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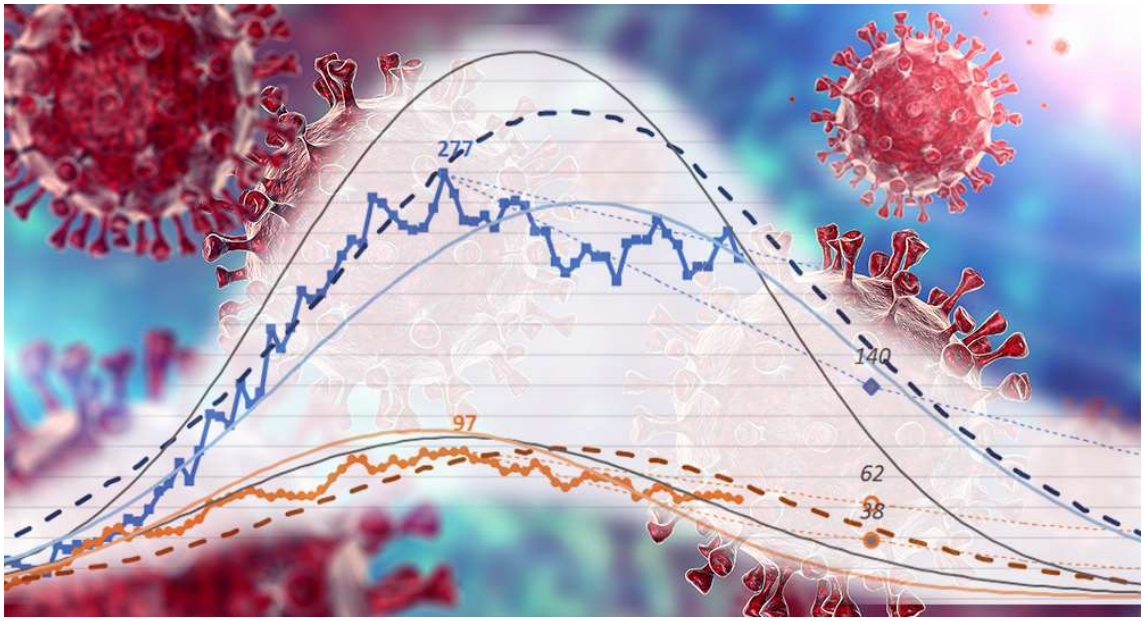

Prediction models for planning health care resources

During the first wave of the Covid-19 pandemic 2020

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Summary

Due to the Covid-19 pandemic, has emphasized a need for planning health care resources based on only a few aggregated data points and little knowledge of the data-generating process.
In the first part of the report, we present the process of our work in spring 2020 during the first wave and especially during the first part with the high demands on health care resources. In the second part of the report, we discuss the logistic growth model (LGM), one of our models used to predict the peak height and the peak timing. We present some different approaches to use the LGM, and compare these to a different data set, Belgium data.

For the Swedish regional data, the LGM on raw observations gave a good estimate on the peak height. The adjusted LGM, using cumulative new inpatient beds, fitted the Swedish regional data to a satisfying degree. For the Belgium data, the LGM on raw observations gave a good estimate on peak height and timing. The adjusted LGM, using cumulative new inpatient beds, did not work for the Belgium data as it gave a too early peak time and a too low peak height.

The experience from our work, in combination with now existing literature, the process in a similar future situation would include better knowledge on how to find and combine data to get as reliable forecasts as possible and to use creativity in combination with theoretical competence.

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Background

The current situation, due to the Covid-19 crisis, has emphasized a need for planning health care resources based on only a few aggregated data points and little knowledge of the data-generating process. This development has also highlighted the importance of useful models giving good enough predictions, which are clinically applicable and flexible over time.
During our work supporting health care planning, trying to continuously predict the number of inpatient beds and intensive care unit beds, we encountered several quite complex models based on different SIR models (1-3), where we tested adjusted versions of these, and also used more pragmatic models such as the logistic growth Model (LGM) (4).
As the future with high probability will put us in to some extent similar situations with new pandemic or epidemic situations, we believe it is important to prepare by presenting and discussing the methodological experience and knowledge this pandemic is giving us.
In many research studies observations are available that illustrates a general “true” pattern, but also including noise or measurement errors etc. The “true” pattern is assumed to follow a nicely behaving mathematical formula. Here, we tried to predict a pattern, but a pattern that could change due to that the disease process changed over time due to factors related to the disease, societal changes and changes in behavior of populations etc.
In this report, we discuss the prediction work in such new circumstances, with little data and a need of fast answers. In Part 1 of this report on the prediction work we did in collaboration with Västra Götalands Region (VGR) during the Covid-19 breakout in the spring of 2020. In Part 2 of the report we focus on the logistic growth model (LGM) that was one of our models, the simplest one, to predict the peak height and the peak timing.

Part 1: Prediction during spring 2020 in VGR

During the spring 2020, the practical aim was to predict the increase of inpatient beds in a future as near as a few weeks, but also the peak height and the peak timing of the first wave. This information was important for health care planning in a short time frame. Data was recorded 4-7 days a week, with an epidemic that was developing fast.

We will below shortly present the methods used in the work with predictions and health care planning during spring 2020.

Swedish Public health authority model

The regions in Sweden got support and predictions from the Public health agency of Sweden (FHM). This was important in the beginning of the pandemic situation. The support was in the form of SIR models of a scenario that was predicted for what might come during the spring. The models did not use Swedish data, as this was scarce in the beginning of the pandemic, but were based on expertise in infectious diseases/virus, as well as data from Wuhan, China and Lombardy, Italy, Figure 1 and Figure 2.

