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Studying the COVID-19 Impact on the Antarctic Glacier Melting Rate

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Abstract

This paper will study the Time Series Antarctic Glacier Mass from April 2002 to March 2021. The objective of this paper is to forecast the Antarctic Glacier Mass level for 2021 to 2041. The Science studied is the Geoscience of the Glacier; the Technology applied is the GRACE-FO satellites to collect the Glacier Ice Sheet Mass data; Engineering focuses on the COVID-19 impact on the Glacier melting rate; and mathematical/statistical tools like Time Series ARIMA models are applied. Although the Glacier melting rate sped up recently before 2020, the COVID-19 situation might have slowed down the rate of glacier melting in 2020 in both Antarctic and Greenland. During 2020 COVID-19 period, Antarctic Glacier Mass seasonal pattern became a smoother single-peak cyclic pattern which is different from the double-peak cyclic pattern in 2002 to 2019. Authors conducted both non-seasonal and seasonal ARIMA models and concluded that only the Seasonal ARIMA Forecasting modeling algorithm can detect more reliable insights of the relatively small pattern change during 2020 period. The COVID-19 factor might have made certain impact on the Antarctic Glacier Melting rate. The Glacier Melting rate may have been slowed down by 20% in the 2020-2021 period.

1 Introduction

This project would study the Antarctic Glacier Mass data from 2002-2021 March. The objective is to use the Time Series platform to examine the time series Glacier data to predict the Glacier crisis for the next twenty years (2021-2041).

1.1 Scientific Research Literature and Technology: GRACE-FO

The global climate has been spiraling out of control due to the Global Warming effect (Arnold 2011). The Gravity Recovery and Climate Experiment Follow-On (GRACE-FO) mission is a partnership between NASA and the German Research Centre for Geosciences (GFZ). GRACE-FO aims to test a new technology designed to dramatically improve the already remarkable precision of its measurement system. GRACE-FO is a successor to the original GRACE mission, which orbited Earth from 2002-2017. Global surface mass anomalies are observed by the GRACE-FO satellites. Over land, red colors indicate below-average terrestrial water amounts, while blue colors show above-average water amounts (including ice, snow, soil moisture and groundwater). Over oceans, red colors indicate below-average ocean pressure, while blue colors show above-average pressure. Ocean pressure changes are related to large-scale ocean current variations, as well as overall sea level changes from ocean mass changes.

1.2 Engineering: Antarctic Glacier Melting Crisis

An Antarctic glacier larger than the UK is at risk of breaking up after scientists discovered more warm water flowing underneath it than previously thought. Over the past few years, teams of scientists have been crisscrossing the remote and inaccessible region on Antarctica's western edge to try to understand how fast the ice is melting and what the consequences for the rest of the world might be. "What happens in west Antarctica is of great societal importance," said Dr Robert Larter [1], a scientist with the British Antarctic Survey and principal investigator with the International Thwaites Glacier Collaboration. Glacier melting is the biggest factor in future sea level rise [2].

1.3 Mathematics: Time Series and Forecast

Time Series Analysis and Forecasting modeling were utilized on the GRACE-FO Glacier Mass data. Climatology research has used Time Series and Forecasting model such as ARIMA to forecast the weather temperature and study the global warming trend [3]. In this paper, the Time Series Decomposition and Smoothing Models will be compared on their Forecasting Capabilities for the next 20 years (2021-2041).

2 Data Collection and Sampling Plan

The data source for this paper is from the NASA GRACE-FO satellites' data of the Antarctic Ice Sheet Mass Trend as shown in Figure 1 which collects monthly averages of the images collected from satellites.

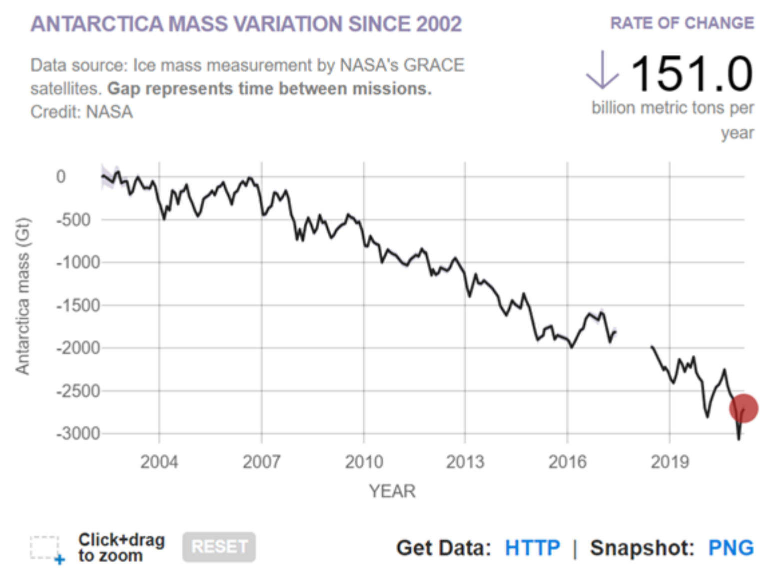

Figure 1: Antarctic Monthly Mass Trend

The Glacier Mass raw data was uploaded to the JMP platform from the NASA GRACE-FO website as shown in Figure 2.

