

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

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SUSAN Conference 2021, Kenya

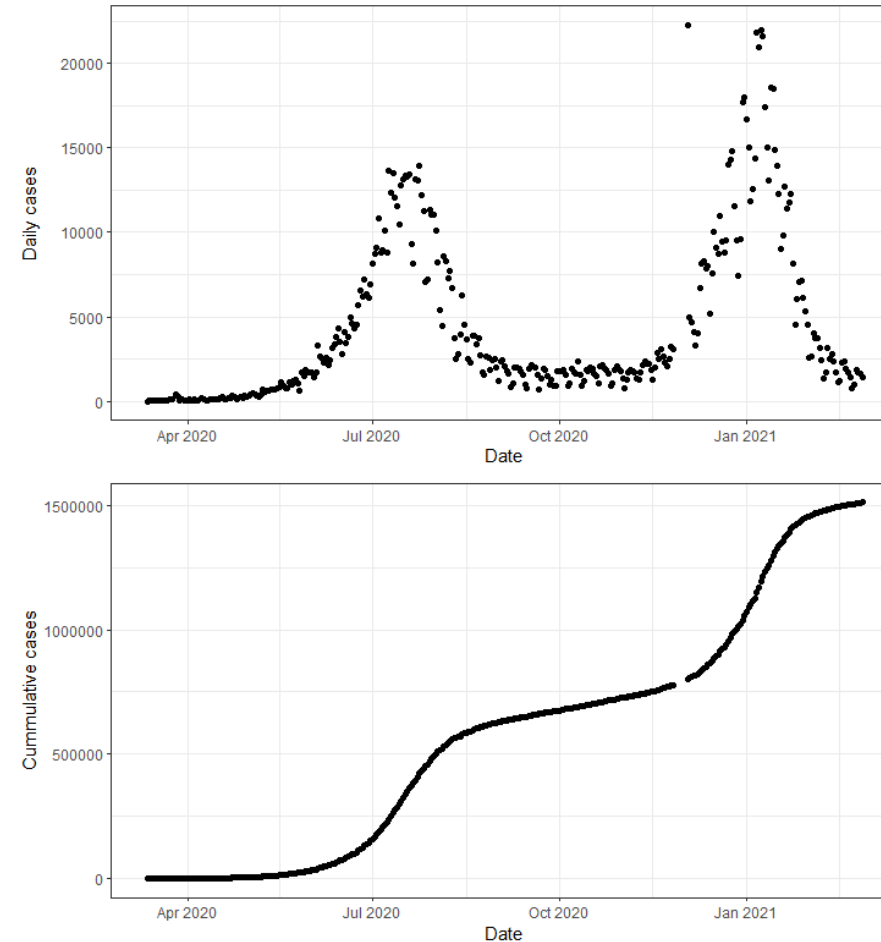


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Introduction

- 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 COVID-19 outbreak.

