# Flexible Bayesian Nowcasting – Application to COVID-19 fatalities in Sweden

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**Abstract**

The real-time analysis of infectious disease surveillance data, e.g. time-series of reported cases or fatalities, can help to provide situational awareness about the current state of a pandemic. This task is challenged by reporting delays that give rise to *occurred-but-not-yet-reported* events. If these events are not taken into consideration, this can lead to an underestimation of the counts-to-be-reported and, hence, introduces misconceptions by the interpreter, the media or the general public - as has been seen for example for reported fatalities during the COVID-19 pandemic.

*Nowcasting* methods provide close to real-time estimates of the complete number of events using the incomplete time-series of currently reported events by using information about the reporting delays from the past. In this report, we consider nowcasting the number of COVID-19 related fatalities in Sweden. We propose a flexible Bayesian approach that considers temporal changes in the reporting delay distribution and, as an extension to existing nowcasting methods, incorporates a regression component for the (lagged) time-series of the number of ICU admissions. This results in a model considering both the past behavior of the time-series of fatalities as well as additional data streams that are in a time-lagged association with the number of fatalities.

# 1 Introduction

The real-time analysis of infectious disease surveillance data, e.g. time-series of reported cases or fatalities, can help to provide situational awareness about the current state of a pandemic during the pandemic and can be used by public health agencies and governments for monitoring the disease development and planning of preventive actions Metcalf et al. (2020); Wu et al. (2021). This task is challenged by reporting delays that give rise to *occurred-but-not-yet-reported* events which may lead to underestimation of the complete number of reported events. The problem is illustrated in Figure 1 with data of Swedish COVID-19 related fatalities as of 2020-11-24, where the reported number of fatalities per day is showing a declining trend when in reality the number of fatalities per day was currently increasing. However, the reporting for this period of time was not complete until mid February 2021, in other words almost to 3 months later. *Nowcasting* methods (Donker et al., 2011; Höhle and an der Heiden, 2014; McGough et al., 2020) tackle this problem by providing close to real-time estimates of the complete number of events using the incomplete time-series of currently observed events and information about the reporting delay from the past.

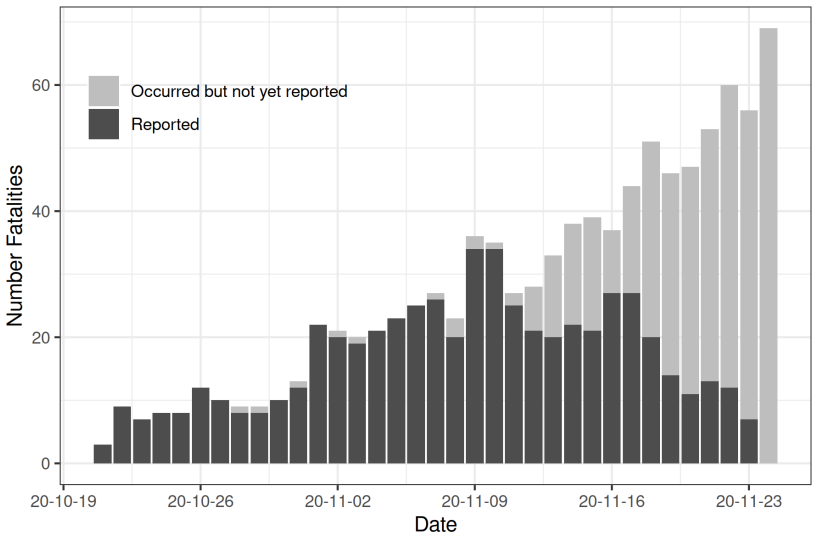


Figure 1: Number of fatalities per day, reported (black bars) and unreported (grey bars) as of 2020-11-24. The figure shows the actual reported situation of Swedish COVID-19 related fatalities on that day, where the reported number of events shows a declining trend but when in reality (as known in hindsight) it was increasing.