2002
Source
Columns (6/0)
Antarcti...tonnes)
Year
Month
Year-Month
Antarcti...rended)
Antarcti...it cycle)
Rows
All rows 219
Selected 0
Excluded 0
Hidden 0
Labeled 0

	Antarctic mass (Gigatonnes)	Year	Month	Year-Month	Antarctic mass (Gigatonnes) (Detrended)	Antarctic mass (Gigatonnes) (Remove 12 unit cycle)
1	•	2002	1	01/2002	•	•
2	•	2002	2	02/2002	•	•
3	•	2002	3	03/2002	•	•
4	0	2002	4	04/2002	-312.2540246	141.67839272
5	18.36	2002	5	05/2002	-281.1661726	51.559262294
6	•	2002	6	06/2002	•	•
7	•	2002	7	07/2002	•	•
8	-59.82	2002	8	08/2002	-321.1626167	-285.6739764
9	45.54	2002	9	09/2002	-203.0747647	-166.6549122
10	62.69	2002	10	10/2002	-173.1969127	-78.98839272
11	-69.03	2002	11	11/2002	-292.1890607	-102.2292623
12	-49.78	2002	12	12/2002	-260.2112087	34.395583658
13	-48.71	2003	1	01/2003	-246.4133567	130.28564995
14	-200.03	2003	2	02/2003	-385.0055048	25.823976382
15	-171.49	2003	3	03/2003	-343.7376528	40.70491224
16	-43.66	2003	4	04/2003	-203.1798008	98.018392724
17	0.79	2003	5	05/2003	-146.0019488	33.989262294
18	•	2003	6	06/2003	•	•
19	-128.94	2003	7	07/2003	-250.2762448	-307.9356499
20	-122.41	2003	8	08/2003	-231.0183929	-348.2639764
21	-130.92	2003	9	09/2003	-226.8005409	-343.1149122
22	-48.06	2003	10	10/2003	-131.2126889	-189.7383927
23	-107.58	2003	11	11/2003	-178.0048369	-140.7792623
24	-273.11	2003	12	12/2003	-330.8069849	-188.9344163

Figure 2: Glacier Mass Monthly Row Data File

3 Time Series Basic Analysis

Conduct JMP 16 Time Series and Forecasting Platforms on the Glacier Mass data. The main objective in this Section: any change in Antarctic glacier melting rate during COVID-19 period in 2020-2021?

3.1 Control Chart Analysis

To visualize Antarctic Glacier Mass trend from 2002-2021, JMP Control Chart Builder platform was used. In Figure 3, the Glacier Mass data was plotted in Individual Control Chart format [4-7]. Y Axis is the Antarctic Mass data and X axis is the Month/Year time domain. Y axis scale was set zero at the 2002 April. The Mass data reported was compared relatively to the 2002 April data in Gigatons (GT). The downward trending pattern was observed since 2002 and the downward slope was getting steeper after 2007. An interesting finding is that the Glacier Mass melting rate was slowed down in Antarctic in 2020. This observation may be related to COVID-19 factor. Authors have also found a similar trending observation happened in Greenland in 2020. Between September 2018 and August 2019, the Greenland Ice Sheet set a record for ice loss (532 plus or minus 58 billion metric tons). Between September 2019 and August 2020, the rate of ice loss from the Greenland Ice Sheet was much lower (293 plus or minus 66 billion metric tons), but still above the 2002–2020 average measured by GRACE. Average ice loss for Greenland over the full 18-year record was 268 plus or minus 14 billion metric tons per year. This slow down observation may be due to less Human activity and air pollution globally during COVID-19 pandemic period. Authors have been monitoring this COVID-19 factor and may share more findings in next Antarctic Glacier Mass Time Series publication.