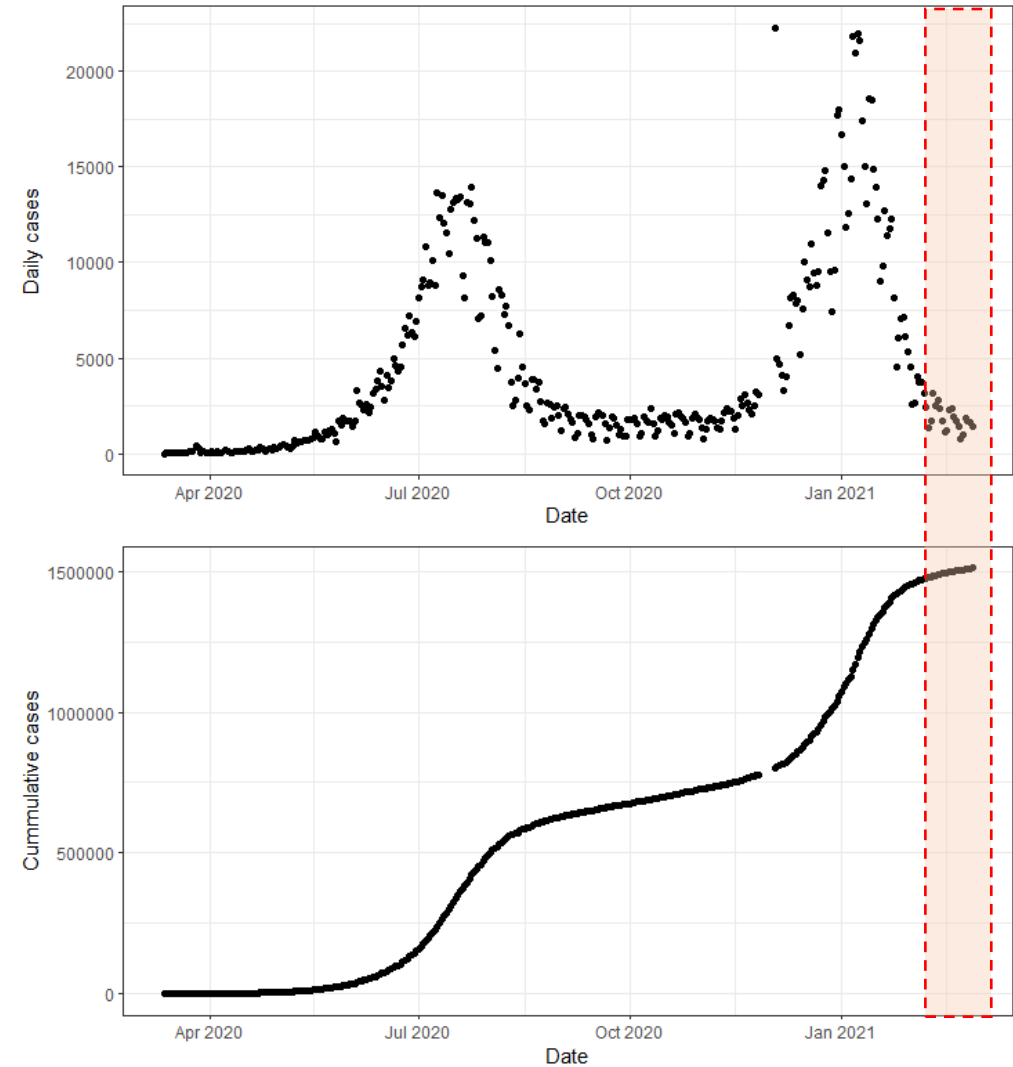
Reported COVID 19 cases in South Africa (12 March 2020-27 February 2021)



<https://raw.githubusercontent.com/dsfsi/covid19za/master/data/>

Aim

- Can we predict the cumulative number of cases k days a head?
- How can we measure the performance/accuracy of our prediction?



Modelling approach

- We consider a Negative binomial distribution for modelling the number of daily COVID 19 cases to account for possible overdispersion.

$$Y_t \sim \text{NB}(\mu_t, \delta)$$

- We consider four temporal models to capture the trend over time
- Models were fitted within the Bayesian framework using *INLA* assuming non informative priors

