Short-term forecasting of total number of confirmed COVID-19 cases in South Africa: A Bayesian temporal modelling approach

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Abstract

To be updated.

Author summary

To be updated.

Introduction

Coronaviruses (COVID-19) is an infectious disease that may cause respiratory infections ranging from the common cold to more severe diseases. The novel COVID-19 outbreak was first detected in December 2019 in Wuhan, China. The outbreak later spread to every province of mainland China and 188 other countries, with more than 118 million confirmed cases and more than 2.63 million deaths as of March 8, 2021 [REF]. The first COVID-19 case was reported in South Africa on 5 March 2020 [REF]. As of March 8, 2021, the number of confirmed COVID-19 cases in Africa represents around 3% of the infection worldwide. South Africa had the highest burden of COVID-19 cases in the African region, with 1.5 million reported cases and 50,678 confirmed COVID-19 related deaths[REF].

During this period, countries, including South Africa, have adopted various measures to control the virus's spread, including border closure, mandatory use of fabric masks, contact tracing, and stay-at-home measures. Due to the uncertainties about the disease and the need to make informed policy decisions, modelling has taken centre stage in supporting critical policy discussions surrounding COVID-19. COVID-19 modelling studies generally follow one of two general approaches—the phenomenological and mechanistic models. Phenomenological models are statistical models that use generic strategies such as regression to provide quantitative projections that policymakers may need to allocate resources or plan interventions in the short term. On the other hand, mechanistic models use parameters and functional forms to represent our knowledge and assumptions on transmission, disease, and immunity to produce a long-term forecast.

Several authors implemented phenomenological and mechanistic models to describe the early course of COVID-19 in South Africa and produce short-term and long-term forecasts using the data from the early phase of the epidemic[1]. In this paper we present (1) South Africa's one year COVID trajectory and (2) fit a series of temporal models to produce short term predictions of the number of reported cases expected for a period of 10 days ahead.

Methods

Data

We downloaded data from Coronavirus COVID-19 (2019-nCoV) Data Repository for South Africa maintained by Data Science for Social Impact research group at the University of Pretoria (https://github.com/dsfsi/covid19za). The data repository captures the daily number of new cases, number of tests, number of deaths and recoveries. Our primary outcome of interest was the daily number of newly diagnosed COVID-19 cases and the unit of time used in modelling was a day. We used the daily case reports from March 12, 2020, until February 27, 2021, in our analysis.

Statistical analysis

We considered four widely used temporal models to study the evolution of the number of daily COVID-19 cases. We let $Y(t)$ denote the daily number of newly diagnosed COVID-19 cases at time t and $\mu(t)$ represent the expected number of cases at time t. We considered a Negative binomial distribution for $Y(t)$ to account for possible overdispersion. That is, $Y(t) \sim NB(\mu(t), \delta)$, where δ is the overdispersion parameter. We considered four temporal models to capture the trend over time: a random walk of order one ($RW(2)$), a random walk of order ($RW(2)$), an autoregressive model of order one ($AR(1)$), and an autoregressive model of order two ($AR(2)$) [2] which are presented in Table 1.

Table 1. Model formulation for the Bayesian temporal models fitted to COVID-19 outbreak data. Note that $Y(t)$ is the daily number of COVID-19 cases and $Y(t) \sim NB(\mu(t), \delta)$.

Model	
$AR(1)$	$log(\mu(t)) = \alpha + u_t,$ $u_1 \sim N(0, \tau_u(1-\rho^2)^{-1}),$ $u_t = \rho u_{t-1} + \epsilon_t, \quad t = 2, \ldots, n,$ $\epsilon_t \sim N(0, \tau_\epsilon),$
$AR(2)$	$log(\mu(t)) = \alpha + u_t,$ $u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \epsilon_t, \quad t = 2, \ldots, n,$ $\epsilon_t \sim N(0, \tau_\epsilon),$
$RW(1)$	$log(\mu(t)) = \alpha + u_t,$ $u_t - u_{t-1} \sim N(0, \tau_u), \quad t = 2, \ldots, n,$
$RW(2)$	$log(\mu(t)) = \alpha + u_t,$ $u_t - 2u_{t+1} + u_{t+2} \sim N(0, \tau_u), \quad t = 2, \ldots, n,$

Each models were fitted within the Bayesian framework using *inla* [3]. To complete the specification of each models, we assume the following priors. For both the $RW(1)$ and $RW(2)$, we represent the precision parameter of τ_u as $\theta = log(\tau_u)$ and assume a $\Gamma(10, 100)$ prior for θ. For the $AR(1)$ model, we denote $\theta_1 = log(\tau_u(1-\rho^2))$ where $\Gamma(10, 100)$ prior is specified for θ_1, and we denote $\theta_2 = log\frac{1+\rho}{1-\rho}$ and assume a $N(0, 0.15)$ prior for θ.