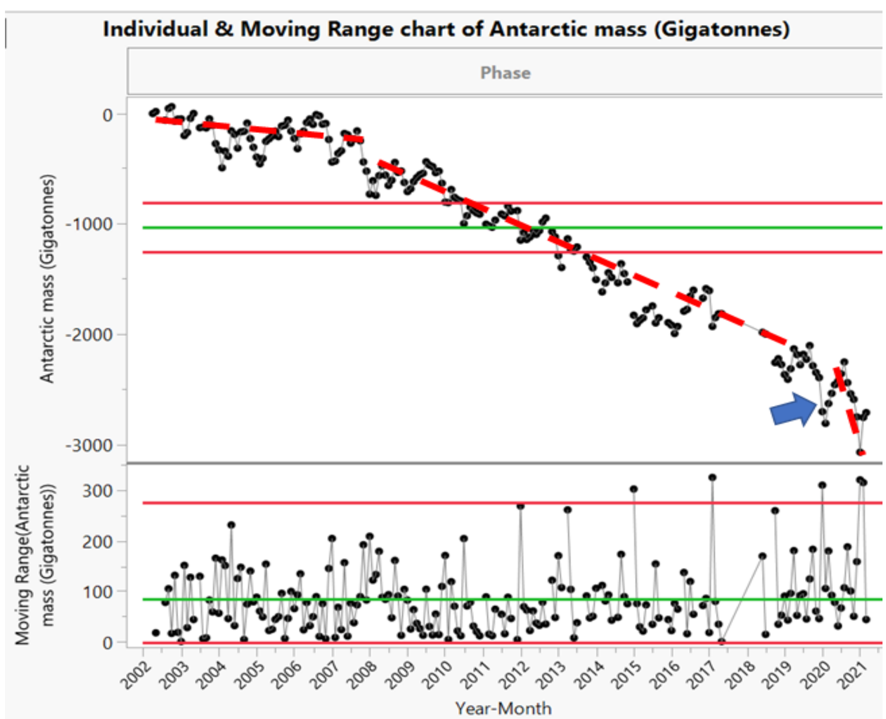

Figure 3: Antarctic JMP Glacier Mass Control Chart Builder Analysis

3.2 Study 2020 Antarctic Glacier Mass Trend

Historical Monthly Antarctic Glacier Mass records were summarized in Figure 4. The lowest points were in the Jan.-Mar. (their warm months). The highest points were in the August to October (their cold months). Interesting portion is their April to July months. There seems another small peak-valley cycle happened in April to July.

	Antarctic mass (Gigatonnes)	
Month	Mean	Std Dev
1	-1242	907
2	-1252	880
3	-1212	872
4	-956	781
5	-954	806
6	-1059	822
7	-1012	775
8	-889	789
9	-790	807
10	-880	894
11	-982	874
12	-1060	852

Figure 4: Summary of Historical Antarctic Glacier Mass Data in 2002-2021

To investigate this double-peak mode, data was rearranged in histogram analysis across 2002-2021 years as shown in Figure 5. Clearly, the Histogram shapes were quite different: double peaks patterns observed before 2020 and single peaks pattern observed in 2020 COVID-19 period.

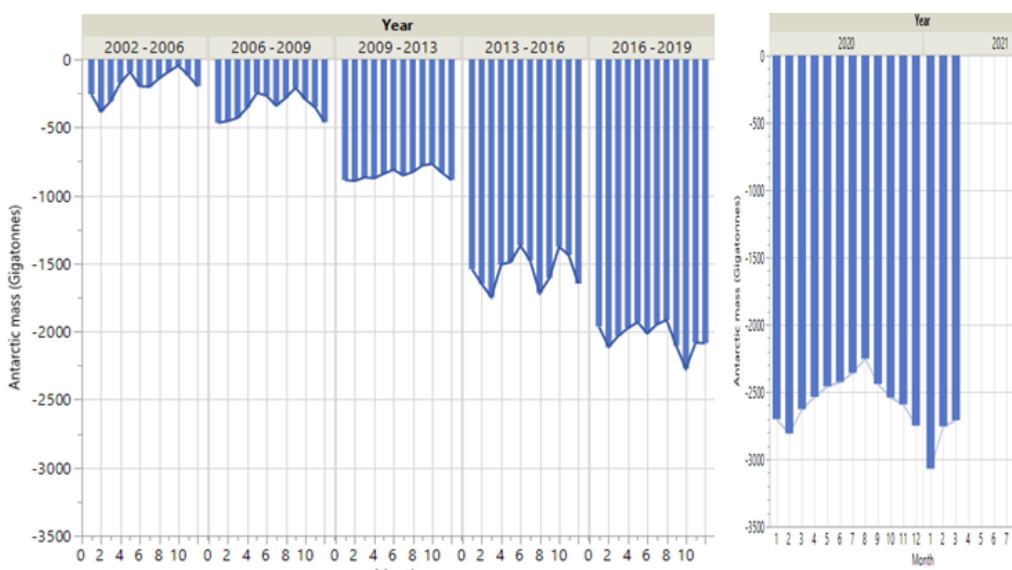

Figure 5: Histogram Analysis of the Historical Antarctic Glacier Mass Data

To further investigate the patterns, year 2019 and year 2020 Antarctic Glacier Mass data were plotted in the Time Series Plot together with 2002-2021 Regression Fit Model and 95% Confidence and Prediction Intervals as shown in Figure 6. During COVID-19 year 2020 period, the Antarctic Glacier Mass pattern was much smoother as a single-peak mountain. Less Human activity during the lock down season may transform the Glacier ecology back to the Natural mode which has reflected a natural seasonal pattern of the Glacier Melting mechanism. Year 2019 Glacier Pattern was a typical curve for 2002-2018. The curve was not in a smooth seasonal pattern from March to July for certain special factors. Somehow, year 2020 could avoid those special factors. At this moment, there is no direct evidence or correlation study between those unknown special factors and COVID-19.