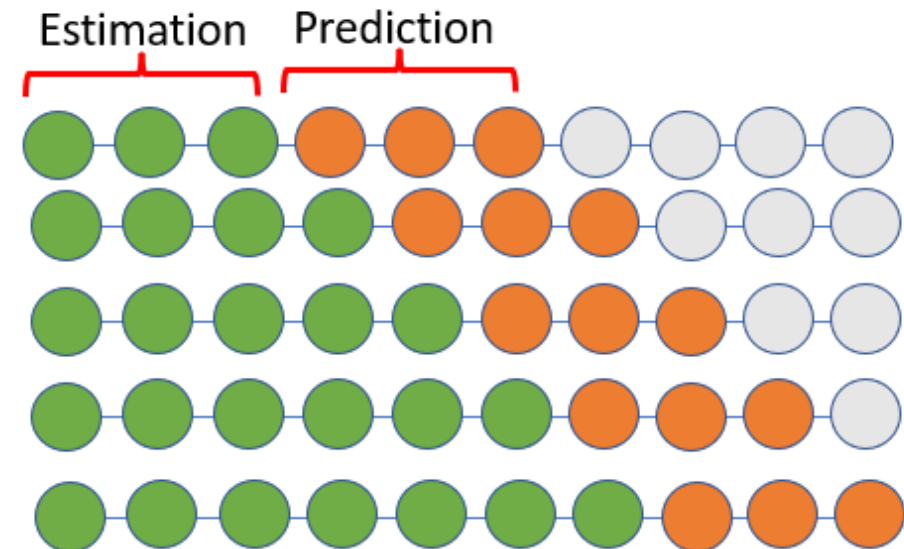
Model	
<i>AR</i> (1)	$\log(\mu_t) = \alpha + u_t,$ $u_1 \sim N(0, \tau_u(1 - \rho^2)^{-1}),$ $u_t = \rho u_{t-1} + \epsilon_t, \quad t = 2, \dots, T,$ $\epsilon_t \sim N(0, \tau_\epsilon),$
<i>AR</i> (2)	$\log(\mu_t) = \alpha + u_t,$ $u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \epsilon_t, \quad t = 2, \dots, T,$ $\epsilon_t \sim N(0, \tau_\epsilon),$
<i>RW</i> (1)	$\log(\mu_t) = \alpha + u_t,$ $u_t - u_{t-1} \sim N(0, \tau_u), \quad t = 2, \dots, T,$
<i>RW</i> (2)	$\log(\mu_t) = \alpha + u_t,$ $u_t - 2u_{t-1} + u_{t-2} \sim N(0, \tau_u), \quad t = 3, \dots, T.$

Model selection

Algorithm 1 Rolling origin cross-validation (ROCV).

- 1: Store the data starting day 1 to day T .
 - 2: Estimation period: initialize the number of initial observation for estimating the model (k)