The short-term prediction performance of all these models were evaluated using mean absolute error (MAE), mean absolute percentage error (MAPE), and chi-squared value. Additionally, the model fits were evaluated by using Deviance information criteria (DIC) [5] and Watanabe–Akaike information criterion (WAIC)[5]. The R-codes that we used for our analyses are available at https://github.com/belayb/COVIDincidenceSA.

Results

The daily number of reported COVID-19 cases from 12 March 2020 to 27 February 2021 is presented in Figure 1. Similar to elsewhere in the world, South Africa pass through a two-wave pandemic. The pandemic first peak was on 07 July 2020, where up to 13944 new COVID-19 cases reported, followed by a second peak in January 2021, where more than 21,000 daily cases reported. Figure 2 presents the cumulative number of reported COVID-19 cases and tests performed. To date, 8,838,937 tests have been conducted, and a total of 1,500,677 cases reported.

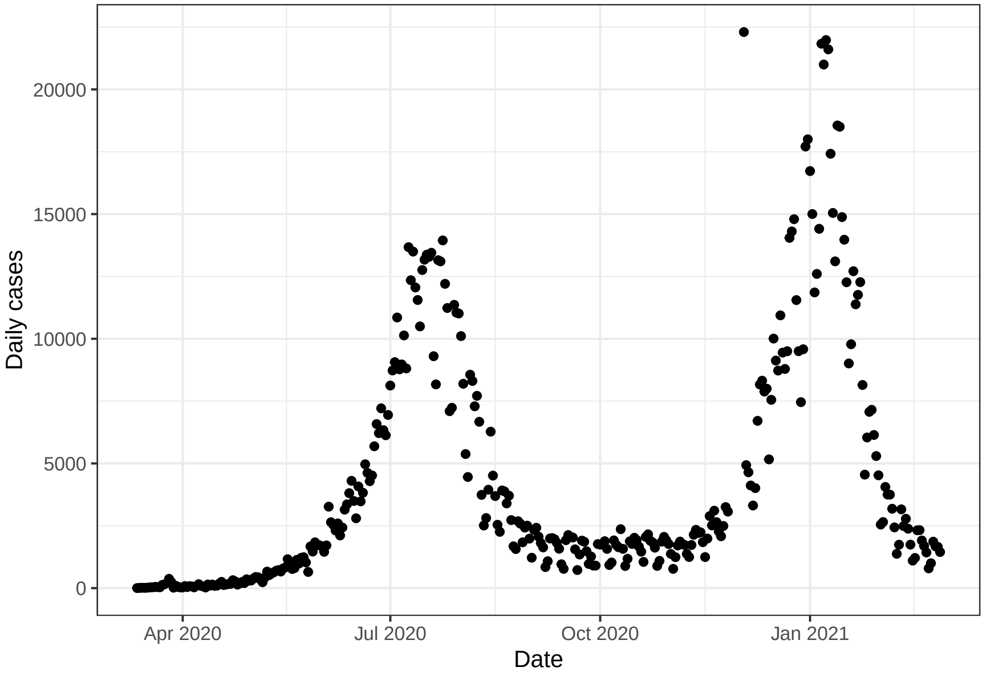

Fig 1. Daily number of COVID-19 cases in South Africa from 12/03/2020-27/02/2021.

