erosion on beaches and other coastal areas. Additionally, tides can affect marine ecosystems by affecting the plant and animal species that thrive in the intertidal zone (the space between high and low tides). Tides also affect navigation in ports and other waterways. There are also significant benefits to predicting tides. Predicting tides can help fishermen to fish. For instance, to increase their financial investment and make better use of their time, professional fisherman learn to fish at periods of peak concentration and follow the tides. Tides can generate energy. Every 24 hours, there are two high tides and two low

tides. Tides' regularity and the swift input and outflow of water can provide renewable energy for coastal areas. Like rivers, hydroelectric facilities may use the flow of water to generate electricity. It lessens the strain that energy has on people.

In order to take advantage of tides and reduce potential loss caused by tides, many authors attempt to predict tides wave. For example, Advanced CIRCulation (ADCIRC) and Nonlinear Autoregressive Exogenous (NARX) neural networks are utilized in tides prediction [4,5]. Understanding the relationship between the Earth-Moon distance and tidal variations is crucial for tides prediction.

We collected data from 2022 for analysis, using Python to achieve data through API and CSV files. In this way, the data in the research are more comprehensive. That's good for using Python to do data prediction. The data introduction in this paper is placed in Section 2, the method description is placed in Section 3, and the results and analysis are placed in Section 4.

2. Method

2.1. Dataset

2.1.1 Water Level Data

The water level data comes from the National Oceanic and Atmospheric Administration, an official United States government website [1]. This website provides accurate information about the height of tides, it records every 6 seconds, which means there will be 600 pieces of data an hour. This website offers CSV files so that every month's data cloud be downloaded directly.

NOAA provides accurate tide and current data to aid in navigation and to keep people and the environment safe. The data is collected from a network of over 200 water level stations located along the coasts of the United States, including Alaska, Hawaii, Puerto Rico, the Virgin Islands, and Guam. The data is used by mariners, fishermen, and other ocean users to plan their activities and avoid dangerous conditions. The data is also used by scientists to study the effects of tides on the environment and to develop models that can predict future changes in sea level. NOAA's tide and current data is available online and can be accessed by anyone who needs it. The data is updated in real-time and is used by a wide range of organizations, including government agencies, research institutions, and private companies. By providing accurate and reliable data on tides and currents, NOAA helps to ensure the safety of people who work and play on the ocean.

2.1.2 Earth-Moon Distance Data

The Earth-Moon Distance data is able to download from comes from NASA [2] It provides JSON files which include the distance data. The data is recorded every 1 hour, so there will be 24 pieces of data a day. In the JSON file, it provides all the distance data for the entire of 2022.

The dataset of Earth-Moon Distance is achieved by Lunar Reconnaissance Orbiter (LRO), which has been operated since 2009. NASA uses LRO to research everything on the moon such as the shape of it or the hole on it. NASA also explores the orbit of the moon and the name phases of it.

2.2. Decomposition Method

2.2.1 Seasonal Decomposition of Time Series (STL)

A crucial step in time series analysis is the breakdown of time series data into its component parts. This deconstruction is essential for improving predicting accuracy as well as understanding the underlying patterns and behaviors of the data. As the world becomes increasingly digitized, the frequency of data collection has surged, leading to high-frequency datasets. Such datasets, which can range from daily to hourly or even minutely intervals, often exhibit multiple seasonal patterns. Recognizing and accurately decomposing this multiple seasonality is vital for various real-world applications.

Historically, Time series data have been broken down using a variety of techniques., such as the Seasonal Decomposition of Time Series (STL), X-11, X-12-ARIMA [7-9], among others. While the reliability and effectiveness of these technologies have made them useful in several applications, they

primarily cater to time series with a singular seasonality. However, with the advent of high-frequency data, the need for methods capable of handling multiple seasonal patterns has become paramount. Recent advancements have seen the introduction of methods tailored for this purpose, such as the Seasonal-Trend Decomposition by Regression (STR) introduced by Dokumentov and Hyndman and others by Wen et al. [10,11].