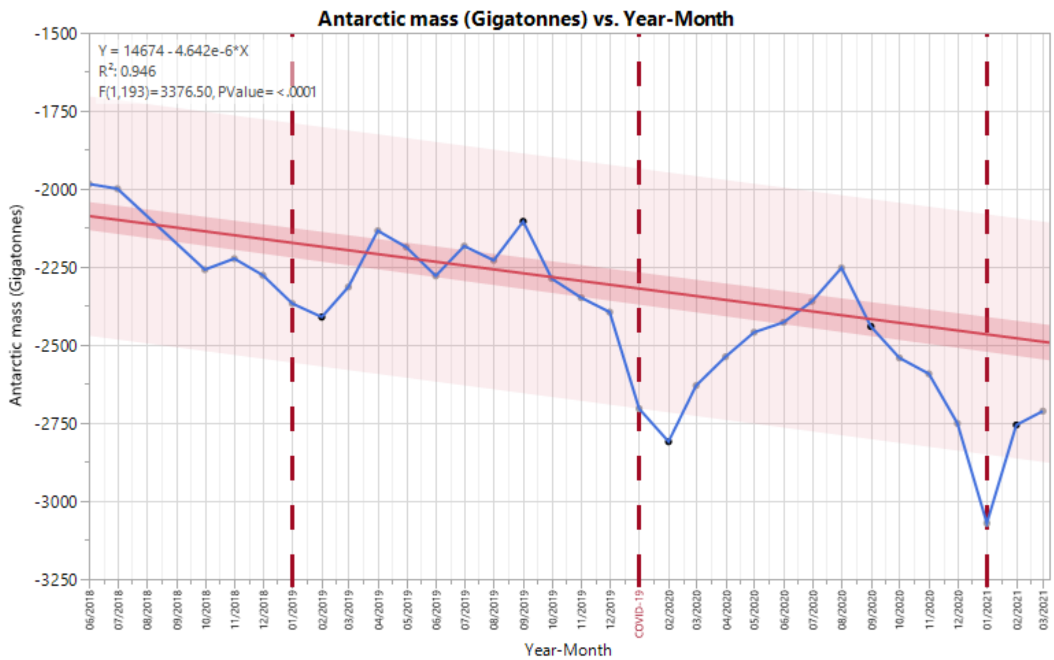

Figure 6: Compare Antarctic Glacier Mass data between year 2019 and year 2020

4 Time Series ARIMA Model

To further study the COVID-19 factor, authors would conduct the Time Series ARIMA model w/wo including the 2020 Jan.-2021 Mar. data for direct model comparison.

4.1 Non-Seasonal Time Series Analysis

ARIMA has three mathematical components [8]: Autoregression (AR), Integration (I) and Moving Average (MA). Autoregression (AR): refers to a model that shows a changing variable that regresses on its own lagged, or prior, values. Integrated (I): represents the differencing of raw observations to allow for the time series to become stationary, i.e., data values are replaced by the difference between the data values and the previous values. Moving average (MA): incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations. There are two ARIMA types: one is Non-Seasonal and one is Seasonal. The difference is whether there is a fixed Seasonal component observed or detected in the Time Series Data. A Non-Seasonal ARIMA model is commonly denoted ARIMA(p,d,q). The AR "p" number considers the Autoregression AR module by integrating the historical values in exponentially decaying algorithm. The I "d" number considers the Integration Differencing I module by differencing the data points to detect the trend component. The MA "q" number considers the Moving Average MA module by smoothing the error term exponentially. If any of p, d, or q are zero, the corresponding letters are often dropped. For example, if p and d are zero, then the model would simply be a moving average model, denoted as MA(q). The Seasonal ARIMA model would be addressed in Section 4.2. As shown in Figure 7, Non-Seasonal ARIMA model was conducted w/wo including the COVID-19 period data (Jan.2020- Mar. 2021). The top two Non-Seasonal Models based on the AIC criteria [9,10] are identical between these two cases. Regarding the model goodness of fit, R-Square are similar between two datasets. Due to 15 DF difference, hard to tell which dataset has better ARIMA fit on the other selection criteria. In general, from the non-seasonal ARIMA modeling, we did not detect any significant COVID-19 factor