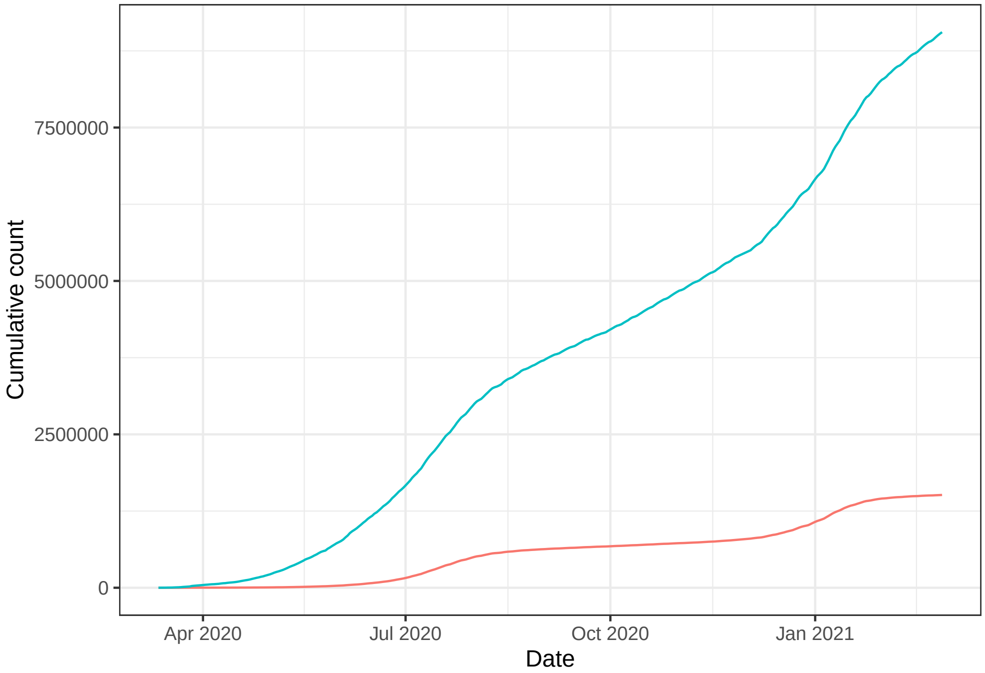

Fig 2. The cumulative number of COVID-19 cases and cumulative number of tests in South Africa from 12/03/2020-27/02/2021. Red-line denote the number of cases and blue-line denotes the number of tests.

Short-term prediction of the total number of reported COVID-19 cases

We fit the four models described in the previous section to the daily reported new COVID-19 cases. The models were fitted to the data from 12/03/2020-07/02/2021 (estimation period). The parameter estimates for each of the fitted models are presented in Supplementary Table S1. Our main interest to produce a short-term forecast for the number of reported cases. Figure S1 - S4 in the supplementary appendix presents the fitted model to the observed data (panel A) and the first-order derivative of the fitted curve for each model. All models considered appear to fit the observed data (within the estimation period) well. Nonetheless, the $AR(1)$, $AR(2)$, and $RW(1)$ tend to overfit the data.

Figure 3 and Table 2 presents 10-days ahead forecasting of the cumulative COVID-19 cases for each model. The $AR(1)$, $AR(2)$, and $RW(1)$ models performed well for the first three forecasting days and overestimated the cumulative cases from day three onward. The overestimation worsens for these models as we move further from the estimation period. On the other hand, the $RW(2)$ performed well, showing a consistent prediction performance throughout the forecasting period. The prediction error $(observed - predicted)$ for $RW(2)$ stays between 1932 and 3222 cases, whereas the prediction error linearly increase for the other models.

Table 3 presents the accuracy metrics for each model. The mean absolute error, mean absolute percentage error and Chi-square statistic favours $RW(2)$ as the best model predictive model. On the other hand, DIC and WAIC favours $RW(1)$ model. This is expected given that the DIC and WAIC evaluate model performance within estimation period.