2.2.2 Multiple Seasonal-Trend Decomposition using Loess (MSTL)

Considering these developments, this study introduces the Multiple Seasonal-Trend Decomposition using Loess (MSTL). MSTL is an extension of the traditional STL procedure, designed specifically to decompose time series data exhibiting multiple seasonal patterns [12]. The primary motivation behind MSTL is to provide a decomposition method that is not only accurate but also computationally efficient, especially for long time series data. Preliminary evaluations on both synthetic and perturbed real-world datasets have shown that MSTL offers competitive results compared to other decomposition benchmarks, all the while maintaining a lower computational cost.

In essence, MSTL stands as a testament to the evolving landscape of time series decomposition, addressing the challenges posed by high-frequency data and multiple seasonality. Its introduction marks a significant step forward in the realm of time series analysis, offering researchers and practitioners an efficient tool to dissect and understand complex time series data.

2.3. Data Processing

The raw water-level data collected from NOAA website contains data point distributed randomly in every hour, which resulted in poor performance of STL and MSTL model in analyzing the data. Consequently, one data point per day is generated using the slicing method in Pandas to check the overall change in trend for data in 2022.

The raw Earth-Moon distance data is utilized without change.

3. Result

Fig. 1 shows the overall data visualization of raw Water Level data (upper image) and raw Moon Earth Distance (down image). Water-level recorded fluctuates around 0 meter to 1 meter. It's worth noticing that some outliers emerged in the middle of January and the end of the year where sudden increment of water-level occurred. It could also be observed that the trend of water-level follows certain pattern throughout the year. In the part of Moon Earth distance, the data fluctuated around 380000 kilometers, which follows the average Earth-Moon distance discovered, with a range of 30000 kilometers. Some patterns could also be observed. Specifically, the Moon Earth Distance change follows a repeating increasing and decreasing trend similar to sine/cosine curve.

Fig. 2 and 3 shows the detailed results of STL model on processed water-level data and raw Moon Earth Distance data. Despite the apparent seasonality extracted from this model, a trend change around a distance of 384000 kilometers with an interval of around 4000 kilometers is obtained. In Fig. 3, the general trend change is obtained as a line that increased quickly and decreased gradually in the year 2022. Combining the two-trend attained by the STL model it can be seen that the two data follows similar trend. Turning to the details, both decreased at the first two months and generally increased for about four months. After that, Moon Earth Distance decreased for about four months. However, in the same period, the water-level only dipped a little and plummeted at the end of the year.

Fig. 4 shows the result of MSTL model on the raw Earth-Moon distance data. In this case, a simple trend change curve is shown, peaked at around April to July in 2022. This corresponds to the change in apogee distance every month, furthest point from earth, calculated by authentic methods and calculator as well as innovative methods [13-15]. It also corresponds with the extent of fluctuation per month of raw data. Specifically, as the moon moved to the furthest point in the year in June, the raw data also illustrated the largest variation from beyond 360000 kilometers to above 4000000

kilometers. Fig. 5 shows the result of MSTL model on processed water-level data. It displayed a single increasing trend ranging from 0.55 to 0.65 meters in the year of 2022.