2002-2021 Including COVID-19 Period

Model Comparison

Report	Graph	Model	DF	Variance	AIC ^	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
☑	☑	ARIMA(1, 1, 1)	175	10197.384	2151.3981	2160.9435	0.986	2145.3981	0.963334		74.959965	72.448281
☑	☑	I(1)	177	10785.478	2159.0394	2162.2212	0.986	2157.0394	0.021110		62.700425	74.804409
☐	☐	IMA(1, 1)	176	10846.548	2161.0360	2167.3996	0.986	2157.036	0.007779		63.129137	74.803350
☐	☐	ARI(1, 1)	176	10846.587	2161.0366	2167.4002	0.986	2157.0366	0.007777		63.049414	74.803733
☐	☐	AR(1)	193	11713.654	2387.0054	2393.5514	0.961	2383.0054	0.000000		.	92.407556
☐	☐	ARMA(1, 1)	192	11774.366	2389.0023	2398.8213	0.961	2383.0023	0.000000		.	92.408142
☐	☐	MA(1)	193	239036.1	2971.5227	2978.0687	0.647	2967.5227	0.000000		.	402.59757
☐	☐	ARIMA(0, 0, 0)	194	685348.46	3174.7316	3178.0046	0.000	3172.7316	0.000000		.	710.03999

2002-2019 Excluding COVID-19 Period

Model Comparison

Report	Graph	Model	DF	Variance	AIC ^	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
☑	☑	ARIMA(1, 1, 1)	160	8582.4782	1942.3764	1951.6577	0.985	1936.3764	0.927749		78.005993	67.226825
☑	☑	I(1)	162	9053.4594	1948.6479	1951.7417	0.984	1946.6479	0.040326		66.638406	68.995913
☐	☐	IMA(1, 1)	161	9100.7843	1950.4897	1956.6772	0.984	1946.4897	0.016057		69.978249	68.864405
☐	☐	ARI(1, 1)	161	9102.1258	1950.5134	1956.7009	0.984	1946.5134	0.015868		69.422994	68.876985
☐	☐	AR(1)	178	10184.665	2178.7192	2185.1051	0.953	2174.7192	0.000000		.	87.578156
☐	☐	ARMA(1, 1)	177	10233.054	2180.5683	2190.1472	0.954	2174.5683	0.000000		.	87.374822
☐	☐	MA(1)	178	196423.18	2707.6696	2714.0555	0.614	2703.6696	0.000000		.	357.76248
☐	☐	ARIMA(0, 0, 0)	179	514316.35	2878.9220	2882.1149	-0.00	2876.922	0.000000		.	612.93623

Figure 7: Non-Seasonal ARIMA Model Analysis

Authors are particularly interested in comparing the ARIMA (0,1,0) model between w/wo COVID-19 data analysis as shown in Figure 8. ARIMA (0,1,0) model may indicate that the second component I= 1 => integrating or differencing (Linear Trend). Parameter estimate t test P-Value > 0.05 => intercept (constant) c is not significant even though a clear downward trend term observed. The downward trend term may be masked by the seasonal component with non-seasonal ARIMA model. P-Values for Parameter Estimate are similar between two datasets which may imply that little No COVID-19 factor detected. The parameter estimates analysis has estimated Intercept = -10.43 and -9.44 (downward trend slope). Though, the t test P-value = 0.18 > 0.05 (could not reject the Null Hypothesis of Intercept= 0). There are two possible reasons of not rejecting the Null Hypothesis: (1) there is a strong seasonal component existing in the Glacier Mass data. In the Non-Seasonal ARIMA model, this strong Seasonal component signal would be treated as Non-Seasonal Noise and weaken the Signal-Noise Ratio in Parameter Estimate t test, and (2) the sample size may not be sufficient. Glacier data was collected in 2002-2021 (20 years). If the seasonal component is very strong (12 months), then 20 years of sample size (signal) may not be sufficient as compared to 12 months Seasonal (Noise) in the Non-Seasonal ARIMA model. Also, the downward slope is about 10% less steeper if excluded the most recent 2020-2021 COVID data. This finding may be against our Hypothesis that the Antarctic Glacier's melting rate has been slowed down during 2020-2021 COVID season. Let's wait and see what Seasonal ARIMA model may find out the same or different regarding the COVID-19 factor.

Model: I(1) — 2002-2021 Including COVID-19 Period

Model Summary

DF	177	Stable	Yes
Sum of Squared Innovations	1909029.53	Invertible	Yes
Sum of Squared Residuals	1909029.53		
Variance Estimate	10785.4776		
Standard Deviation	103.853154		
Akaike's 'A' Information Criterion	2159.03944		
Schwarz's Bayesian Criterion	2162.22122		
RSquare	0.98552619		
RSquare Adj	0.98552619		
MAPE	62.7004251		
MAE	74.8044093		
-2LogLikelihood	2157.03944		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
Intercept	0	-10.42635	7.758467	-1.34	0.1807	-10.426349	-10.426349