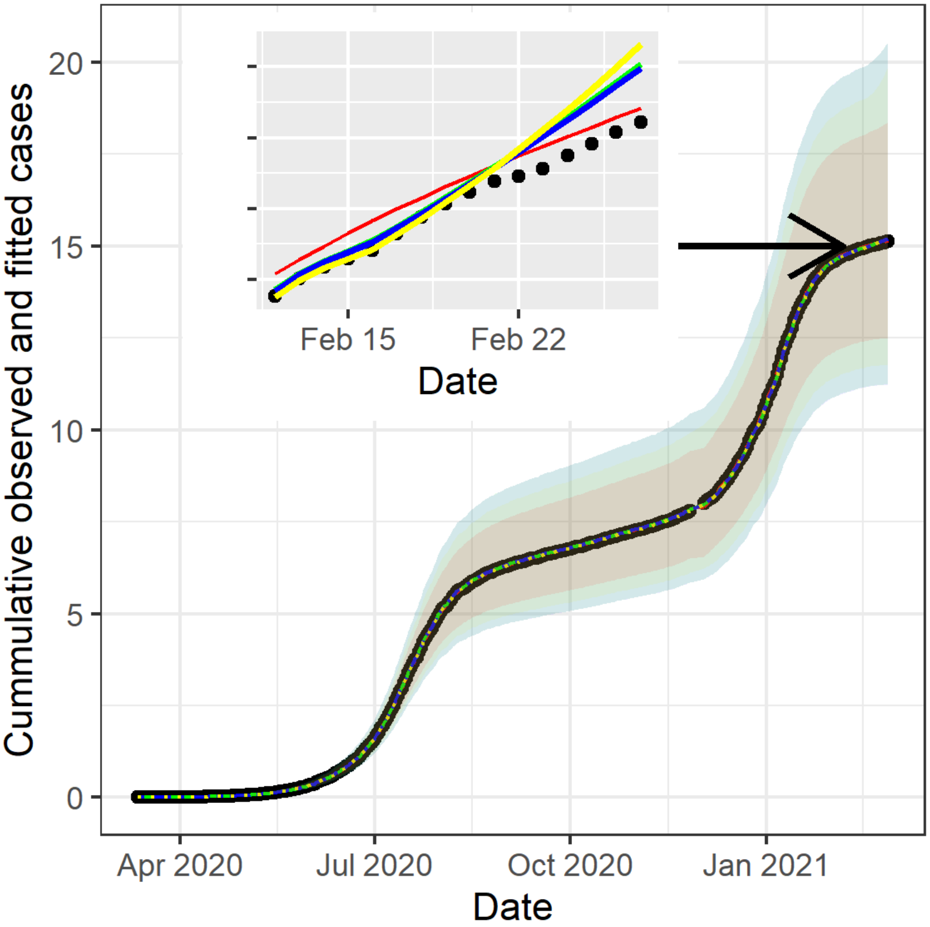

Fig 3. Ten days a head predicted cumulative COVID-19 cases (per 100, 000) in South Africa under the RW1 (yellow line), RW2 (red line), AR1 (green line), and AR2 (blue line) model. Estimation period 12/03/2020-17/02/2021. The black dots are the observed cumulative cases.The shaded bands are the prediction intervals.

Discussion

Reliable and accurate short-term forecasts of COVID-19 cases are critical to understand the progress of the pandemic in a country and to evaluate the impact of intervention measures in controlling the pandemic. This study modelled COVID-19 cases in South Africa at the national level using publicly available data from 12 March 2020 to 17 February 2021. We have evaluated four widely used temporal models for forecasting confirmed cases of COVID-19 for South Africa. Our study showed that these established temporal models could provide robust and accurate short-term forecasts for a period ten days ahead. The random-walk model of order two was superior to the random-walk of order one and autoregressive models in forecasting performance.

This study's strength is that the analysis was based on readily accessible, publicly available data that is updated in real-time. The statistical methods applied are relatively simple, implemented using off-the-shelf open-source software, and are not dependent on any assumptions regarding COVID-19 transmission dynamics.

Table 2. Short-term predictions of total number of reported cases at the national level under the four models. Estimation period 12/03/2020-17/02/2021

Model	Date	Total	Prediction	Prediction Interval	Total - Prediction
RW1	2021-02-18	1498766	1498569	(1171371.01-1905725.92)	197.3859
	2021-02-19	1500677	1500866	(1172282.33-1910642.87)	-188.6823
	2021-02-20	1502367	1503262	(1173049.22-1916495.57)	-894.6407
	2021-02-21	1503796	1505761	(1173711.18-1923283.63)	-1964.7423
	2021-02-22	1504588	1508368	(1174292.27-1931023.86)	-3779.5408
	2021-02-23	1505586	1511087	(1174808.38-1939743.02)	-5500.8398
	2021-02-24	1507448	1513924	(1175270.86-1949474.01)	-6475.6849
	2021-02-25	1509124	1516883	(1175688.37-1960253.97)	-7759.3666
	2021-02-26	1510778	1519971	(1176067.58-1972123.43)	-9193.4282
	2021-02-27	1512225	1523194	(1176413.76-1985125.8)	-10968.6766
RW2	2021-02-18	1498766	1501550	(1243364.14-1808126.44)	-2784.084
	2021-02-19	1500677	1503091	(1244303.4-1810572.89)	-2414.449
	2021-02-20	1502367	1504581	(1245125.49-1813126.02)	-2213.984
	2021-02-21	1503796	1506026	(1245838.81-1815814.63)	-2229.618
	2021-02-22	1504588	1507432	(1246452.98-1818667.83)	-2844.351
	2021-02-23	1505586	1508808	(1246978.01-1821716.68)	-3222.321
	2021-02-24	1507448	1510161	(1247424.13-1824995.35)	-2712.894
	2021-02-25	1509124	1511498	(1247800.94-1828542.17)	-2373.747
	2021-02-26	1510778	1512827	(1248117.46-1832400.55)	-2048.995
	2021-02-27	1512225	1514157	(1248381.83-1836620.02)	-1932.342
AR1	2021-02-18	1498766	1499490	(1118111.85-1994222.05)	-723.8101
	2021-02-19	1500677	1501589	(1119005.83-1998492.97)	-911.8181
	2021-02-20	1502367	1503742	(1119771.48-2003403.42)	-1374.5498
	2021-02-21	1503796	1505948	(1120441.58-2008928.37)	-2152.4467
	2021-02-22	1504588	1508210	(1121036.44-2015054.48)	-3622.1451
	2021-02-23	1505586	1510527	(1121570.32-2021775.18)	-4941.3574
	2021-02-24	1507448	1512901	(1122053.58-2029087.04)	-5452.8340
	2021-02-25	1509124	1515331	(1122494.04-2036989.06)	-6207.3481
	2021-02-26	1510778	1517820	(1122897.79-2045481.78)	-7041.6895
	2021-02-27	1512225	1520367	(1123269.68-2054566.81)	-8141.6604
AR2	2021-02-18	1498766	1499297	(1117410.1-1994516.93)	-530.9910
	2021-02-19	1500677	1501378	(1118308.28-1998709.43)	-701.0323
	2021-02-20	1502367	1503507	(1119078.99-2003512.61)	-1140.4836
	2021-02-21	1503796	1505686	(1119754.71-2008896.75)	-1889.5478
	2021-02-22	1504588	1507912	(1120355.57-2014844.05)	-3324.2951
	2021-02-23	1505586	1510188	(1120895.7-2021343.34)	-4601.9776
	2021-02-24	1507448	1512513	(1121385.41-2028386.98)	-5064.8673
	2021-02-25	1509124	1514887	(1121832.47-2035969.53)	-5763.2504
	2021-02-26	1510778	1517311	(1122242.95-2044087.07)	-6533.4176
	2021-02-27	1512225	1519786	(1122621.69-2052736.67)	-7560.6602