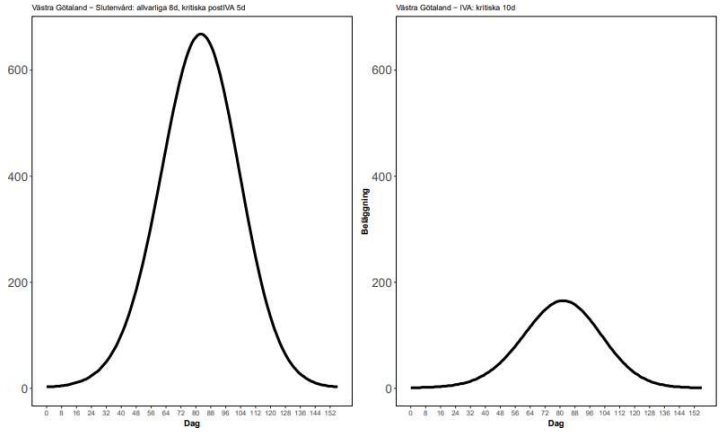

Figure 1. Predictions based on Wuhan data from 2020-03-20 (https://www.folkhalsomyndigheten.se/contentassets/4b4dd8c7e15d48d2be744248794d1438/vardbehov-scenarier-wuhan-grafer-2020-03-nn.pdf)

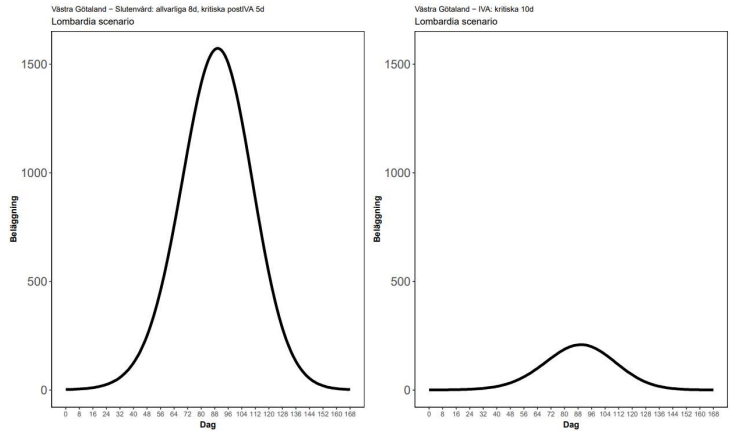

Figure 2. Predictions based on Lombarda data 2020-04-03 (https://www.folkhalsomyndigheten.se/contentassets/4b4dd8c7e15d48d2be744248794d1438/vardbehov-scenarier-om-vardbelastning-baserat-pa-data-fran-lombardiet.pdf)

These models were adjusted when new data were gathered, but still giving high-predicted peak values. The models did not refer to a calendar timing.

In the work during the spring 2020 the start of this model was set to 26 of February 2020, as that was the date of the first registered patient with confirmed Covid-19 infection in VGR. Compared to our model evaluation this would refer to approximately the middle of week 8 in our tables (Table 1-3).

As these models did not include any background information or the daily health care data from the region, the project group from both VGR and University of Gothenburg, wanted to improve the predictions for more exact health care planning in the specific region.

Model based on work from Island and Stockholm

The aim was to predict healthcare utilization (number of ICU beds needed) in VGR. The prediction was made in two steps. First, the expected number of confirmed cases in VGR was modelled according to a Bayesian model where a logistic growth curve model was assumed. Since VGR at that time was in the initial phase of the pandemic, data on the incidence of confirmed cases in different countries (which had reached later phases of the pandemic) was used for parameter estimation. A hierarchical model was used to account for intra-country correlations. Vague normal and exponentially distributed priors were used for location and scale parameters, respectively. The predicted future number of cases in VGR was based on the average posterior predictive distribution of the incidence multiplied by the population size in VGR.

In the second step, healthcare utilization was predicted by multiplying the predicted number of cases with the historically observed proportion of confirmed cases requiring in-patient and ICU care, respectively. The model was re-estimated on a daily basis to enable real-time predictions. An alternative model was also later fitted using data in the different Swedish counties instead of the different countries to estimate the incidence of confirmed cases. The prediction model described above was based on work done by a group on Island and adjusted by a group in Stockholm. This model were then adjusted to regional data in VGR, Figure 3 (Regional model).

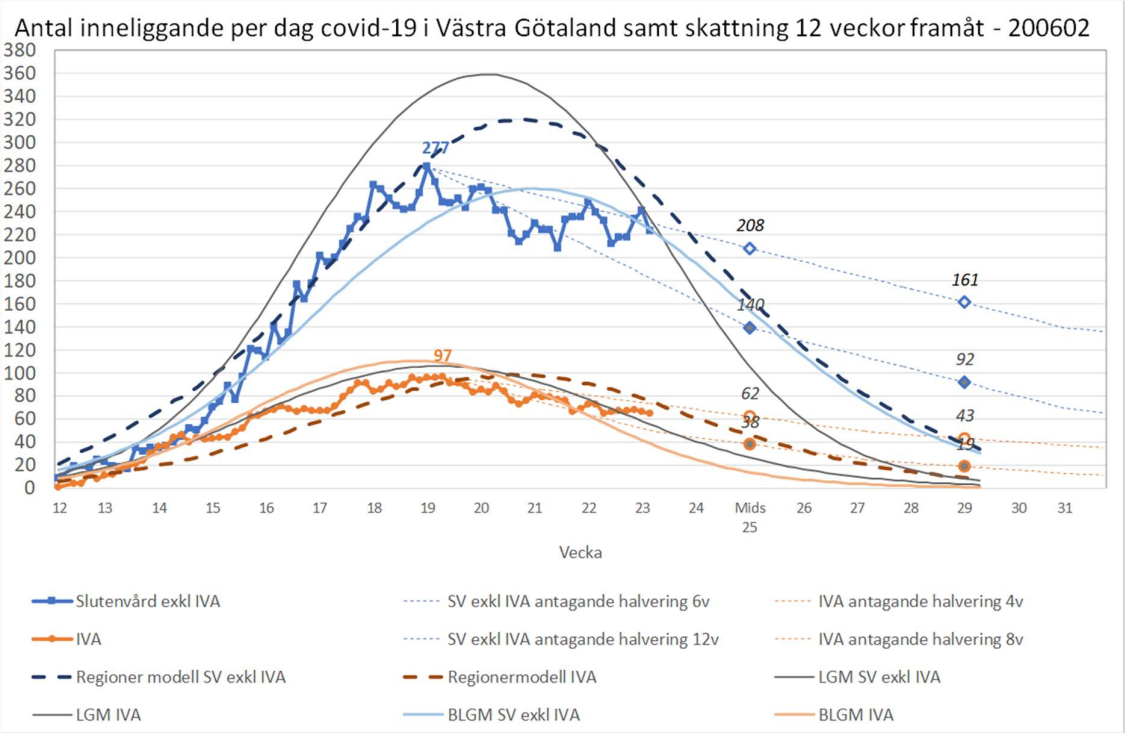

Figure 3. An example including total number of inpatient beds (blue curves) and ICU beds (orange curves). Dashed lines are the "Regional model", black lines are the LGM and light blue line and orange line are the Bayesian version of the LGM (BLGM, with priors dependent on the Stockholm model). Slutenvård = inpatient care and IVA = ICU.

