Long-term scenarios for the number of new hospitalizations during subsequent waves in the Belgian COVID-19 epidemic

Report version 5.1

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Disclaimer

Introduction

This report is an update of the previous report version 5.0 of October 27th 2020. We updated the figures with the new data that have become available by now. In the previous report, we presented four scenarios:

Scenario 1 Continuation of the contact behaviour as before 19 October. This is the worst-case scenario: what would happen if people do not comply to the measures that took effect on 19 October.

Scenario 2 Implementation of the measures that started on 19 October for only 4 weeks. These comprise closing of bars and restaurants, limitation of contacts and code orange at schools, implying a general reduction of contacts during 4 weeks.

Scenario 3 Implementation of the measures that started on 19 October for 6 months.

Scenario 4 Contact behaviour and hence transmission reduction at the level of the March-April 2020 lockdown (with the exception of schools remaining open outside the holidays).

The data of the last two weeks indicate that the pandemic is currently evolving according to Scenario 4, hence the measures taken on October 19 have induced a transmission level similar to that of the March-April 2020 lockdown. Note that the effect of the additional measures taken on November 2 is not yet fully visible in the data due to the delay between infections and hospitalizations.

Four predictive models

This report contains predictions from four different models describing the spread of SARS-CoV-2 (COVID-19) in Belgium. Each model accounts for uncertainty related to factors influencing the disease spread, but by presenting different model outcomes we can also account for structural model uncertainty. This is standard practise when it comes to model-based decision support, e.g. the IPCC considers the outcomes of more than 10 different models for supporting its reports. Moreover, by combining different models we can mutually validate their projections over the course of time. As more data will become available in the next weeks, further model validation and updated prediction results will follow. In general, model predictions should be interpreted with great caution and awareness of the underlying assumptions.

Three of the models used (UHasselt, UGent and UNamur) are compartmental models, which capture the dynamics of the epidemic by dividing the population into different compartments: in its most basic form susceptible, infected, recovered and deceased people. The models differ in the way the compartments are further subdivided to capture the details of the disease dynamics, and hence in the number of parameters to be calibrated and the data used for calibration. The flow between the different compartments is governed by equations based on the known mechanics of disease spread, therefore these models are also called mechanistic models. They can be used to do predictions under different scenarios, by changing the flow of individuals between compartments

based on assumptions on how the disease transmission changes under these scenarios.

The fourth model (VUB) is a data-driven time-varying time-series model: it models the disease spread directly from the data by estimating the parameters in a time series model whose dynamics are similar to what can be expected in a compartmental model. The model is therefore a gray box model which is based on the working principles of compartmental models. The different parameters are calibrated by the measured data up to one week in the past and validated on the most recent data (last week). This model is useful to predict the effect of a continuation of the current situation, but cannot be used to predict different scenarios (for instance a change in contacts or behaviour). Hence, we will only present the three compartmental models for the scenarios that deviate from the current situation.

Some limitations of the four models used in this report are listed below:

- The different scenarios are expressed in terms of changes in social contact behaviour, as a proxy for changes in transmissibility which result from social distancing and hygienic measures taken at different locations, e.g., at work and at school.
- All scenarios are hypothetical and we are not able to discern the more plausible scenario given the unpredictable nature of adjusted social behaviour and future measures.
- The models do not take into account the spatial structure of the population.
- We did not account for seasonality or cross-immunity effects.
- Contact tracing, testing and self-isolation are not incorporated, except for the aggregated effect on reducing the number of high-risk contacts.

More details on the specific properties, assumptions and limitations of each model can be found in the Appendix.

Number of new hospitalizations

The peak in hospitalizations was reached in the beginning of November (as predicted in Scenario 4) and was slightly higher than during the first wave (Figure 1). If the pandemic evolves further according to this scenario, hospitalizations will be at the level of July-August between January and February (Figure 3).

Hospital load

Also the hospital load seems to have reached its peak by now, although this is less clear than for the new hospitalizations due to the delay between both variables (Figure 2). If the pandemic evolves further according to Scenario 4, the hospital load will be at the level of July-August between January and March (Figure 3).