In summary, we have shown the usefulness of established temporal models to provide short term forecasts of the cumulative COVID-19 cases. Such models could help in decision-making when knowledge regarding factors affecting transmission-dynamics of the disease is limited.

Table 3. Accuracy metrics of forecasting for AR1, AR2, RW1, and RW2 models.

Days ahead point forecasts	Mean Absolute Error			
	RW1	RW2	AR1	AR2
One day	567.1704	3403.052	1100.229	975.1169
Two day	1395.0619	3048.159	1503.359	1412.4527
Three day	2309.8792	2756.448	2273.296	2200.8456
Four day	3223.8908	2668.973	3057.519	2971.4183
Five day	4076.6772	2722.319	3756.599	3653.5679
Six day	4677.8180	2760.561	4178.428	4055.0046
Seven day	5121.6867	2691.375	4415.616	4268.1508
Eight day	5897.6715	2928.744	5036.350	4844.4758
Nine day	6041.0341	2896.269	5119.785	4921.4926
Ten day	6218.5109	2884.603	5229.782	5024.2168
	Mean Absolute Percentage Error			
	RW1	RW2	AR1	AR2
One day	0.0003807	0.0022844	0.0007385	0.0006546
Two day	0.0009354	0.0020427	0.0010073	0.0009465
Three day	0.0015467	0.0018446	0.0015218	0.0014734
Four day	0.0021564	0.0017840	0.0020448	0.0019873
Five day	0.0027235	0.0018176	0.0025094	0.0024406
Six day	0.0031213	0.0018410	0.0027877	0.0027055
Seven day	0.0034128	0.0017925	0.0029418	0.0028437
Eight day	0.0039270	0.0019498	0.0033531	0.0032256
Nine day	0.0040213	0.0019282	0.0034079	0.0032762
Ten day	0.0041381	0.0019203	0.0034802	0.0033437
	Chi Square			
	RW1	RW2	AR1	AR2
One day	3.526026	80.43788	10.14578	7.642623
Two day	16.552333	71.66942	22.21648	19.346128
Three day	41.883130	70.78339	46.44967	42.301887
Four day	79.235781	71.27488	79.45425	72.947524
Five day	128.010230	72.74404	119.51466	109.013108
Six day	185.934034	72.11017	162.88745	146.770096
Seven day	254.268157	71.58625	210.31240	187.416759
Eight day	293.981286	75.31508	235.73996	209.342520
Nine day	309.899980	74.36227	242.98123	215.549116
Ten day	333.287057	74.05306	253.91151	225.029683
	Information Criteria			
DIC	5059.06	5447.40	5278.87	5284.00
WAIC	5123.56	5460.81	5286.90	5294.74