Simple use of LGM and LGM Bayesian

As a simple alternative model we used a logistic growth model (LGM) and a Bayesian version of the LGM. The data used in the LGM was not the raw number of daily inpatient beds. Instead, we used the cumulative new inpatient beds per day, which is a monotonically increasing measure, like the s-curve. After fitting a LGM using the cumulative new inpatient beds per day, we adjusted the model by subtracting lag number of day (using the infliction point to decide when to start subtracting). This to incorporate that patients both were admitted to and left the hospital. Hence, the model therefore were bell shaped.

Time series and time series in combination with neural networks

Whether it was the number of inpatient care cases, the number of ICU cases or the number of deaths, at least initially, the data were recorded as daily counts. Hence, the natural modelling approach is using a discrete time stochastic process, in particular a time series model. An advantage of taking on a time series approach is that there is a substantial battery of forecasting methods available (see the documentation for the R package 'forecast' for a good and recent overview). The

idea employed was to use an ensemble of other, potentially more crude, forecasts as covariates which were incorporated into a suitable time series model. Such a procedure may be viewed as a way of “weighting” different forecasts to obtain a more sophisticated final forecast. Here we chose to employ an autoregressive feed-forward neural network with a single hidden layer; such a model may be viewed as a generalization of an AR(IMA) process where we allow non-linear combinations of the historical input observations and it is this non-linearity which motivates the use of these models (in contrast to classical time series models). To add extra stability, we average our final neural network forecasts with an ARIMA forecast, which is more rigid; this way we combine long-term stability with local flexibility.

The plots below illustrate step wisely generated forecasts of inpatient care cases, within the VGR region (the y-axis reflects the number of cases and the x-axis the time in days from the beginning of the study), Figure 4. The incorporated covariates were historical observations in combination with four different external forecasts/prognoses (entitled 1) FHM-Wuhan, 2) Regional, 3) LGM, and 4) LGM Bayes). The first plot shows the forecast when we have data up to the 21st of March 2020, the second when we have added 7 additional days of data, and the final one when we have added 14 (=7+7) days. The last data series turned out to run up until the plateau of the peak of the first wave of Covid-19 in Sweden.

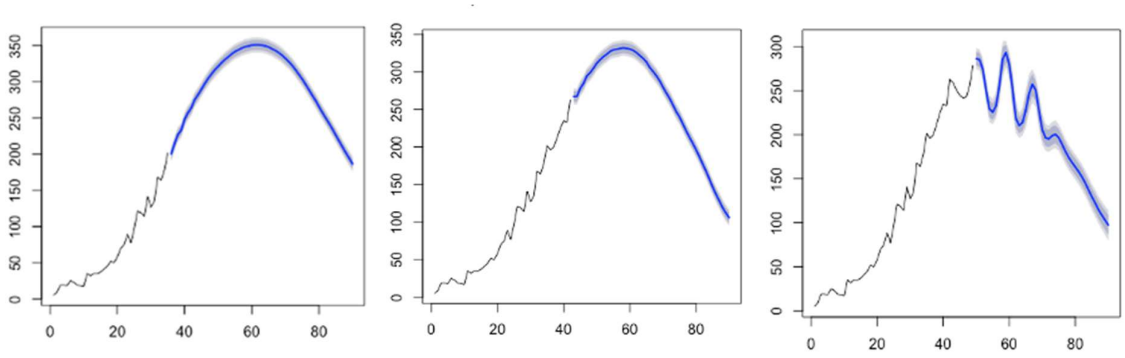

Figure 4. Step wisely generated forecasts of inpatient care cases within the VGR region. The first plot shows the forecast when we have data up to the 21st of March 2020, the second when we have added 7 additional days of data, and the final one when we have added 14 (=7+7) days. The y-axis reflects the number of cases and the x-axis the time in days from the beginning of the study.

Part 2: A simple algorithm - LGM

The simple adjusted LGM did a good job in VGR during spring 2020. This could be due to that we were “lucky” to choose a curve pattern working for that specific increase and peak. To understand when this model fits this kind of temporally evolving epidemic data can help us to understand if it is useful in future situations, and its limitations.

We will now compare the model using data from VGR with Belgium. The Belgian data was characterized by a “sharp” increase and the VGR data by more fluctuations. The Belgium data was also a larger dataset than the regional Swedish data.

Materials and methods

The analyses were based on publicly available data, which consisted of the number of inpatient beds for patients with Covid-19. Data consisted of daily registrations, where there might have been missing data for some days. Data for several countries in Europe were available. We chose to download data from the Western region of Sweden (VGR) and Belgium.

Models directly predict the number of beds needed. Hence, they contained no step predicting the spread of the infection. This will impose losing some important information, but at the same time not introducing unsure estimates of a quantity as well as risking overfitting, which over-parametrized models tend to suffer from. The basic model we used in this approach is a Logistic growth model.

Logistic Growth Model (LGM)

The logistic growth model (LGM) we used is the logistic equation, with the parameters r (the growth rate), N0 (the initial population size) and K (the carrying capacity) (4). The logistic equation describes the size Nt at time t:

$$N_t = \frac{N_0 K}{N_0 + (K - N_0) e^{-rt}} \qquad (1)$$

where Nt is the number of counts at time t, N0 is the initial count, K is the carrying capacity, and r is the growth rate.

The R-package SummarizeGrowth was used (5).

The Nt is an s-curve growing towards the peak and stays at the maximum (peak) level, just a probability distribution function. The derivative reflects the increase rate and is bell-shaped. In this use, we see the cumulative curve as the approximation of the growth of inpatient beds needed each day and use the maximum (the plateau) as the predicted peak level. The time when the maximum is first reached as the peak

time. In reality, inpatient beds can go both up and down, even if the general trend is increasing, during the increase phase.

Three ways the LGM will be used

Direct use of LGM on registered inpatient beds used
Here we use the raw observations, total of beds reported each day. We estimate the LGM by letting Nt, in equation (1), be the number of inpatient beds needed for each day.

Direct use of LGM on cumulated new inpatient beds
Here we use the cumulated new inpatient beds per day. That is, cumulated positive increments between days. First the new number of beds between two adjacent days are calculated (a decrease of number of inpatient beds gives a value of 0, while an increase gives the value of the increase). The cumulative new inpatient beds per day is a monotonically increasing measure, like the s-curve. If the true data have many small decreases during the increase phase, the cumulative new inpatient bed will over-estimate the number of inpatient beds needed.
We estimate the LGM by letting Nt, in equation (1), be the cumulative new inpatient beds per day.

The adjusted LGM on cumulated new inpatient beds
Here we also use the cumulative new inpatient beds per day and estimate the LGM as in the previous section, but the model was adjusted to incorporate that patients both were admitted to and left the hospital. This model therefore were bell shaped as the number of inpatient beds first increased and the decreased.