 - 3: Prediction period: Set the number of days a head where the prediction is sought (w)
 - 4: **while** $k + w \leq T$ **do**
 - 5: Fit the proposed models using observations $t = 1, \dots, t = k$
 - 6: Hold out the next $k + 1, \dots, k + w$ observations
 - 7: Discard the remaining $T - (k + w)$ observations
 - 8: Compute predictive error metrics
 - a) Compute DIC and WAIC in the estimation period,
 - b) $MAE = \frac{\sum_{t=k+1}^{k+w} |C_t - C_t^*|}{w}$,
 - c) $MAPE = \frac{1}{w} \sum_{t=k+1}^{k+w} \left| \frac{C_t - C_t^*}{C_t} \right|$,
 - d) $Chi - Squared = \sum_{t=k+1}^{k+w} \frac{(C_t - C_t^*)^2}{C_t}$,
 - 9: $k = k + 1$
 - 10: **end while**
-

where C_t and C_t^* denotes the observed and predicted cumulative cases at time t , respectively.



Model selection

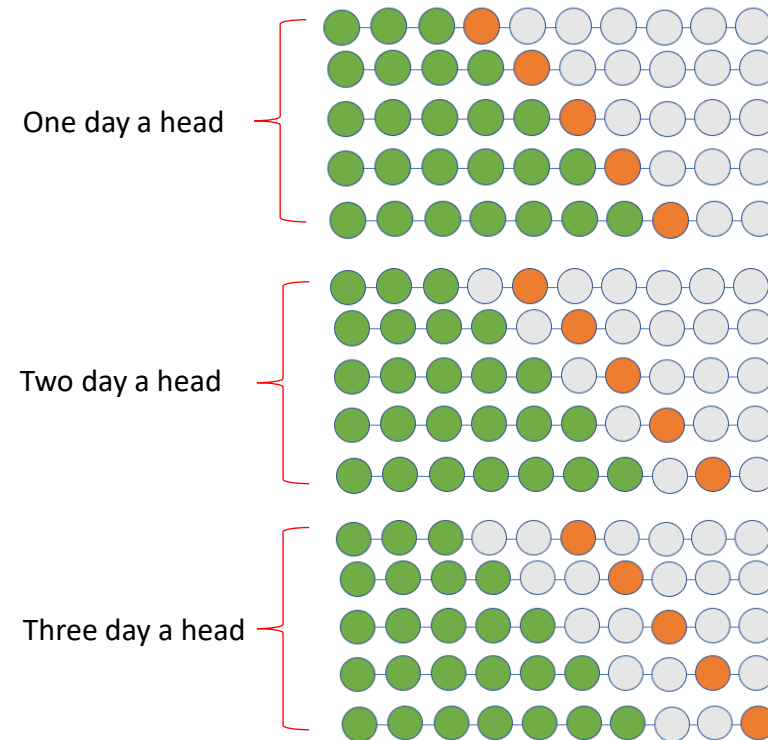
Algorithm 2 Modified rolling origin cross-validation (MROCV).