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Appendix

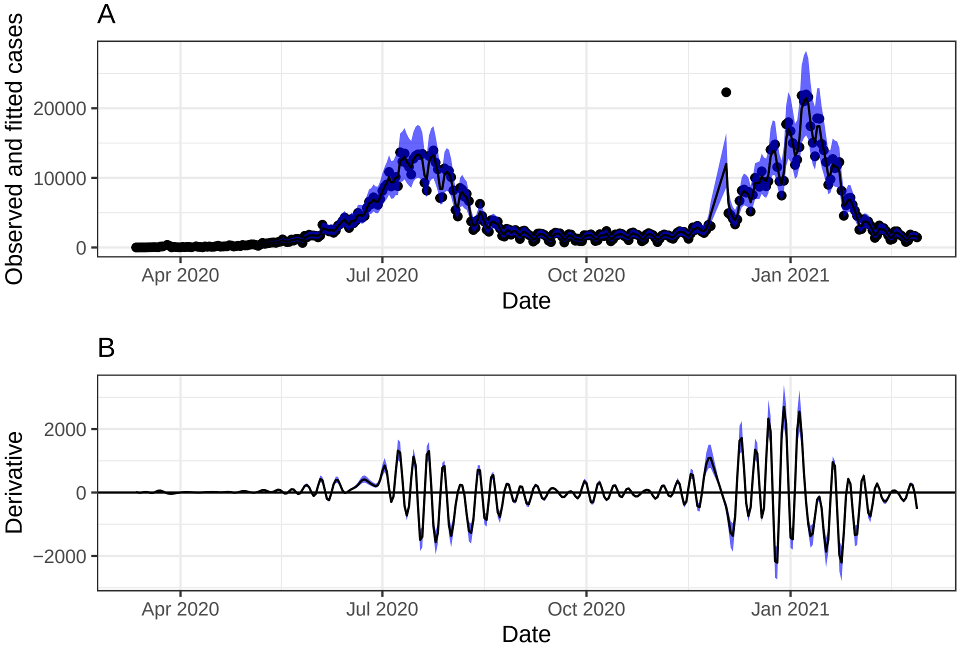

Fig S1. AR1 model for the daily confirmed COVID-19 cases in South Africa 12/03/2020-27/02/2021. Panel A-fitted and observed data. The balck dotes are the observed number of daily cases, the black solid line the fitted curve, and the blue shaded area is the 95% credible interval. Panel B-first-order derivative of the fitted curve along with the 95% credible interval.

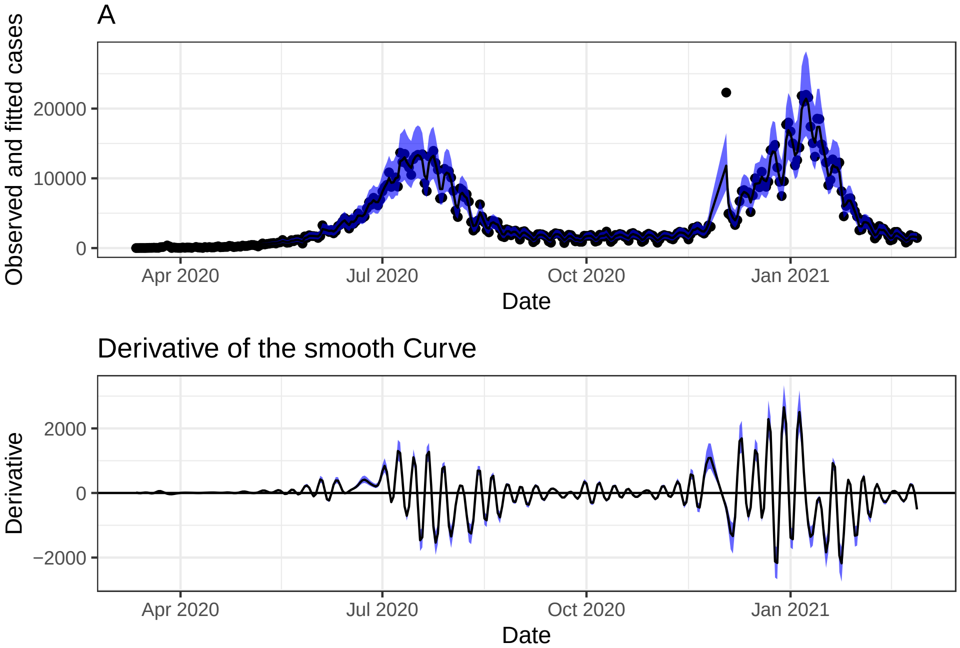

Fig S2. AR2 model for the daily confirmed COVID-19 cases in South Africa 12/03/2020-27/02/2021. Panel A-fitted and observed data. The balck dotes are the observed number of daily cases, the black solid line the fitted curve, and the blue shaded area is the 95% credible interval. Panel B-first-order derivative of the fitted curve along with the 95% credible interval.