The model used the cumulative positive increments between days as above, but was adjusted by decreasing the curve by subtracting lag number of day (using the infliction point to decide when to start subtracting). The infliction point, where the accumulated number does not increase in growth rate, was seen as an estimated point where patient might leave the hospital after treatment.

After the inversion point ti, the CumGrowth (ti) was subtracted by the number of beds from time 1 (ie CumGrowth (t = 1), calling this BedsNeeded (ti). The next day CumGrowth (ti + 1) - CumGrowth (t = 2), and so forth. The focus in this work was not to estimate the downturn, but this was a way to obtain a better estimate of the increasing curve and the peak time, as it also adjusted for patients leaving the hospital.

Development of predictions over time

In reality during the spring 2020 we calculated new prediction models approximately 1 time per week. Therefore, in the discussion below, we calculated the models on the

VGR data and Belgium data every 7 days. To show the development of predictors over time we used an algorithm calculating a prediction each 7th day. These calculations proceeded as long as the hospitalization process was increasing.

The practical view of a peak to be reached was assumed after two weeks of decline in the observations. Hence, we needed a date when we could consider the first peak to be present. We calculated 7-day differences in inpatients beds. As long as these increased, we considered the increase ongoing. The date when these differences were stable or decreased for 2 weeks or more were considered the peak date.

We also theoretically considered what a possible pattern of the differences moving up and down would indicate. It would mean that the process of hospitalization did not follow the S-curve in a close manner. This either could mean a strong departure from the bell-shape making the calculations un-valid or might be a short departure and the LGM could still be a good enough prediction after some more data. In the period of the first peak this pattern was not seen neither in the VGR nor in the Belgium data.

At each 7th day calculation we estimated a model and measures of interest were growth rate (r), initial population size (N0), peak height (carrying capacity K), derivative (r*K/4) and the time at which the population density reaches ½ K (the inflection point T_mid).

Data material

The international data was retrieved from the webpage of the European Centre for Disease Prevention and Control. The Swedish regional data from the west part of Sweden (VGR) were retrieved from the public regional page. The data included data both from the peaks from the spring of 2020, but also from the peaks of the autumn of 2020. This means that we divided the data into parts only including one major peak.

In practice when we predicted using a logistic growth model (LGM) we needed a starting time, the start of the outbreak, and we then used the incoming data for each day to make new prediction of estimation of the model and the peak height and peak timing.

Here in the model investigation we wanted to validate these predictions in comparison with the observed data. For the model validation we needed to define an observed ending time, that is the observed peak time and the observed peak height. Hence, we did not have the aim to predict the decrease in the outbreak. In the present discussion of model performance the predications were done every 7th day. In reality, this depends of the needs of the health care and the speed of the increase. During some periods in the actual pandemic situation, the predictions during spring 2020 where mostly done 2-3 times per week.

Results

Swedish regional data

The actual ongoing prediction during spring 2020, started in mid-April (week 4 in Table 1-Table 3).

In the present discussion of model performance, we defined the first Covid-19 episode in the VGR-data to start in 2020-03-17 and end in 2020-08-12 (https://www.vgregion.se/covid-19-corona/statistik-covid-19-i-vastra-gotaland/). The method for defining the start and ending of the episode is described above.

Raw observations

The simplest model is here the direct use of fitted values in a LGM. The drawback with this model was that it predicted the increase in the number of inpatient beds, but did not estimate the expected decrease after a peak, Table 1 and Figure 5. Our purpose was not to estimate the decrease, but to identify the maximum number of beds (peak). In the cumulative S-curves in Figure 5 the maximum height is in the plateau.

Table 1. Parameters in the LGM on raw inpatient beds.

Time point Start date 2020-03-17	**Growth rate r** Estimate (se)	**Initial population size N_0** Estimate (se)	**Carrying capacity K** Estimate (se)	**Derivate r*K / 4** Estimate	**T_mid** Estimate	**Observed maximum during the period around peak 1**
1 week	1.12 (0.317)	0.769 (0.731)	27.811 (1.894)	7.8	3.177	Observed max **375** 2020-05-04
2 weeks	0.219 (0.053)	6.727 (2.046)	117.896 (46.091)	6.5	12.832	
3 weeks	0.199 (0.02)	7.506 (1.328)	134.427 (11.163)	6.7	14.179	
4 weeks	0.111 (0.012)	13.731 (2.004)	525.613 (193.052)	14.6	32.682	
5 weeks	0.118 (0.007)	12.608 (1.516)	363.562 (29.286)	10.7	28.209	
6 weeks	0.105 (0.005)	14.874 (1.372)	444.373 (21.998)	11.7	31.978	
7 weeks	0.115 (0.004)	12.898 (1.23)	394.4 (8.727)	11.3	29.539	
8 weeks	0.127 (0.005)	10.32 (1.246)	361.399 (5.285)	11.5	27.676	