Nowcasting methods have connections to insurance claims-reserving Kaminsky (1987) and its epidemiological applications trace back to HIV/AIDS modelling (Kalbfleisch and Lawless, 1989; Zeger et al., 1989; Lawless, 1994). A

Bayesian approach to Nowcasting, which constitutes the foundation of our method, was developed by Höhle and an der Heiden (2014). Nowcasting methods has been used in COVID-19 analysis for daily infections Greene et al. (2021); Li and White (2021), and fatalities Schneble et al. (2020); Altmejd et al. (2020); Bird and Nielsen (July 2020). Most nowcasting methods are focused on estimating the reporting delay distribution; however, an epidemic contains a temporal dependence since the disease transmission is correlated from one time point to the next. Taking the temporal dependence into account has been shown to improve the nowcasting performance McGough et al. (2020); Günther et al. (2020). Another approach to nowcasting, not considering the delay distrubution, is to use other data sources that are sufficiently correlated with the time series of interests, see e.g. the Machine Learning approach by Peng et al. (2021).

As an extension to existing Nowcasting methods, we propose a method that allows for flexibility in the reporting delay structure and additionally incorporates further correlated data streams. Our approach for nowcasting Swedish COVID-19 fatalities is based on a Bayesian hierarchical model that considers temporal changes in the reporting delay distribution and incorporates a regression component for the (lagged) time-series of the number of Intensive Care Unit (ICU) admissions.

The surveillance data used for the analysis in this paper are daily counts of fatalities and ICU admissions of people with a laboratory-confirmed SARS-CoV-2 infection in Sweden. The data is publicly available from the website of the Public Health Agency of Sweden FHM, where new reports are published daily throughout Tuesday to Friday (excluding public holidays). The aggregated daily counts are updated in retrospective at each reporting date, this implies that the published time series on reported COVID-19 fatalities will always show a declining trend as the events are associated with a reporting delay (see Figure 1 for an illustrative example). The reporting delay can not be observed in a single published report but can be obtained by comparing the aggregated numbers of fatalities of each date from previously published reports.

In the present work, we present methodological details of our approach and compare the results to existing nowcasting methods to illustrate the implication of incorporating an additional regression component associated with the number of fatalities.

# 2 Method

In this section we present the methodological details of our approach, which follows closely the notation introduced in Günther et al. (2020). In particular, our nowcasting model has two distinct elements; (1) the underlying epidemic curve and (2) the delay distribution.

## 2.1 Flexible Bayesian Nowcasting

Let $n_{t,d}$, be the number of events occurring on day $t = 0, ..., T$ and reported with a delay of $d = 0, ..., \infty$ days, such that the reporting occurs on day $t + d$. The goal of Nowcasting is to infer the total number of events $N_t$ on day $t$ based on the information available on the current day $T > t$. The sum $N_t$ can be written as

$$N_t = \sum_{d=0}^{\infty} n_{t,d} = \sum_{d=0}^{T-t} n_{t,d} + \sum_{d=T-t+1}^{\infty} n_{t,d},$$

where the first sum is observed and the second sum is yet unknown. This can be illustrated by the so called reporting triangle, seen in Fig 2. In the figure, the upper triangle with green boxes (solid line) are showing the reported events and red boxes (dashed line) illustrates what is yet unreported and is estimated with the Nowcasting model. In practice, we allow for a maximum delay of $D$ days.

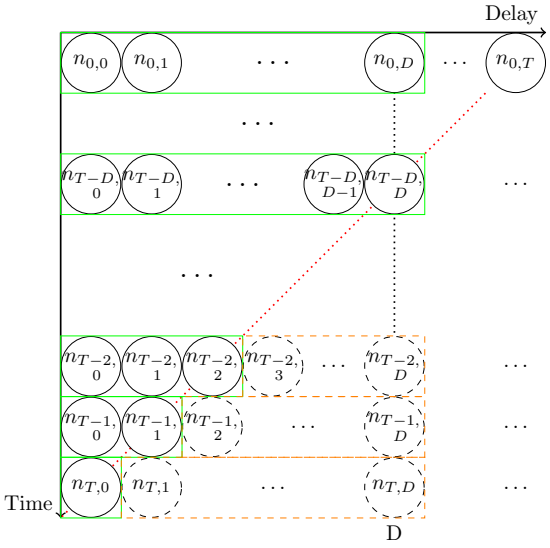


Figure 2: The reporting triangle. Green boxes (solid line) where $t \leq T - D$ are showing the reported cases on day $T$, while the red boxes (dashed line) corresponding to $t \geq T - D$ is yet unreported on day $t + D$.

The number of events occurring on day $t$ with a delay of $d$ days is assumed to be negative binomial distributed

$$n_{t,d}|\lambda_t, p_{t,d} \sim \text{NB}(\lambda_t \cdot p_{t,d}, \phi),$$

with mean $\lambda_t \cdot p_{t,d}$ and overdispersion parameter $\phi$.