Table S1. Parameter estimates for each model

Model		mean	sd	Lower	upper
AR1	(Intercept)	6.109	2.441	0.145	10.569
	Size	28.955	8.389	16.805	49.397
	Precision for time	0.158	0.112	0.023	0.438
	Rho for time	0.995	0.004	0.985	0.999
AR2	(Intercept)	6.307	1.659	2.475	9.299
	Size	28.399	8.492	15.999	49.001
	Precision for time	0.236	0.126	0.066	0.547
	PACF1 for time	0.992	0.005	0.980	0.998
	PACF2 for time	0.007	0.085	0.006	0.177
RW1	(Intercept)	7.565	0.001	7.564	7.587
	Size	53.685	24.186	24.47	116.45
	Precision for time	0.231	0.044	0.15	0.23
RW2	(Intercept)	7.603	0.017	7.570	7.637
	Size	10.422	0.911	8.734	12.319
	Precision for time	0.036	0.014	0.016	0.070

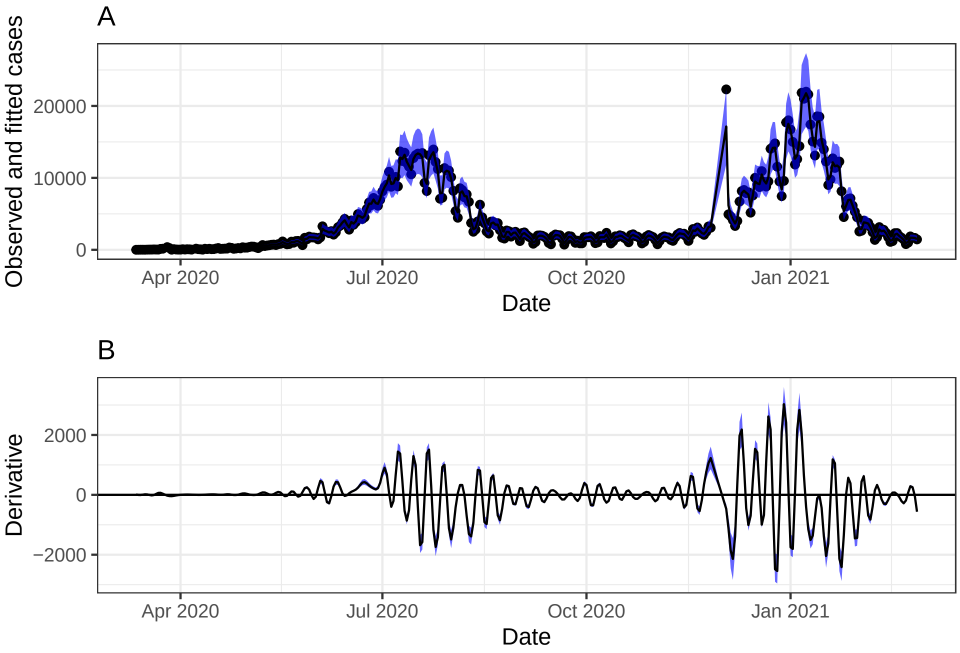

Fig S3. RW1 model for the daily confirmed COVID-19 cases in South Africa 12/03/2020-27/02/2021. Panel A-fitted and observed data. The balck dotes are the observed number of daily cases, the black solid line the fitted curve, and the blue shaded area is the 95% credible interval. Panel B-first-order derivative of the fitted curve along with the 95% credible interval.

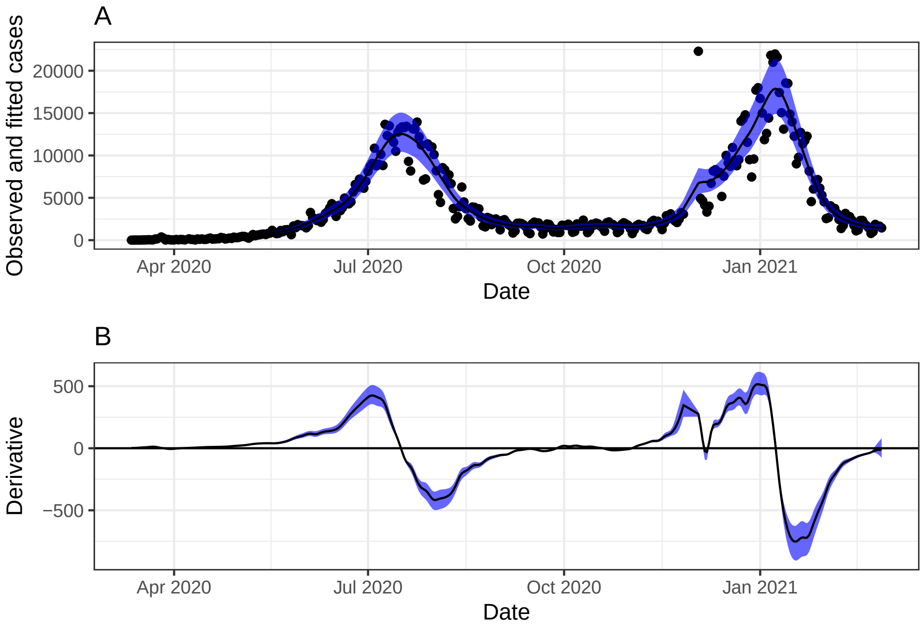

Fig S4. RW2 model for the daily confirmed COVID-19 cases in South Africa 12/03/2020-27/02/2021. Panel A-fitted and observed data. The balck dotes are the observed number of daily cases, the black solid line the fitted curve, and the blue shaded area is the 95% credible interval. Panel B-first-order derivative of the fitted curve along with the 95% credible interval.