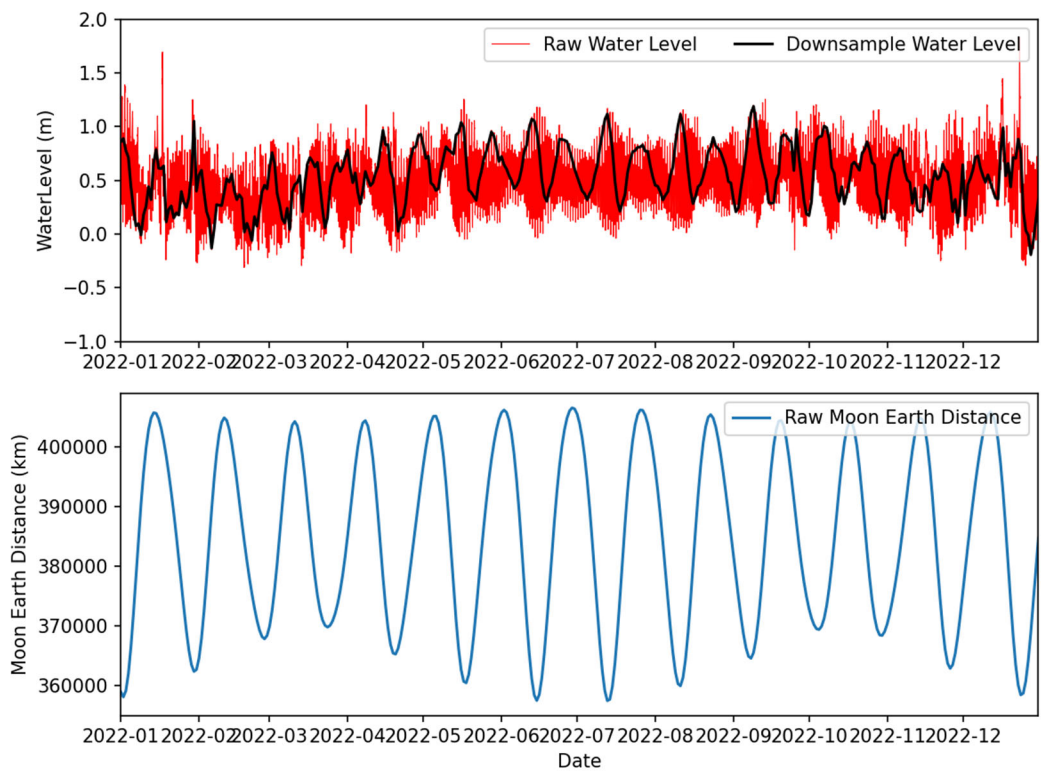


Fig. 1 Data Visualization: Water Level and Moon Earth Distance

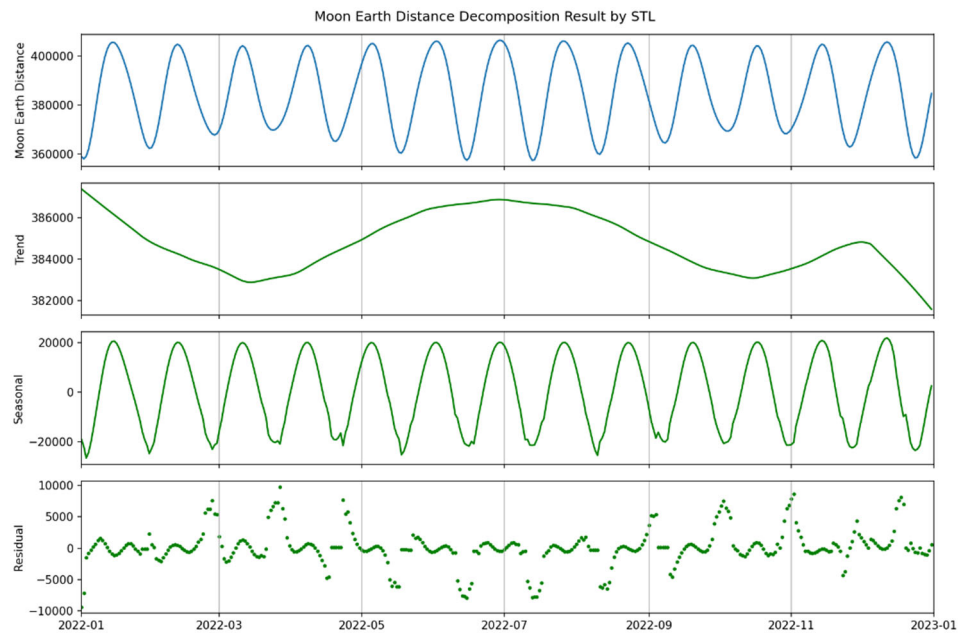


Fig. 2 Decomposition Result of Moon Earth Distance by STL

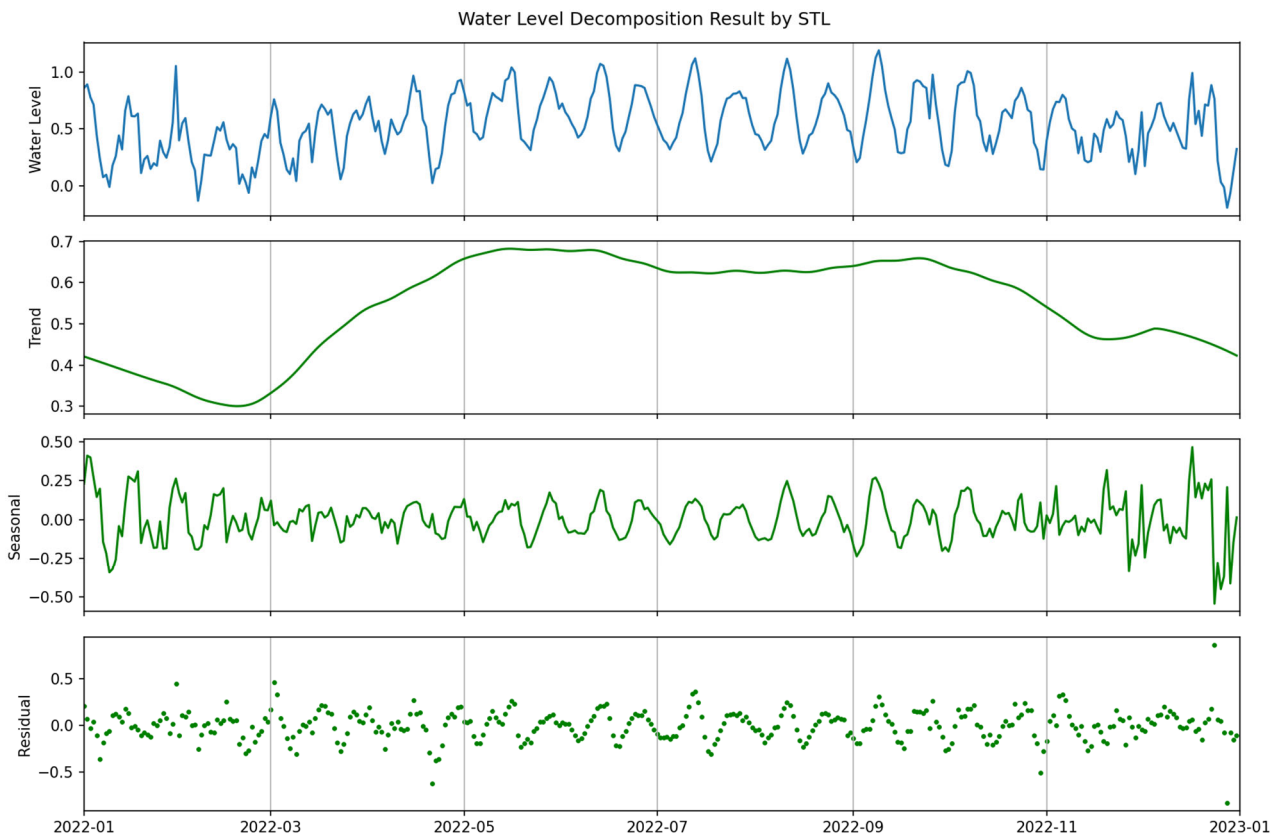


Fig. 3 Decomposition Result of Water Leve by STL

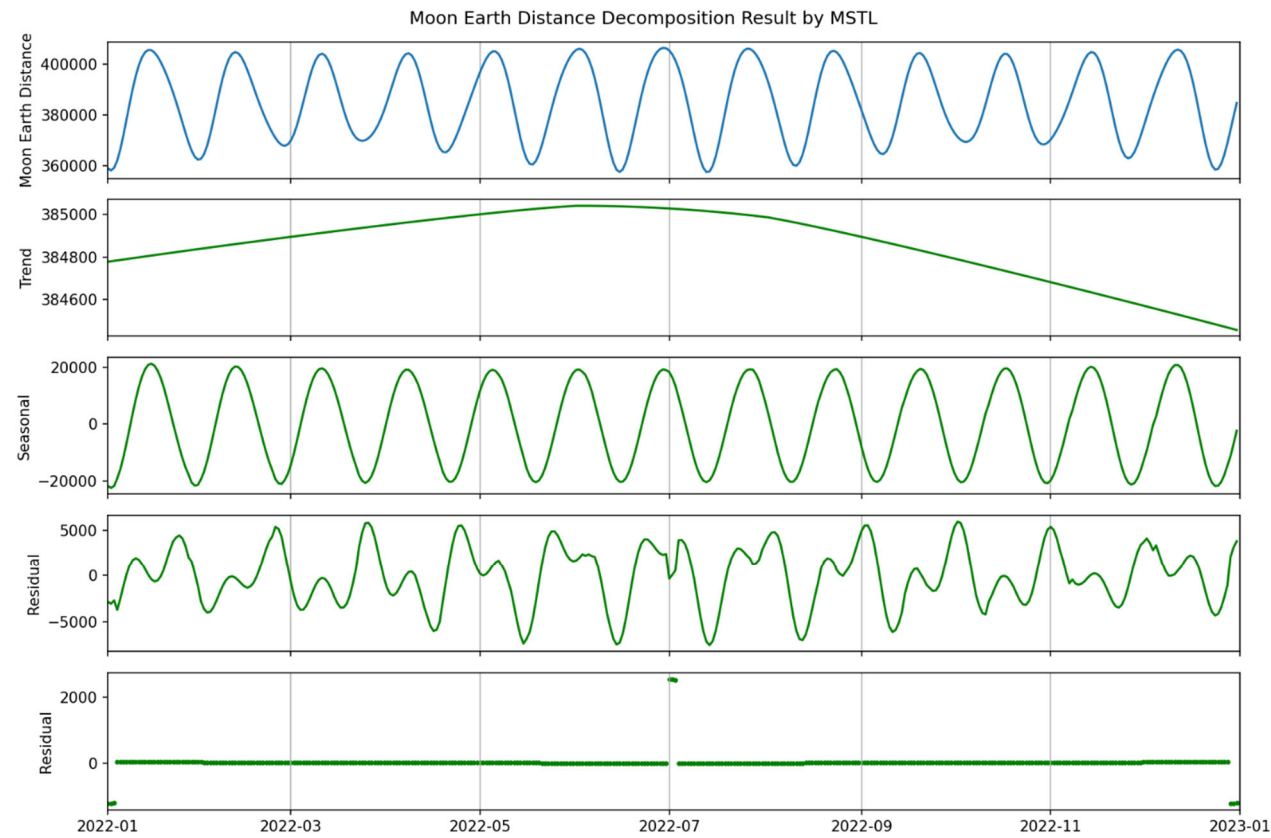


Fig. 4 Decomposition Result of Moon Earth Distance by MSTL

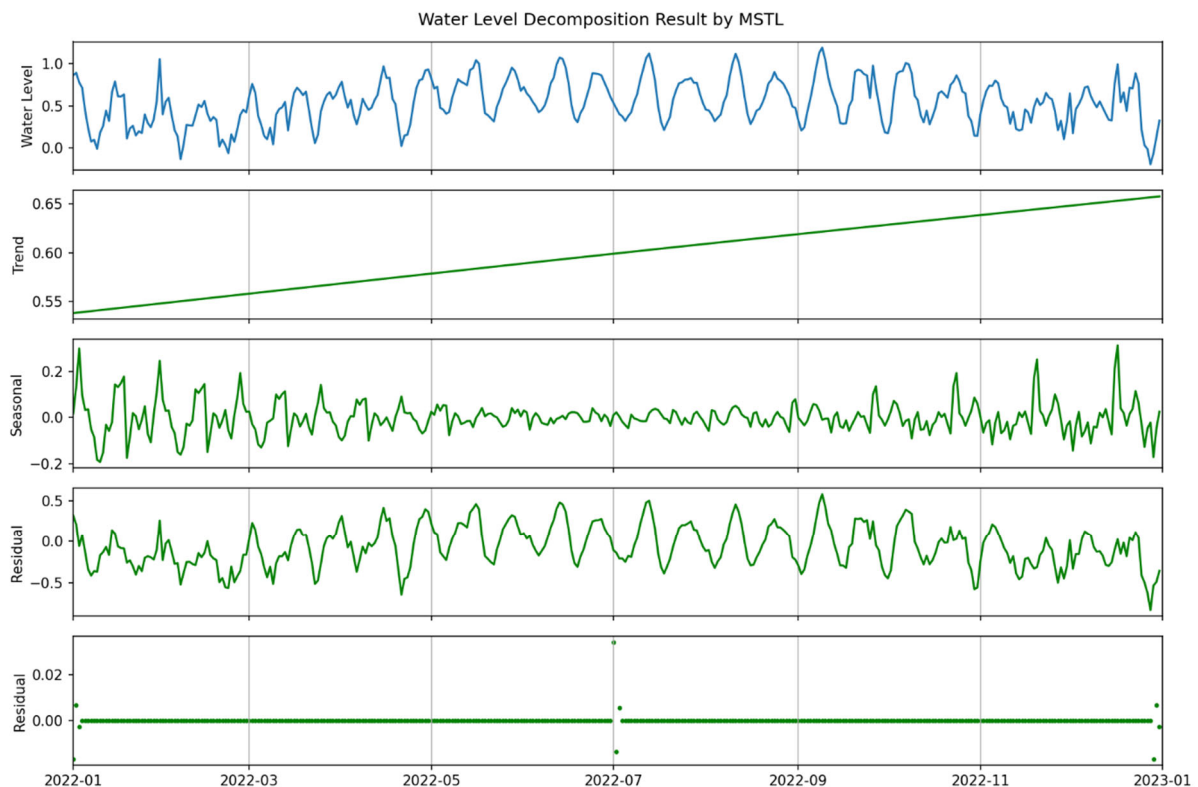


Fig. 5 Decomposition Result of Water Leve by MSTL

4. Summary

Based on the decomposition results from STL and MSTL, it's evident that water level data has periodic components similar to the Earth-Moon distance. This relationship suggests that as the Moon approaches the Earth, tidal phenomena become more pronounced. The Earth-Moon distance typically follows a sine and cosine curve, and while tidal fluctuations are generally regular, occasional anomalies do occur. Both phenomena exhibit a seasonal pattern. Recognizing these patterns can aid coastal city residents and fishermen in avoiding tidal hazards and offer insights for tidal power stations. However, this research has limitations. Slicing the water-level data might overlook certain outliers or characteristics, potentially affecting the accuracy of the STL and MSTL models. Additionally, data spanning multiple years is needed to validate the models' efficacy in analyzing trend changes. A potential solution could involve using other algorithms, like sliding average algorithms, to process raw data and reduce data point omissions.

Authors Contribution

All the authors contributed equally, and their names were listed in alphabetical order.

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