#### 2.1.1 *First component: The epidemic curve*

Let $\lambda_t = \mathbb{E}[N_t]$ denote the expected number of events on day $t$. We specify a baseline model for $\lambda_t$ as

$$\log(\lambda_t)|\lambda_{t-1} \sim N(\log(\lambda_{t-1}), \sigma^2), \tag{1}$$

where $t = 0, ..., T$ and $d = 0, ..., D$. Time $t = 0$ is assumed to be the start of the the pandemic or the observation period. This approach to model $\lambda_t$ as a Random Walk on the log scale is proposed by Günther et al. (2020) and we will use it as a benchmark model.

As an extension of Eq. (1), we assume that we can predict the total number of events with an additional data stream having a time-lagged association with the event of interest. The additional data stream is assumed to be ahead in time compared to the time series of interest, e.g., due to the tracked event being a more earlier state in a typical COVID-19 disease progression, or because of smaller reporting delays. We denote the additional data stream at time $t$ as $m_t$ and specify the extended model for $\lambda_t$ as

$$\log(\lambda_t)|\lambda_{t-1}, m_{t-\text{lag}}, \sim N(\beta_0 \log(\lambda_{t-1}) + \beta_1 \log(m_{t-\text{lag}}), \sigma^2), \tag{2}$$

where the $\beta_0$ and $\beta_1$ are regression coefficients, such that $\lambda_t$ is assumed to be a linear combination of its prior value and the additional time series $m$ with some specified time lag. We note that in the case of $\beta_0 = 1$ and $\beta_1 = 0$ the two models specified in Eq. (1) and Eq. (2) become identical.

#### 2.1.2 *Second component: The delay distribution*

The model for the delay distribution at day $t$ is specifying the probability of a reporting delay of $d$ days for a fatality occurring on day $t$. We denote this conditional probability

$$p_{t,d} = P(\text{delay} = d|\text{fatality day} = t).$$

Similarly to Günther et al. (2020), we model the delay distribution as a discrete time hazard model $h_{t,d} = P(\text{delay} = d|\text{delay} \geq d, W_{t,d})$ as

$$\text{logit}(h_{t,d}) = \mathbb{1}_{rep}(\gamma_d + W'_{t,d}\eta), \tag{3}$$

where $d = 0, ..., D-1, h_{t,D} = 1$, $\gamma_d$ is a constant, $W_{t,d}$ being a vector of time- and delay-specific covariates and $\eta$ regression coefficients. The indicator function $\mathbb{1}_{rep}$ enforce the reporting probability to be zero for non-reporting days. In Günther et al. (2020) it is shown how the reporting probabilites are derived from Eq. (3).

### 2.2 Implementation

The implementation is a hierarchical Bayesian model for nowcasting based on Höhle and an der Heiden (2014) and Günther et al. (2020) in R (R Core Team, 2021) and the inference for the Bayesian hierarchical models is performed using Markov Chain Monte Carlo using Stan (Stan Development Team, 2020).

# 3 Results

## 3.1 Application to fatalities

We apply our Nowcasting method to reported COVID-19 fatalities in Sweden and use the change in number of new ICU admissions as the additional data stream. We let $N_t$ be the daily total number of fatalities. We further let the change in ICU admission be the observed signal, $m_t$, as we assume that an increase in ICU admissions will also mean an increase the number of fatalities with some delay. In Sweden, ICU admissions are associated with less reporting delay than the fatalities.

## 3.2 Retrospective Nowcasting Evaluation

We use a retrospective evaluation to assess the performance of our model, in which we compare the model performance to the now assumed to be known true number of COVID-19 related fatalities in Sweden. The evaluation period ranges from August 29 2020 to April 6 2021 and contains 101 reporting days (Tuesday to Friday excluding public holidays). The evaluation period is chosen such that it covers the second wave of COVID-19 related fatalities in Sweden. The time series of number of fatalities and weekly ICU admissions can be seen in Appendix Fig. 7.

In the discrete time hazard model in Eq. (3), we are using linear effects of the time with break-points every two weeks before the current day and a categorical weekday effect. The reporting probability is forced to be zero on non-reporting days (Saturday-Monday) and we use a maximum delay of $D = 35$ days.