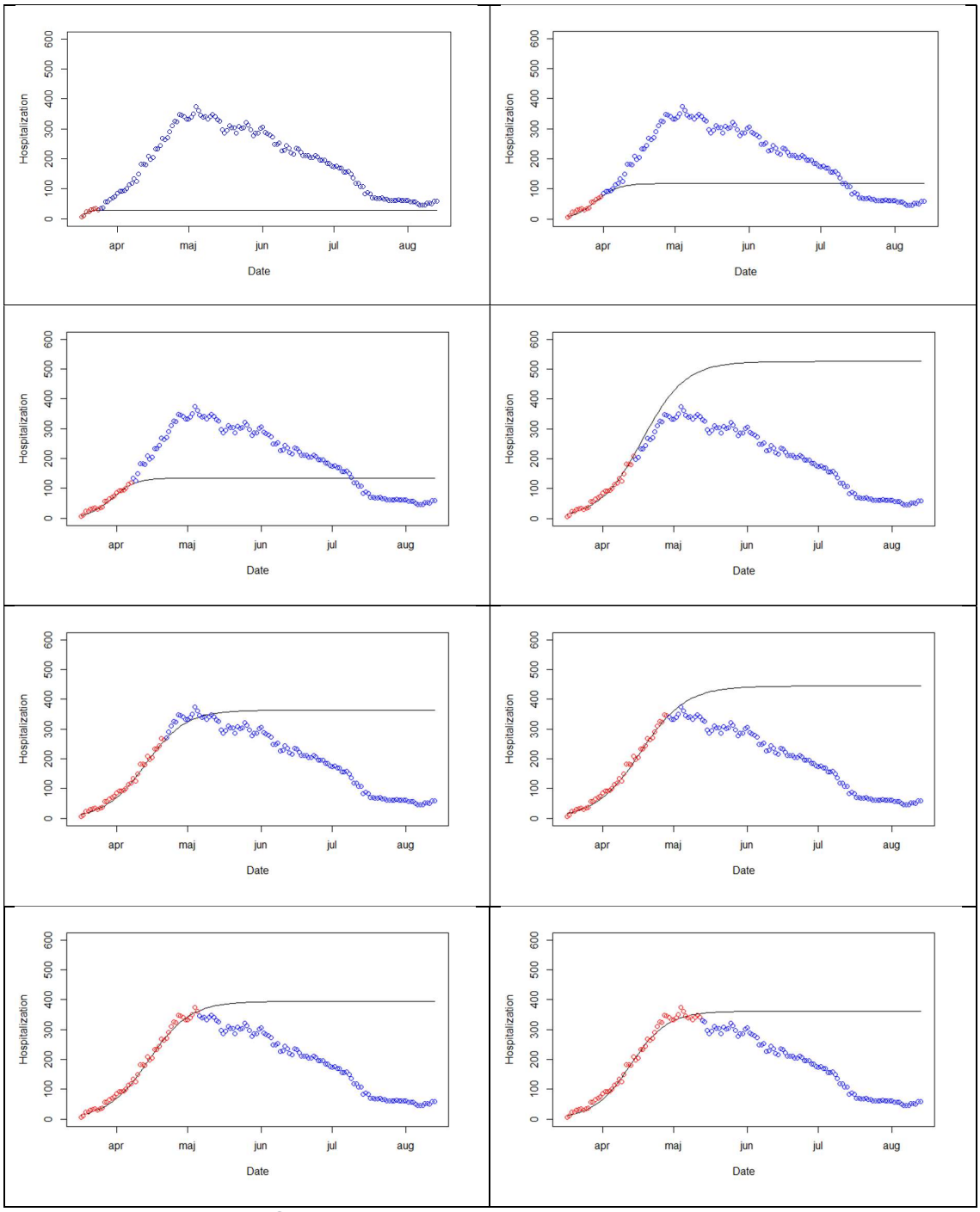

Figure 5. The predicted LGM (line) based on the original data (dots). The red dots are the observations available at the prediction time.

Direct use of LGM on cumulative new inpatient beds

The use of an LGM on the cumulative new inpatient beds per day we do mainly for illustration, Table 2 and Figure 6. This gives a monotonically increasing measure, like the s-curve. If the true data have many small decreases during the increase phase, the cumulative new inpatient bed will over estimate the number of inpatient beds needed. We calculated the cumulative new inpatient beds mainly for the next section using an adjusted direct use of LGM on these cumulative values.

Table 2. Parameters in the LGM on cumulative new inpatient beds. This is the model used both for the direct use of the LGM. The adjusted model was based on this model. Hence, this model was then adjusted to give a decrease in beds after the peak (adjusted direct use of LGM on cumulated new inpatient beds).

Time point Start date 2020-03-17	**Growth rate r** Estimate (se)	**Initial population size N_0** Estimate (se)	**Carrying capacity K** Estimate (se)	**Derivate r*K / 4** Estimate	**T_mid** Estimate	**Observed maximum during the period around peak 1**
1 week	1.12 (0.317)	0.769 (0.731)	27.811 (1.894)	7.8	3.177	Observed max **375** 2020-05-04
2 weeks	0.219 (0.053)	6.727 (2.046)	117.896 (46.091)	6.5	12.832	
3 weeks	0.199 (0.02)	7.506 (1.328)	134.427 (11.163)	6.7	14.179	
4 weeks	0.111 (0.012)	13.731 (2.004)	525.613 (193.052)	14.6	32.682	
5 weeks	0.116 (0.006)	13.161 (1.404)	436.661 (36.18)	12.7	29.991	
6 weeks	0.109 (0.004)	14.438 (1.157)	487.481 (19.253)	13.3	32.015	
7 weeks	0.114 (0.003)	13.382 (1.015)	456.026 (8.396)	13.0	30.702	
8 weeks	0.114 (0.003)	13.419 (0.851)	456.35 (4.705)	13.0	30.719	