Model: I(1) — 2002-2019 Excluding COVID-19 Period

Model Summary

DF	162	Stable	Yes
Sum of Squared Innovations	146666043	Invertible	Yes
Sum of Squared Residuals	146666043		
Variance Estimate	9053.45942		
Standard Deviation	95.1496685		
Akaike's 'A' Information Criterion	1948.64794		
Schwarz's Bayesian Criterion	1951.74169		
RSquare	0.98392772		
RSquare Adj	0.98392772		
MAPE	66.6384064		
MAE	68.9959125		
-2LogLikelihood	1946.64794		

Parameter Estimates

Term	Lag	Estimate	Std Error	t Ratio	Prob>|t|	Constant Estimate	Mu
Intercept	0	-9.439448	7.430668	-1.27	0.2058	-9.4394479	-9.4394479

Figure 8: Non-Seasonal ARIMA Model and Parameter Estimate w/wo COVID-19 period

4.2 Seasonal Time Series Analysis

In addition to Non-Seasonal ARIMA model, the Seasonal ARIMA model has added the Seasonal Component as (p, d, q) (P, D, Q)m. (P, D, Q) is based on the Seasonal pattern. m= 12 here is representing 12 months in a season (year). For example, in previous ARIMA (1,1,1) model, "d=1" means the trend component d=1 is a straight line in Forecasting. "d=1" is the differencing (delta) is constant between any two consecutive months, resulting in a constant slope of linear trend. In Seasonal ARIMA model, the "D=1" component would compare the same month of two consecutive years (season = one year). This "D=1" component in the Seasonal ARIMA model could detect any year to year non-linear long-term trend in addition to non-Seasonal "d=1" linear trend model. To simply the Seasonal ARIMA model list for model comparison, the Non-Seasonal ARIMA portion has been limited to I(1). Both the AR and MA modules would be addressed in Seasonal portion (P,D,Q) better. Non-Seasonal I (1) was kept in the Seasonal ARIMA model because it may make more sense to consider both the local linear trend of differencing between two consecutive months and the global non-linear trend of differencing between two consecutive years based on 12 months of a Season. Through these model selection list, we may directly compare the strength of the short term trend Vs. the long term trend through the Seasonal ARIMA Model analysis. The relative strength of these two trend methods may indicate whether the Antarctic Glacier may melt faster in the next 20 years. As shown in Figure 9, the top Seasonal ARIMA models are ARIMA (0,1,0)(0,1,1)12 same for w/wo COVID period. Seasonal ARIMA models were ranked based on AIC criteria as shown in Figure 9. ARIMA (0,1,0)(0,1,1)12 was identified as the best model. Previous non-Seasonal I (1) was on the bottom. This new Seasonal ARIMA model may indicate four major findings: (1) Seasonal component is very strong in Antarctic Glacier Melting forecasting, (2) Non-Linear long term trend "D=1" is significant, (3) Autoregression can be ignored in ARIMA, and (4) Moving Average method is necessary in ARIMA.

Model Comparison — 2002-2021 Including COVID-19 Period

Report	Graph	Model	DF	Variance	AIC ^	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
☑	☑	Seasonal ARIMA(0, 1, 0)(0, 1, 1)12	142	10764.574	1752.4447	1758.3843	0.987	1748.4447	0.719820		40.440597	61.979200
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 1, 1)12	141	10849.195	1754.4228	1763.3322	0.987	1748.4228	0.267725		40.240381	62.018713
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 1, 0)12	142	11610.319	1760.5585	1766.4981	0.986	1756.5585	0.012455		39.800649	66.297904
☐	☐	Seasonal ARIMA(0, 1, 0)(0, 1, 0)12	143	13807.891	1782.4022	1785.3720	0.984	1780.4022	0.000000		48.302923	71.137889
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 0, 1)12	175	8310.8597	2124.4716	2134.0170	0.988	2118.4716	0.000000		54.600886	64.560322
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 0, 0)12	176	9575.9072	2140.2722	2146.6358	0.987	2136.2722	0.000000		56.562634	69.144073
☐	☐	Seasonal ARIMA(0, 1, 0)(0, 0, 1)12	176	9992.2064	2147.1390	2153.5025	0.987	2143.139	0.000000		59.312703	70.874107
☑	☑	I(1)	177	10785.478	2159.0394	2162.2212	0.986	2157.0394	0.000000		62.700425	74.804409

Model Comparison — 2002-2019 Excluding COVID-19 Period

Report	Graph	Model	DF	Variance	AIC ^	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
☑	☑	Seasonal ARIMA(0, 1, 0)(0, 1, 1)12	127	7930.7758	1534.8583	1540.5780	0.987	1530.8583	0.706305		43.783544	54.857455
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 1, 1)12	126	8031.1673	1536.6141	1545.1936	0.987	1530.6141	0.293578		43.174966	54.752947
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 1, 0)12	127	9502.447	1552.2700	1557.9896	0.985	1548.27	0.000117		43.495682	60.180079
☐	☐	Seasonal ARIMA(0, 1, 0)(0, 1, 0)12	128	12024.307	1578.9967	1581.8565	0.982	1576.9967	0.000000		52.640753	65.795781
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 0, 1)12	160	6922.6274	1913.2733	1922.5546	0.987	1907.2733	0.000000		57.132352	60.452697
☐	☐	Seasonal ARIMA(0, 1, 0)(1, 0, 0)12	161	8128.3022	1933.2993	1939.4868	0.986	1929.2993	0.000000		60.874553	64.513225
☐	☐	Seasonal ARIMA(0, 1, 0)(0, 0, 1)12	161	8440.7022	1938.8789	1945.0664	0.985	1934.8789	0.000000		63.374081	65.903559
☑	☑	I(1)	162	9053.4594	1948.6479	1951.7417	0.984	1946.6479	0.000000		66.638406	68.995913