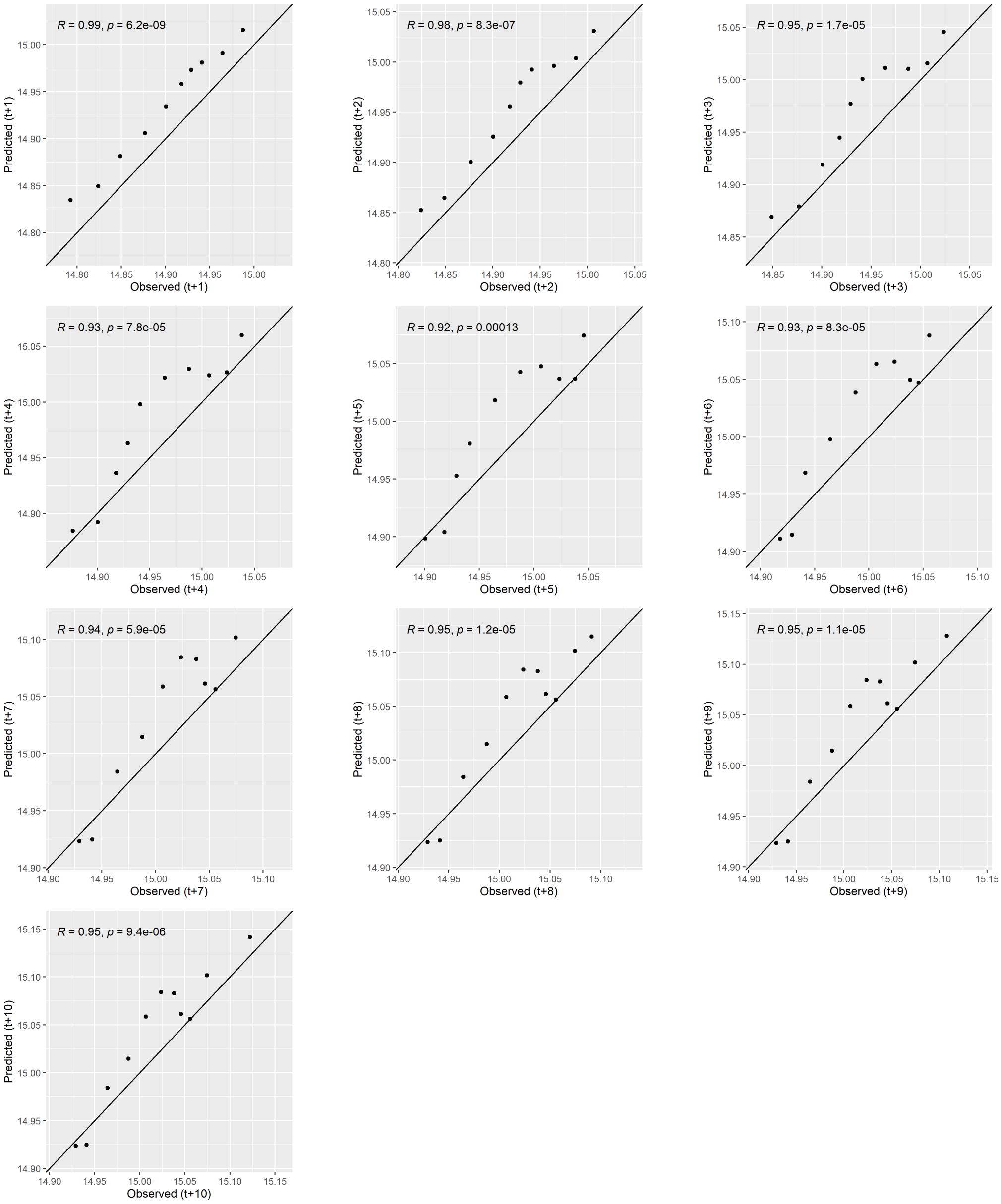

Fig S5. Predicted vs observed cumulative COVID-19 cases per 100, 000 in South Africa under the RW(2) model. Base estimation period day 0 - 12/03/2020 to day t - 07/02/2021. The estimation period was expanded until 17/02/2021 one day at a time