To evaluate the performance of our nowcasting method, the posterior samples of the total number of events, $\hat{N}_t = \sum_{d=0}^{D} \hat{n}_{t,d}$ are extracted for each reporting date of the evaluation period for both the benchmark model and the ICU-model data. Figure 3 is showing the model results for a single day, 2020-11-24. For this reporting date, we see that the baseline model and the extended model which includes the ICU data provide fairly similar results and that both models provide reasonable estimates of the (at that time) unknown total number of reported fatalities.

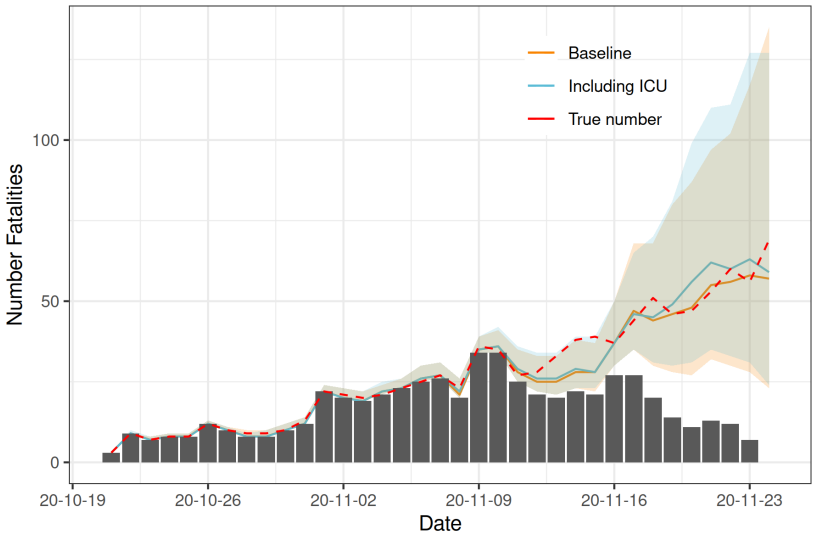


Figure 3: Model performance when "now" is 2020-11-24. The black bars are the number of fatalities known at the reporting date and the red (dashed) line is showing the true number, only known in retrospect. The orange and blue color represent the results of the baseline model in Eq. (1) and the model including ICU data in Eq. (2) respectively. The solid lines are the median of the posterior predictive distribution of $\hat{N}_t$ and the shaded areas are the 95% Bayesian prediction interval.

To assess the model performance over the whole evaluation period, the samples of $\hat{N}_t$ are evaluated at each reporting day for that current day (when the reporting delay is equal to zero days. In other words, it is the estimates of the complete number of event on the actual reporting day day are evaluated for each reporting day in the evaluation period. In Figure 3, this corresponds to evaluating the model prediction at Nov 24. The model performance at "now" over the evaluation period can be seen in the Appendix (Figure 6). To quantify the the model performance, we use as in (Günther et al., 2020) the following four metrics; 1) root mean squared error (RMSE), 2) log scoring rule (logS), 3) continuous rank probability score (CRPS), and 4) the prediction interval coverage (PI). The RMSE is calculated with a point estimate being the median of the posterior samples of $\hat{N}_t$, while the scoring rules logS and CRPS are assessing the quality of the probabilistic forecast by considering the full posterior distribution of $\hat{N}_t$ Gneiting and Raftery (2007). For the PI, we provide coverage frequencies of 95% prediction intervals for the number of fatalities per day.

Figure 4 is showing the model performance evaluated by the CRPS over the evaluation period. From the figure, we can see that the baseline model performs better during a short period in November, but overall the extended model including ICU data has a slightly lower score and hence better performance. The remaining scoring rules, the RMSE and LogS, entail similar results (seen in Appendix Figure 7).