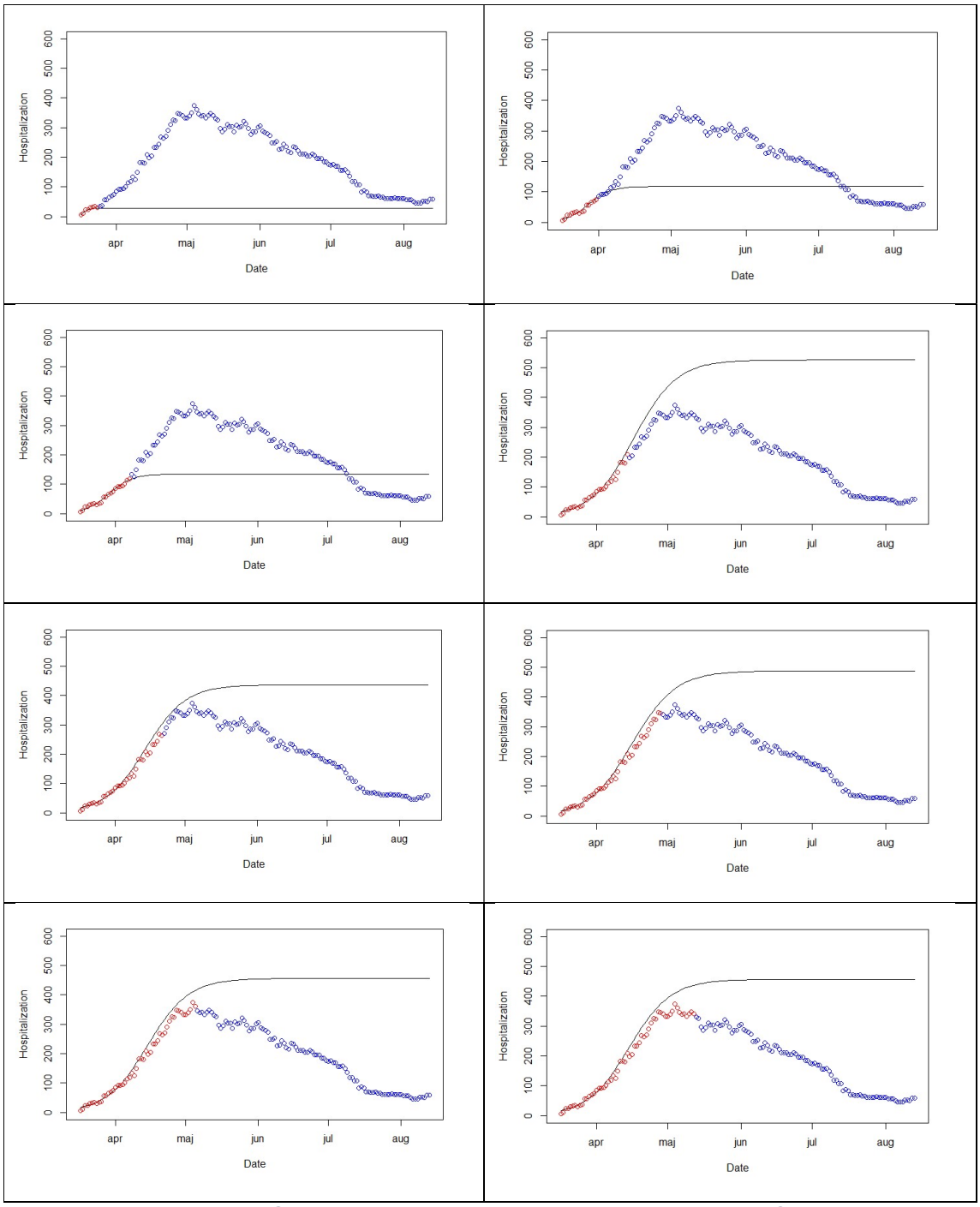

Figure 6. The predicted LGM (line), using cumulative new inpatient beds. Original data are presented as dots, and the red dots are the observations available at the prediction time.

The adjusted use of LGM on cumulated new inpatient beds

This was how we used LGM in the VGR work, but we also worked with the average between this and the model provided by FHM for VGR, Figure 7.

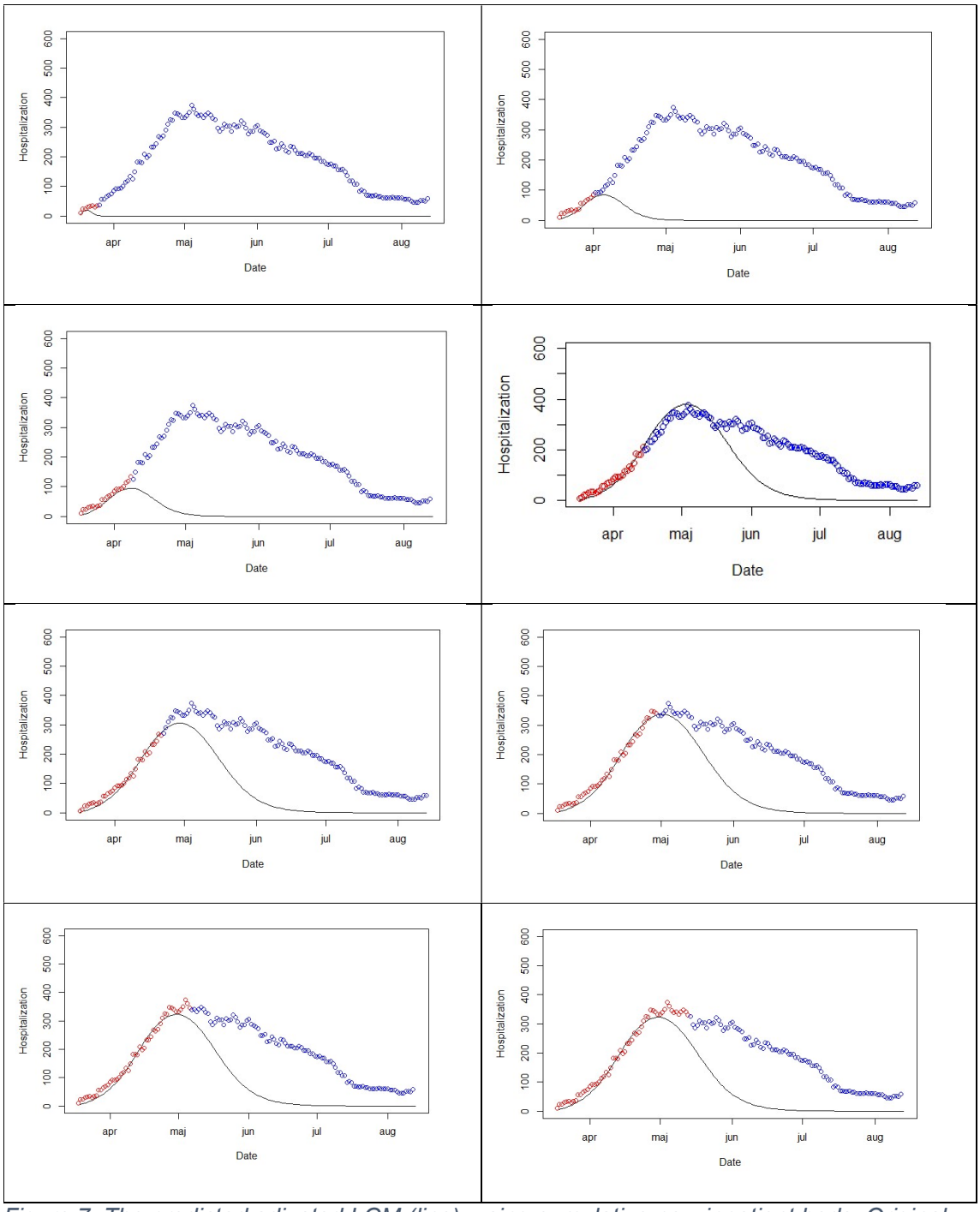

Figure 7. The predicted adjusted LGM (line), using cumulative new inpatient beds. Original data are presented as dots, and the red dots are the observations available at the prediction time.

Peak height and peak timing Swedish regional data

In Table 3 the weekly estimated peak heights and peak timings are presented, both for the raw LGM model and the adjusted LGM model. The observed peak height was 375 inpatient beds and at day 49.

Table 3. The weekly estimated peak heights and peak timings, and the related observed values.