Figure 9: Remove Seasonal Component Analysis

In Figure 10 Seasonal ARIMA Model Summary and Parameter Estimates, the MA module t test was significant (P-value < 0.05) and the Intercept Trend component was relatively weaker (P-Value > 0.05). The significant MA term may indicate the importance of the smoothing out the random error noise for forecasting in the Seasonal ARIMA model [9]. Even the nonlinear long term intercept is not significant, the yearly decaying slope is still -2.38 GT/year as compared to -10.43 GT/month or -125 GT/year. Even with less than 2% contribution of this non-linear trend term, after 10 years, the contribution or impact of the Forecasting accuracy will be near 20% (faster Glacier melting rate than the non-seasonal forecasting). Therefore, the Seasonal ARIMA model has significantly upgraded the forecasting power of the long-term Glacier Forecasting. If excluding the COVID-19 period, the yearly decaying slope is steeper at -2.91 GT/year. The COVID-19 period has slowed down the long-term yearly Glacier melting rate which is not consistent with the previous Non-seasonal ARIMA model. The possible reason is that the COVID-19 period has a different seasonal pattern in 2020 which has helped removed or mitigated the random noise level, resulting in a stronger seasonal component and trend component.

Model: Seasonal ARIMA(0, 1, 0)(0, 1, 1)12

2002-2021 Including COVID-19 Period

Model Summary

DF	142	Stable	Yes
Sum of Squared Innovations	1528569.52	Invertible	Yes
Sum of Squared Residuals	1574430.25		
Variance Estimate	10764.5741		
Standard Deviation	103.752465		
Akaike's 'A' Information Criterion	1752.44471		
Schwarz's Bayesian Criterion	1758.38434		
RSquare	0.98705993		
RSquare Adj	0.98698883		
MAPE	40.4405967		
MAE	61.9792001		
-2LogLikelihood	1748.44471		

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
MA2,12	2	12	0.632670	0.100669	6.28	<.0001*
Intercept	1	0	-2.381520	4.317669	-0.55	0.5821

Constant Estimate	Mu
-2.3815202	-2.3815202

Model: Seasonal ARIMA(0, 1, 0)(0, 1, 1)12

2002-2019 Excluding COVID-19 Period

Model Summary

DF	127	Stable	Yes
Sum of Squared Innovations	1007208.53	Invertible	Yes
Sum of Squared Residuals	1080869.11		
Variance Estimate	7930.77582		
Standard Deviation	89.0549034		
Akaike's 'A' Information Criterion	1534.85833		
Schwarz's Bayesian Criterion	1540.57796		
RSquare	0.98706084		
RSquare Adj	0.98698336		
MAPE	43.7835445		
MAE	54.8574546		
-2LogLikelihood	1530.85833		

Parameter Estimates

Term	Factor	Lag	Estimate	Std Error	t Ratio	Prob>|t|
MA2,12	2	12	0.760786	0.101940	7.46	<.0001*
Intercept	1	0	-2.908076	3.234437	-0.90	0.3703

Constant Estimate	Mu
-2.9080765	-2.9080765

Figure 10: Seasonal ARIMA Model Summary and Parameter Estimates

4.3 Seasonal Time Series Forecasting

Seasonal ARIMA model [10-12] has significantly upgraded the forecasting power of the long-term Glacier Forecasting. As shown in the Figure 11, both non-seasonal and seasonal ARIMA forecasting were side by side compared. On the left hand chart, including COVID-19 period, the Seasonal ARIMA model has shown the seasonal pattern and faster decaying trend than the non-Seasonal model. After excluded the COVID-19 period data, there is less difference in Forecasting between the non-seasonal ARIMA trend slope and the seasonal ARIMA trend slope This new observation may be related to our previous “two-peak” Vs, “one-peak” seasonal pattern. We may consider this hypothesis: during the COVID-19 period, the seasonal pattern recovered to its natural one-peak pattern and enhance the 12 months-seasonal component. Therefore, in the left chart including the COVID-19 period, the trend component is less masked by the seasonal component, resulting in a stronger trend component in the seasonal ARIMA. On the right hand chart, excluding COVID-19 period, there is much smaller trend forecasting difference between the Non-Seasonal and Seasonal ARIMA model. The seasonal ARIMA forecasting has less power to improve the long-term yearly trend component. In general, the 2020 COVID period has not just changed the seasonal month-month pattern but also improved the detection capability of the long-term yearly year-year decaying trend.