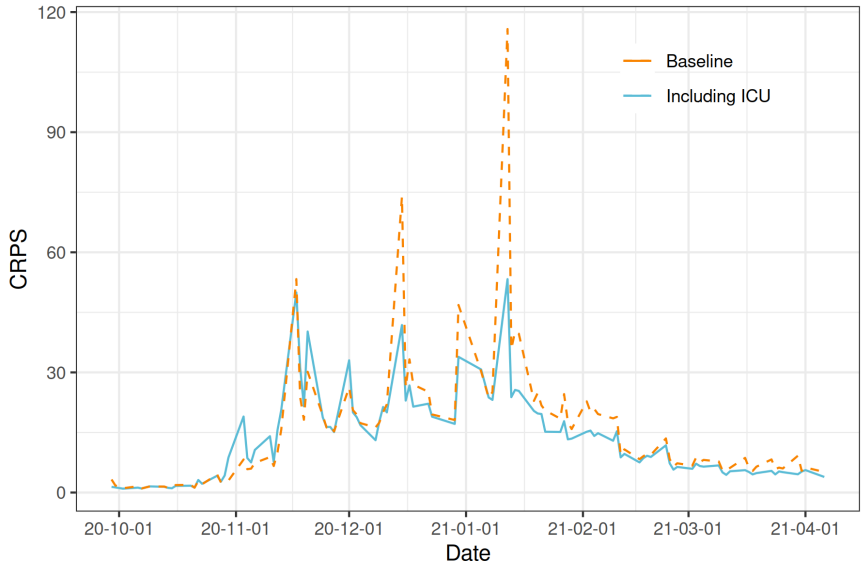


Figure 4: **Retrospective model evaluation by the CRPS.** The figure shows the scoring rule of the model evaluation at the current day for each reporting day from 2020-09-29 Sep to 2021-04-06. The orange (dashed) line represents to the baseline model in Eq. (1) and the blue (solid) line the model in Eq. (2).

Table 1 shows the average values of the evaluation metrics over the whole evaluation period, including the coverage frequency of the 95% prediction interval. The average values of the RMSE, LogS and CRPS entail that the models perform very similar but that the model including the ICU data performs slightly better than the baseline model. The coverage of the 95% prediction interval is 94% for both models. In other words, the proportion of times the prediction intervals contain the actual number of fatalities is very close to the nominal level, which is a sign for good model calibration.

| **Score** | **Baseline** | **Including ICU** |
|---|---|---|
| RMSE | 11.8 | 11.7 |
| logS | 4.43 | 4.32 |
| CRPS | 15.4 | 13.3 |
| 95% PI | 94 | 94 |

Table 1: **Performance measures for the retrospective evaluation.** The results are averaged over the evaluation period. Baseline refers to the model in Eq. (1) and Including ICU refers to the model in Eq. (2).

The similar performance of the two models can be explained by the estimates of the regression coefficients seen in Figure 3.2. As previously mentioned in Section 2.1.1, the two models are equal when $\beta_0 = 1$ and $\beta_1 = 0$.

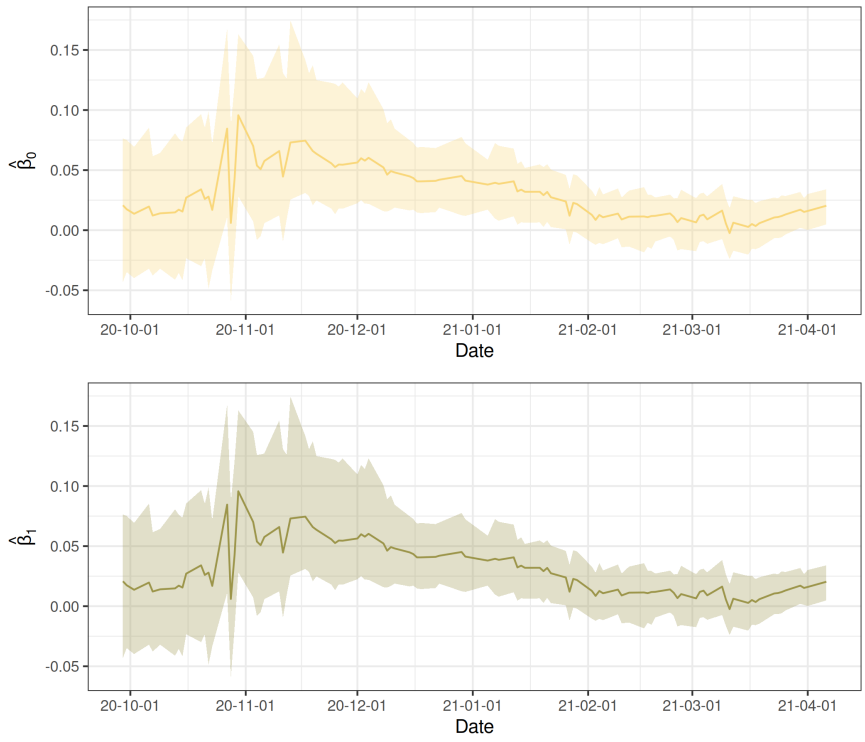


Figure 5: Regression coefficients estimates of the ICU-model. The solid lines are the median of the posterior distribution and the shaded areas correspond to the 95% credible intervals of $\hat{\beta}_0$ (top) and $\hat{\beta}_1$ (bottom).