- 1: Store the data starting day 1 to day T .
 - 2: Estimation period: initialize the number of initial observation for estimating the model (k)
 - 3: **while** $w \leq 10$ **do**
 - 4: **while** $k + w \leq T$ **do**
 - 5: Fit the proposed models using observations $t = 1, \dots, t = k$
 - 6: Prediction period: Hold out the next $k + 1, \dots, k + w$ observations
 - 7: Discard the remaining $T - (k + w)$ observations
 - 8: Store predicted and observed cumulative cases (C_t, C_t^*)
 - 9: AE:

$$AE_{kw} = |C_{k+w} - C_{k+w}^*|,$$
 - 10: APE:

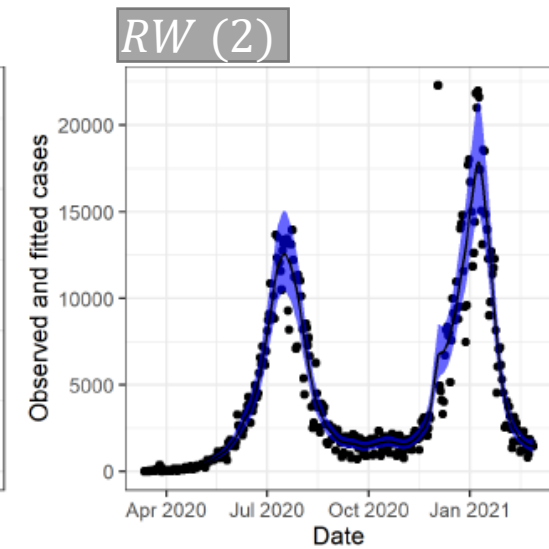
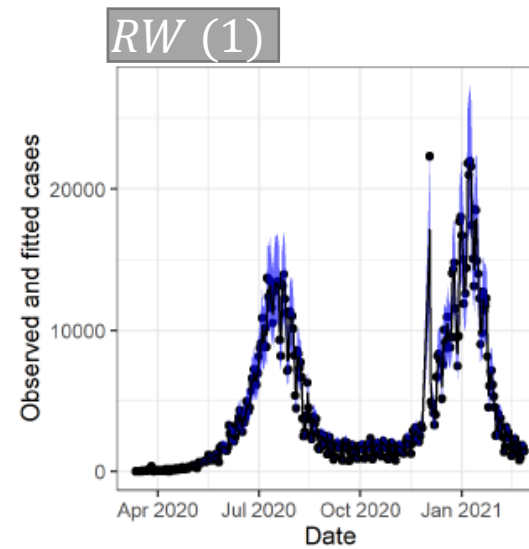
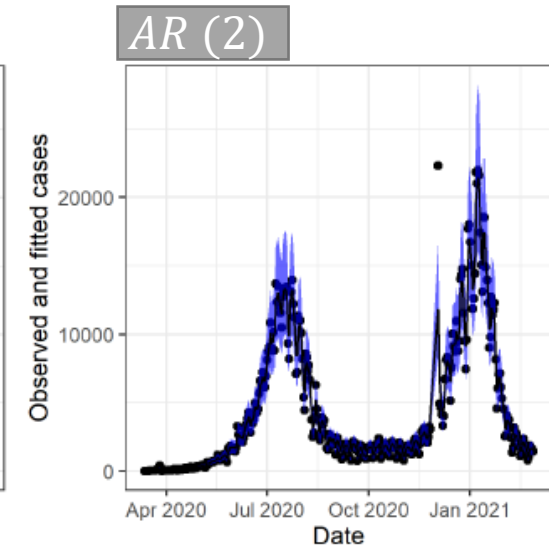
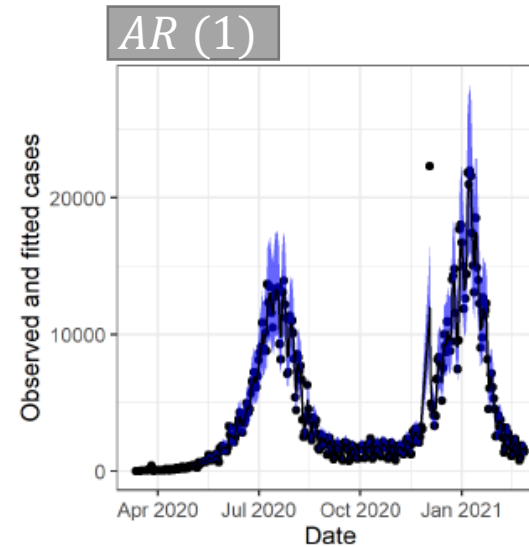
$$APE_{kw} = \left| \frac{C_{k+w} - C_{k+w}^*}{C_{k+w}} \right|,$$
 - 11: OE2:

$$OE2_{kw} = \frac{(C_{k+w} - C_{k+w}^*)^2}{C_{k+w}}$$
 - 12: $k = k + 1$
 - 13: **end while**
 - 14: Compute $MAE_w = \frac{\sum AE_{kw}}{K}$, $MAPE_w = \frac{1}{K} \sum APE_{kw}$, and $Chi - Squared_w = \sum OE2_{kw}$, where K is the number of estimation period.
 - 15: $w = w + 1$
 - 16: **end while**
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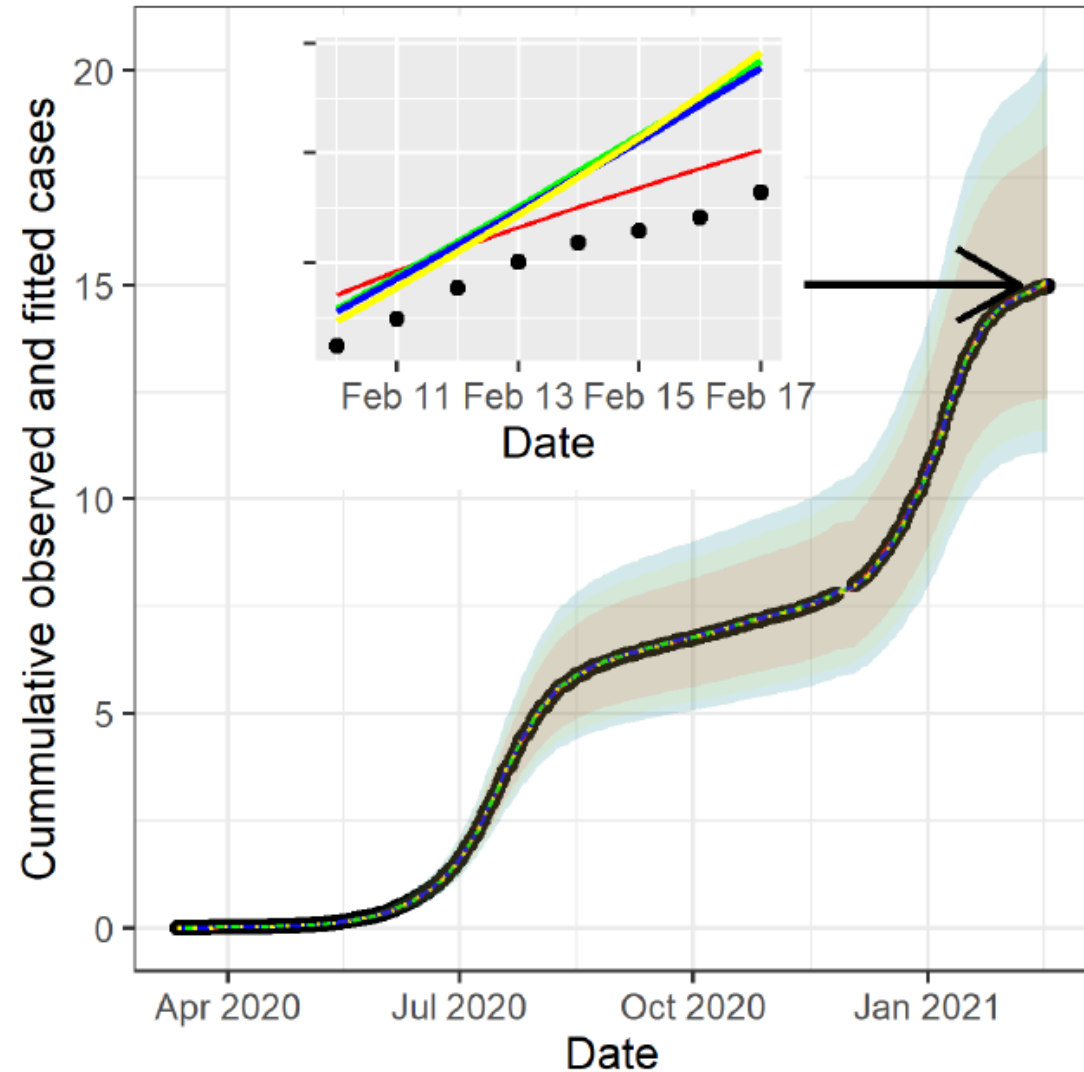
Application