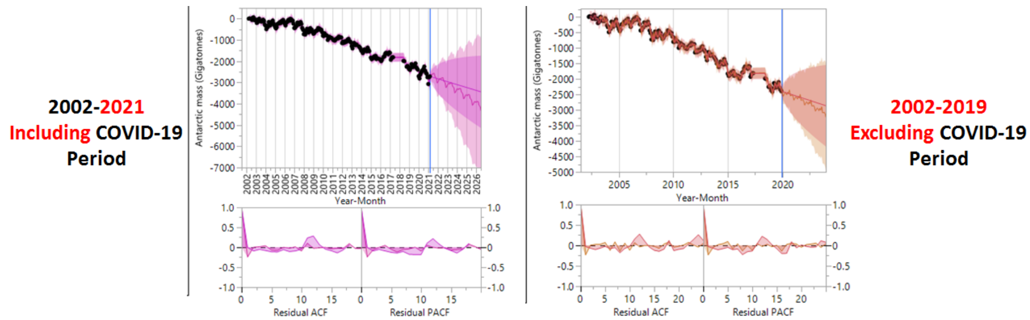

Figure 11: Seasonal ARIMA Forecasting w/wo COVID Period

4.4 Validate COVID-19 Factor on Antarctic Glacier Melting

To investigate the COVID-19 factor on comparing the Seasonal ARIMA Forecasting results as shown in Figure 12, the Blue Curve is the actual data from 2020 Jan.-2021 Mar. Glacier Mass Data collected and the Red curve is the forecasted data based on the Seasonal ARIMA model built based on the data from 2002 Apr.to 2019 Dec. If Blue and Red lines are overlapping each other, the COVID period data has little impact on the Forecasting for 2021-2041. During the COVID plotted period, there is smaller deviations during the Antarctic's colder months but larger deviations in warmer months. This observation may indicate that the Antarctic Glacier Mass pattern is different during 2020 COVID period. Though, with limited Glacier Mass sample data and sample size, we may not draw meaningful conclusions. Can consider to add other critical information such as Temp, Humidity, Air Pollution data.

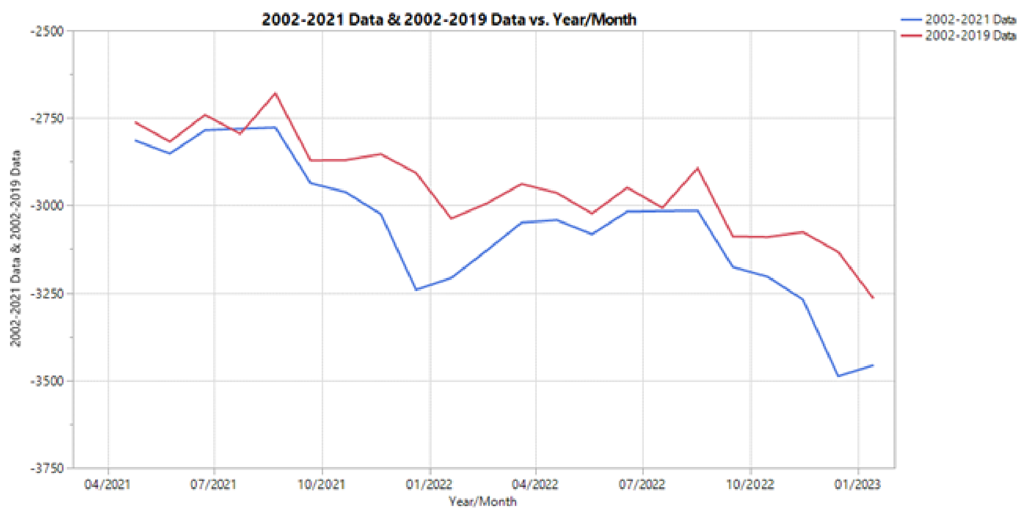

Figure 12: Validate COVID-19 period factor in Seasonal ARIMA model

5 Conclusions

The COVID-19 impact on the Antarctic Glacier Melting was conducted through the Time Series ARIMA Model. Although a significant deviation on both the Non-Seasonal ARIMA and Seasonal ARIMA modeling was not observed, the "1-Peak" Seasonal Pattern in 2000 differed substantially from the "2-Peaks" Seasonal Pattern from 2002 to 2019. A stronger Forecasting "Trend" component in the

Seasonal ARIMA model was observed as compared to the non-Seasonal ARIMA model. Nevertheless, due to the limited Glacier Mass sample data and sample size, other critical information such as temperature, humidity, and air pollution data may be needed to draw more meaningful conclusions.

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