Observed peak during the investigated dates (Peak = maximum value during the outbreak)			375	
Observed time for observed peak			2020-05-04 Day 49	
Time point	**Raw LGM model (cumulative)**		**Adjusted LGM model (Bell shaped)**	
Start date 2020-03-17	**Estimated peak Height K (se)**	**Estimated peak Timing** (t_mid*2)	**Estimated peak height (K)**	**Estimated peak Timing** (estimated from adjusted LGM)
1 week	27.811 (1.894)	Day 6	17.67	Day 3
2 weeks	117.896 (46.091)	Day 26	71.97	Day 18
3 weeks	134.427 (11.163)	Day 28	80.73	Day 21
4 weeks	525.613 (193.052)	Day 65	379.88	Day 48
5 weeks	363.562 (29.286)	Day 56	305.33	Day 43
6 weeks	444.373 (21.998)	Day 64	342.38	Day 47
7 weeks	394.4 (8.727)	Day 59	322.54	Day 46
8 weeks	361.399 (5.285)	Day 55	322.85	Day 45

Belgium data

In the present discussion on model performance, we identified the first Covid-19 wave in the Belgium data. 2020-03-15 to 2020-07-17. The Belgium data were retrieved from the webpage of the European Centre for Disease Prevention and Control (6). Above the method for defining the start and ending of the episode is described.

Direct use of LGM raw observation

As for the Swedish regional data we here start with the simplest model, the direct use of observed values in a LGM, Table 4 and Figure 8

Table 4. Parameters in the LGM on raw inpatient beds.

Time point Start date 2020-03-15	**Growth rate r** Estimate (se)	**Initial population size N_0** Estimate (se)	**Carrying capacity K** Estimate (se)	**Derivate r*K / 4** Estimate	**T_mid** Estimate	**Observed maximum during the period around peak 1**
1 week	0.635 (0.058)	34.603 (8.652)	1807.004 (164.469)	286.9	6.198	2020-04-06 observed max **5759**
2 weeks	0.316 (0.022)	126.465 (21.16)	5882.505 (499.868)	464.7	12.094	
3 weeks	0.333 (0.01)	111.836 (11.521)	5554.163 (66.51)	462.4	11.664	
4 weeks	0.332 (0.007)	112.937 (8.735)	5569.421 (29.005)	462.3	11.686	

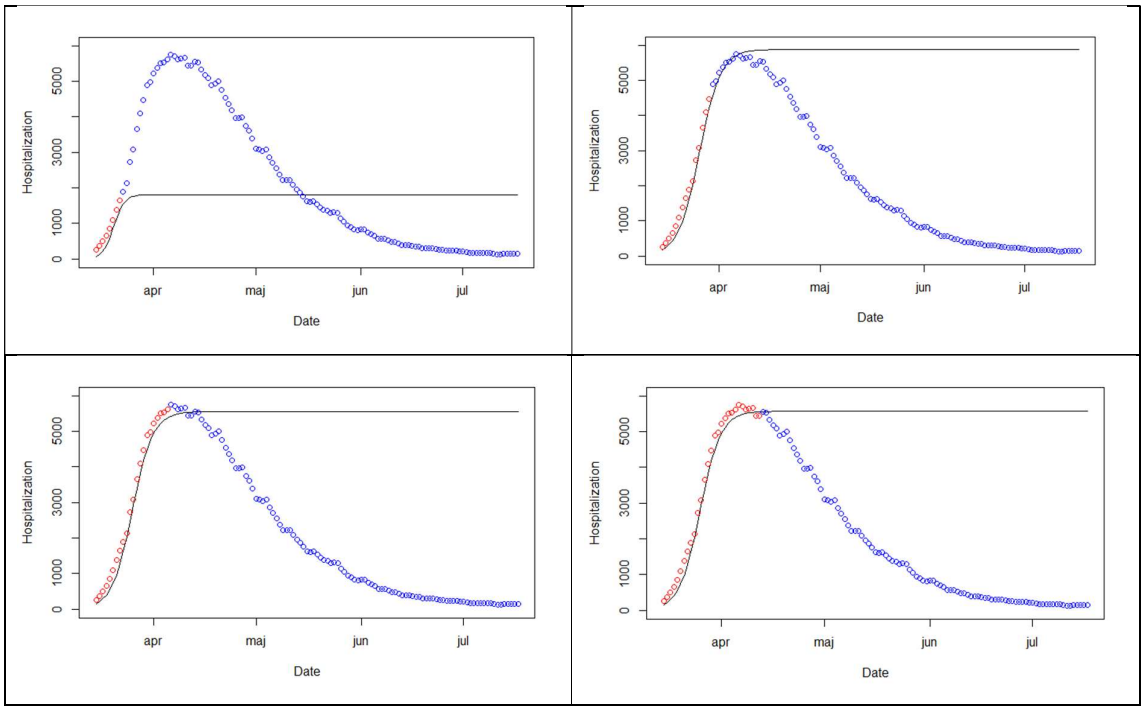

Figure 8. The predicted LGM (line) based on the original data (dots). The red dots are the observations available at the prediction time.

The adjusted LGM on cumulated new inpatient beds

This was how we used LGM in the VGR work, here used on the Belgium data presented in Figure 9.

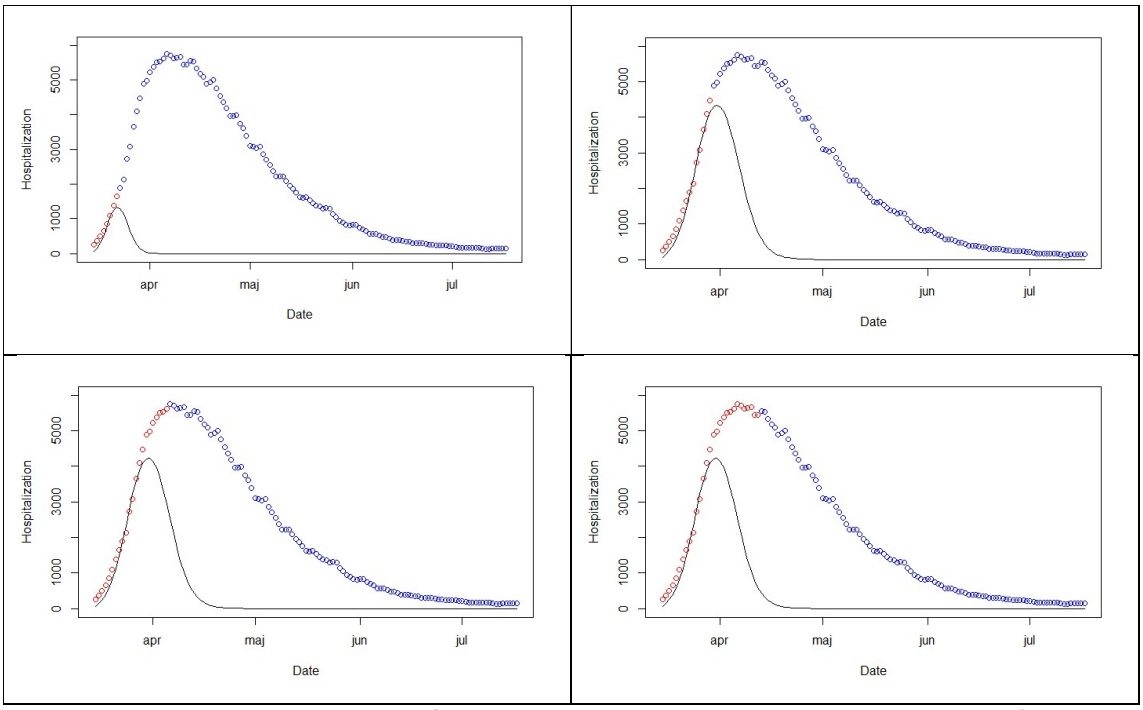

Figure 9. The predicted adjusted LGM (line), using cumulative new inpatient beds. Original data are presented as dots, and the red dots are the observations available at the prediction time.