### 3.3 ICU Admissions

We also apply the Nowcasting method to reported ICU admissions with confirmed Sars-Cov2 infection where the additional data source is the number of confirmed cases. This model has not yet been retrospectively evaluated, but will be continuously monitored and evaluated as the pandemic progress.

## 4 Discussion

In our presented work we provide an alternative to Altmejd et al. (2020) for real-time estimates for the number of Swedish COVID-19 fatalities. Even though fatalities are a lagging indicator in order to obtain situational awareness about the pandemic, and is not without difficulties itself, it is often used an indicator to assess burden of disease. Hence, with the emergence of the omicron variant and relating to the discussions about its severity, monitoring the time series of reported deaths will be of importance. We aim to monitor

and evaluate our approach in real-time as cases unfold. Current nowcast estimates of COVID-19 fatalities and ICU admissions in Sweden can be found on https://staff.math.su.se/fanny.bergstrom/covid19-nowcasting.

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# Appendix

Figure 6 is showing results from the retrospective evaluation. The figure is showing the performance of the model for the evaluated at the most current day for each reporting date in the evaluation period.

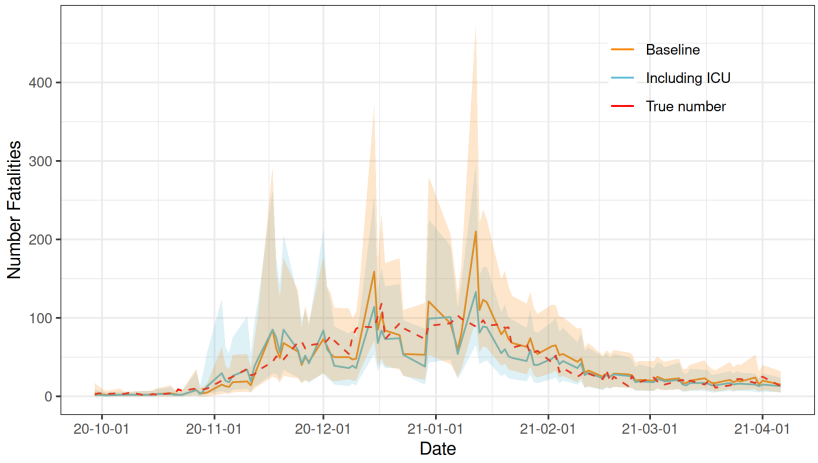


Figure 6: Model performance over the evaluation period October 2020 to April 2021. The orange represents to the baseline model in Eq. (1) and the blue the model including ICU in Eq. (2). Solid lines are the median of the posterior predictive distribution of $\hat{N}$ and the shaded area is the 95% credible interval.

Figure 7 show the evaluation by the RMSE and Log Score over the whole evaluation period for the model including ICU and the baseline model. The figures are complimentary to Figure 4 where the CRPS is shown.

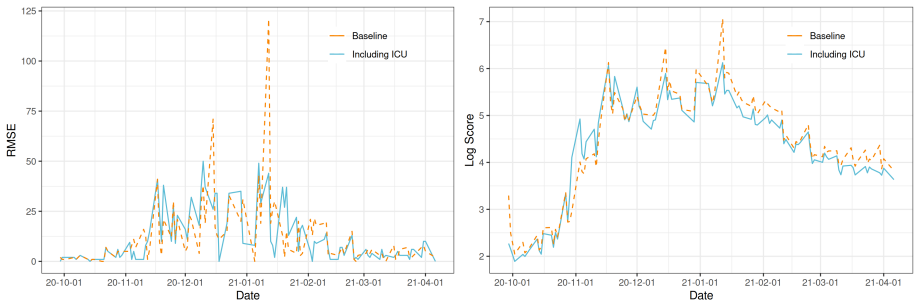


Figure 7: Model evaluation by the RMSE (left) and Log Score (right). The models are evaluated at each reporting day from October 2020 to April 2021.