- The four models described in the previous section were fitted to the daily reported new COVID-19 cases.
 - Estimation period fixed from 2/03/2020 to 07/02/2021
 - All models considered appear to fit the observed data (within the estimation period) well.
 - $AR(1)$, $AR(2)$, and $RW(1)$ models tend to overfit the data
 - $RW(2)$ model produces a smooth line as predicted model



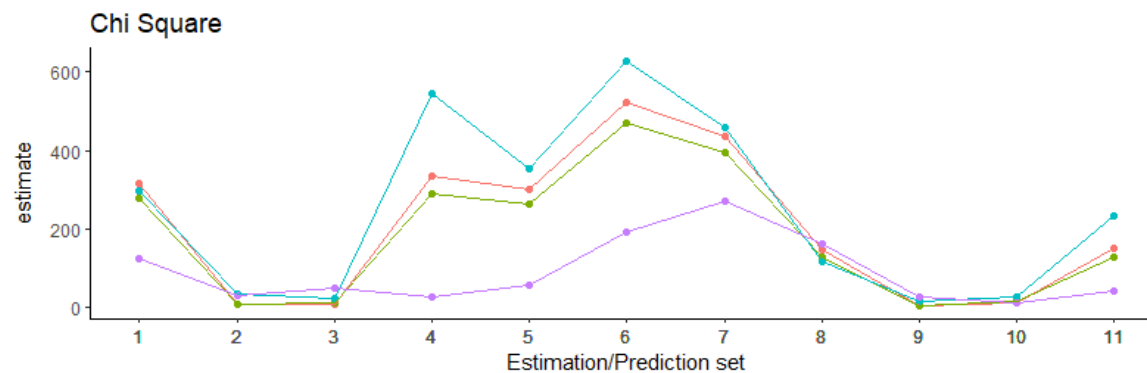
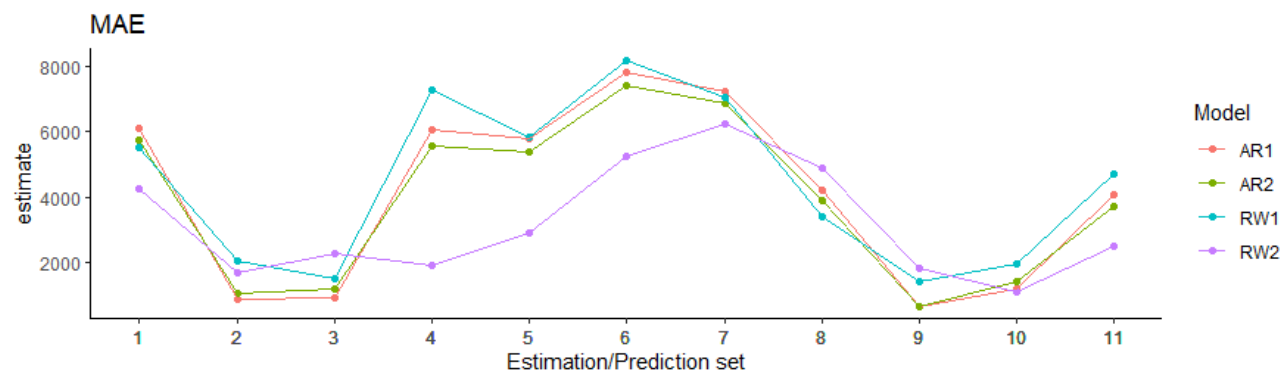
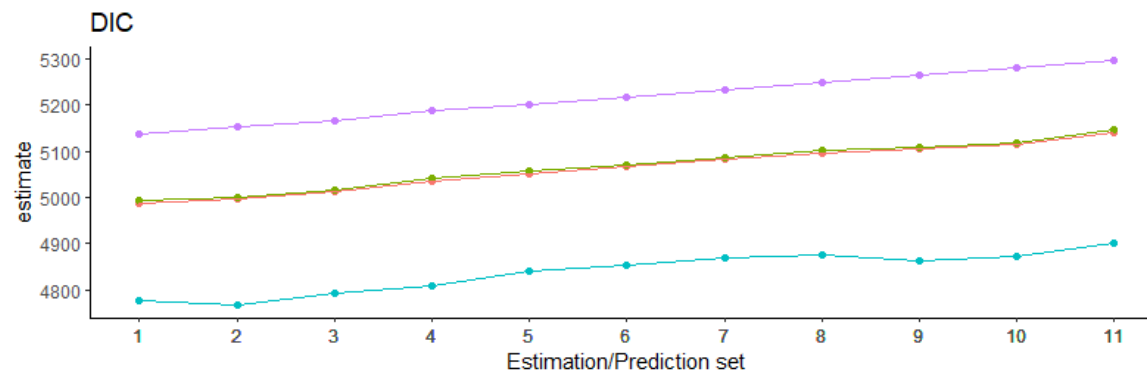
Application

- We produce 10-days ahead forecasting, up to 17/02/2021, 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 $RW(2)$ model performed well, showing a consistent prediction performance throughout the forecasting period