Peak height and peak timing Belgium models

In Table 3 the weekly estimated peak heights and peak timings are presented, both for the raw LGM model and the adjusted LGM model. The observed peak height was 5759 inpatient beds and at day 23.

Table 5. The weekly estimated peak heights and peak timings, and the related observed values.

Observed peak during the investigated dates (Peak = maximum value during the outbreak)			5759	
Observed time for observed peak			2020-04-06	Day 23
Time point	**Direct LGM model**		**Adjusted LGM model**	
Start date 2020-03-15	**Estimated peak height (K)**	**Estimated peak Timing** (T_mid*2)	**Estimated peak height**	**Estimated peak Timing** (estimated from adjusted LGM)
1 week	1807.004 (164.469)	Day 12	1336.547	Day 8
2 weeks	5882.505 (499.868)	Day 24	4343.665	Day 17
3 weeks	5554.163 (66.51)	Day 23	4222.591	Day 17
4 weeks	5569.421 (29.005)	Day 23	4226.125	Day 17

Discussion

For the Swedish regional data, the LGM on raw observations gave a good estimate on the peak height, but a stable plateau at a time point later than the true peak timing. The adjusted LGM, using cumulative new inpatient beds, fitted the Swedish regional data to a satisfying degree. In week 4, the peak height and peak timing were predicted to values of practical use. The prediction at week 4, and from there on, indicated that the true peak should be seen in week 8.

For the Belgium data, the LGM on raw observations gave a good estimate on peak height and timing from week 2 and forward. The adjusted LGM, using cumulative new inpatient beds, did not work for the Belgium data as it gave a too early peak time and a too low peak height. One explanation could be that the observed high increase rate affects the rate of the “patients leaving the hospital”, our way of estimating the decrease in patient beds. Hence, the patient’s recovery time (time to discharge) is in the adjusted model correlated to the admission rate, which is not a relevant connection.

In the Belgium model, the modelled theoretical initial population size was much smaller than the empirical value. The initial population size in the Belgium data was 266 beds. Therefore, the estimation of the LGMs starts with different starting numbers depending on the start of accessible data. This also implies that the theoretical initial population size in the Belgium model will be underestimated, and hence the area under the curve. For the VGR data, the empirical and model estimates were closer to each other. In a logistic growth model the carrying capacity (peak height) is highly correlated with the area under the empirical curve and the area under the logistic curve (5), and also partly correlated to the growth rate(5).

The adjusted LGM has the benefit of handling that the numbers of beds used each day can vary in a small degree, as the model can handle the increase or decrease in daily bed numbers, during the increase of the breakout. It also includes the overall pattern of an increase, a peak and a decline. The limitation is that the increase and the decline follows a symmetric pattern. Therefor this is not a suitable algorithm for predicting the speed of the decline, but even more important is that the adjustment starts already in the increase phase also in this symmetric way. It is a very simplified way to think that patients are supposed to leave the hospital in the same speed as they entered. The importance of this is probably more important in smaller data sets, as the Swedish regional data. There the daily number of beds, during the increase towards the peak, still varied with small numbers up and down. In larger data sets, as the national Belgium data, each daily value of beds was an increase during the increase towards the peak.

One limitation of these public data is the issue of the “start” of registration. The health care sector quite suddenly needed prognostic support and in the specific problem discussed here, the care beds used each day were for example registered and publicly available in Västra götaland from 2020-03-17 and for Belgium 2020-03-15. This was not the point when patients started to be hospitalized due to Covid-19. This is the first registration, and hence the number of Covid-19 related hospital beds needed were for Västra Götalandsregionen six beds and for Belgium 266 beds.

In models predicting inpatient beds or ICU beds during spring 2020 we focused on estimation of peak height and peak time. What we can see from the literature, other researcher´s work on estimating peak height and peak time, is based on complex epidemiologic SIR-type models including assumptions on several parameters (3). In our work with the LGM we focused on a simpler model including less parameters and based on simple publicly available data.

Several researchers looked at models forecasting one up to fourteen days ahead. To our knowledge, other researchers with the same focus did not estimate peak height or peak time, but forecasting only one day ahead up to models for fourteen days ahead (7-10). Some of these papers use data from the first wave and predict the decline of the number of care beds needed, not predicting the acute phase with increasing number of inpatient beds of spring 2020.

Another group, Manca et al. 2020, also used a Logistic model, as one model among several different models (8). However, the data they used to estimate the models were from the beginning of the pandemic in early 2020 including data after the peak in the first wave. Hence, they did not predict the peak or peak time.

The use of time series and neural networks in combination that we used were also thought of by other researchers (11). Thought, they did not use external forecasts/prognoses as covariates, as we did with four previous prediction models.

In most of other studies, only one data set is presented. We presented the data we worked with during spring 2020, hence the VGR data. For a comparison in the reflective work after the first wave, we also presented the different LGM approaches also for Belgium data. Studies not including a comparison might a lack an important validation step.

We were not alone to view the LGM as a potential model (8), but there is no theoretical reason why the LGM or adjusted LGM on cumulated new beds would generally work on data from different countries or regions. A model with a “bell shape”, but not necessarily symmetric, is relevant to assume. The process of the increase in inpatient beds towards the first peak had no general theoretical pattern. It was dependent on factors as the spread of the disease, age, comorbidity, mobility and interaction between citizens, recourses of admitting patients to hospitals and other known and unknown factors. The aim of this work, and of the practical work

during spring 2020, was not to find the best fitting model. It was to find a working procedure and to get experience for future work. One important discussion in the practical work was also how close to theory one needs to be or was a pragmatic view good enough.

The experience from our work, in combination with now existing literature, the process in a similar future situation would include better knowledge on how to find and combine data to get as reliable forecasts as possible and to use creativity in combination with theoretical competence.

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