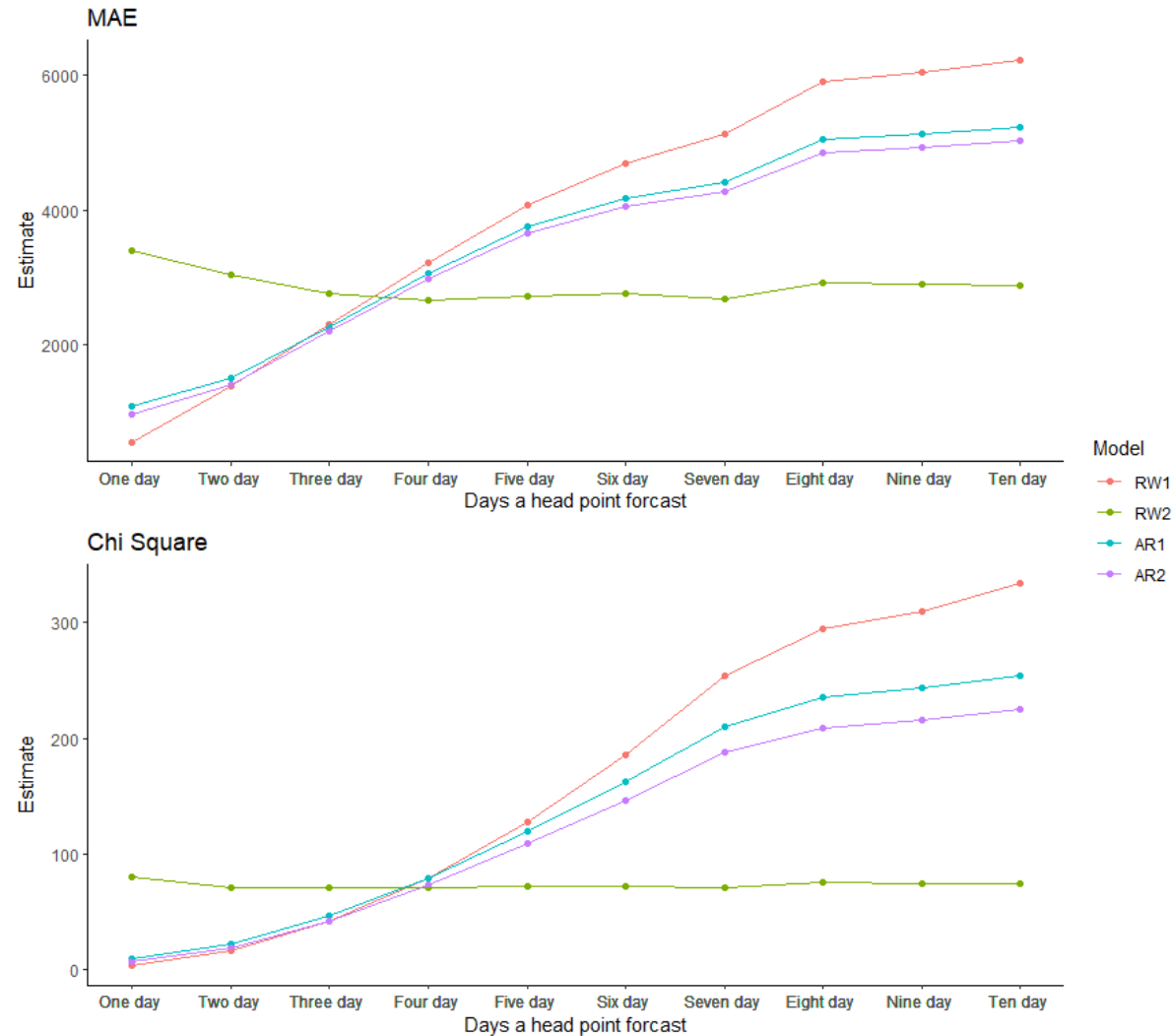


Prediction performance – Algorithm (1)

Estimation/ Prediction set	Estimation Period	Prediction Period
1	12/03/2020-07/02/2021	08/02/2021-17/02/2021
2	12/03/2020-08/02/2021	09/02/2021-18/02/2021
3	12/03/2020-09/02/2021	10/02/2021-19/02/2021
4	12/03/2020-10/02/2021	11/02/2021-20/02/2021
5	12/03/2020-11/02/2021	12/02/2021-21/02/2021
6	12/03/2020-12/02/2021	13/02/2021-22/02/2021
7	12/03/2020-13/02/2021	14/02/2021-23/02/2021
8	12/03/2020-14/02/2021	15/02/2021-24/02/2021
9	12/03/2020-15/02/2021	16/02/2021-25/02/2021
10	12/03/2020-16/02/2021	17/02/2021-26/02/2021
11	12/03/2020-17/02/2021	18/02/2021-27/02/2021



Prediction performance – Algorithm (2)



Conclusion

- We modelled COVID-19 cases in South Africa at the national level using publicly available data from 12 March 2020 to 27 February 2021.
- We have evaluated four widely used temporal models for forecasting confirmed cases of COVID-19 for South Africa.
- The analysis was based on readily accessible, publicly available data that is updated in real-time.
- The statistical methods applied are implemented using o-the-shelf open-source software and are not dependent on any assumptions regarding COVID-19 transmission dynamics.
- 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.

R code

The source code for producing the results presented is available at

[belayb/COVIDincidenceSA: Modelling COVID-19 incidence and forecasting - South Africa \(github.com\)](https://github.com/belayb/COVIDincidenceSA: Modelling COVID-19 incidence and forecasting - South Africa)