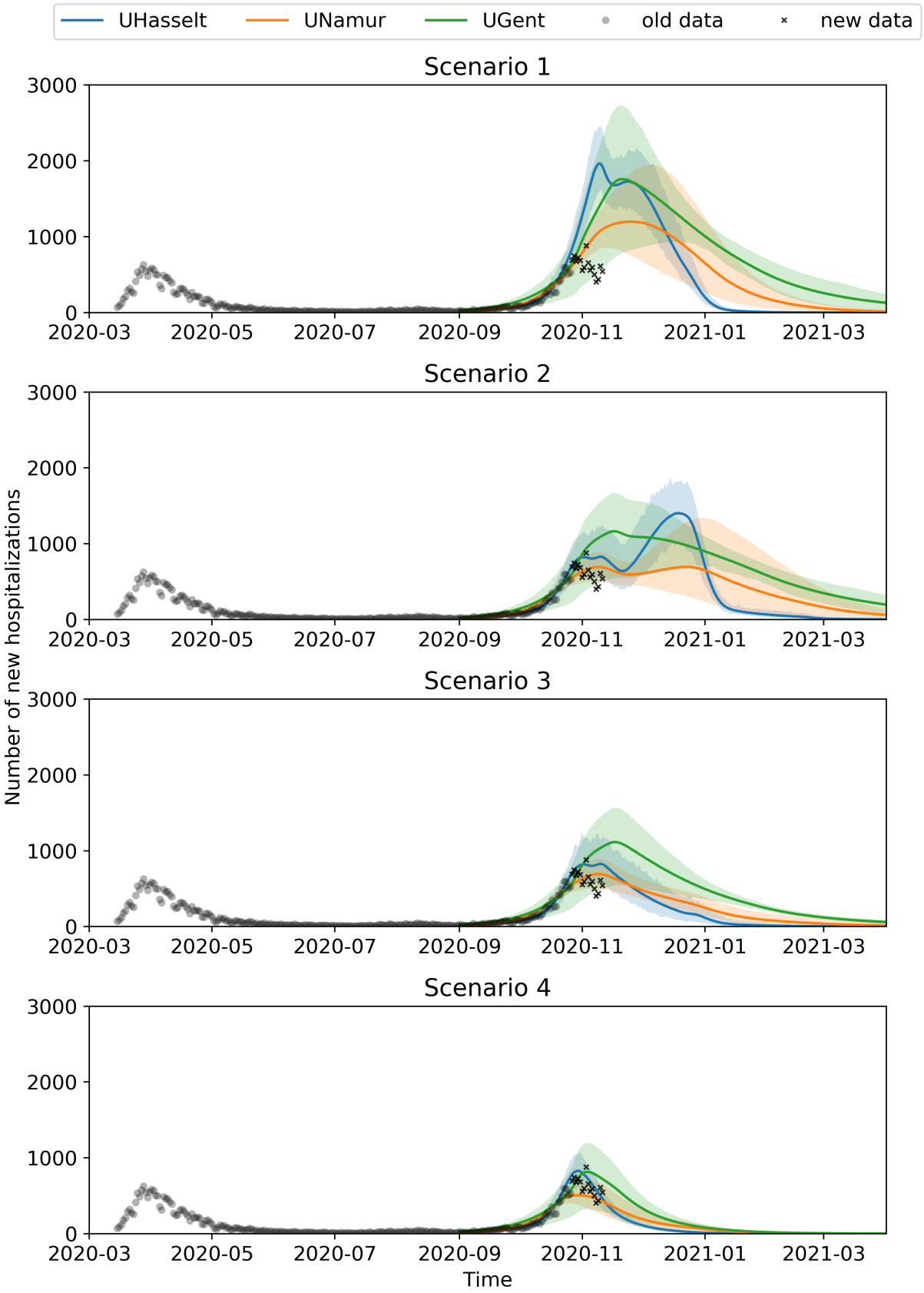

Figure 1: Long-term prediction of the number of new hospitalizations for the different scenarios and models: mean value with 95% prediction interval.

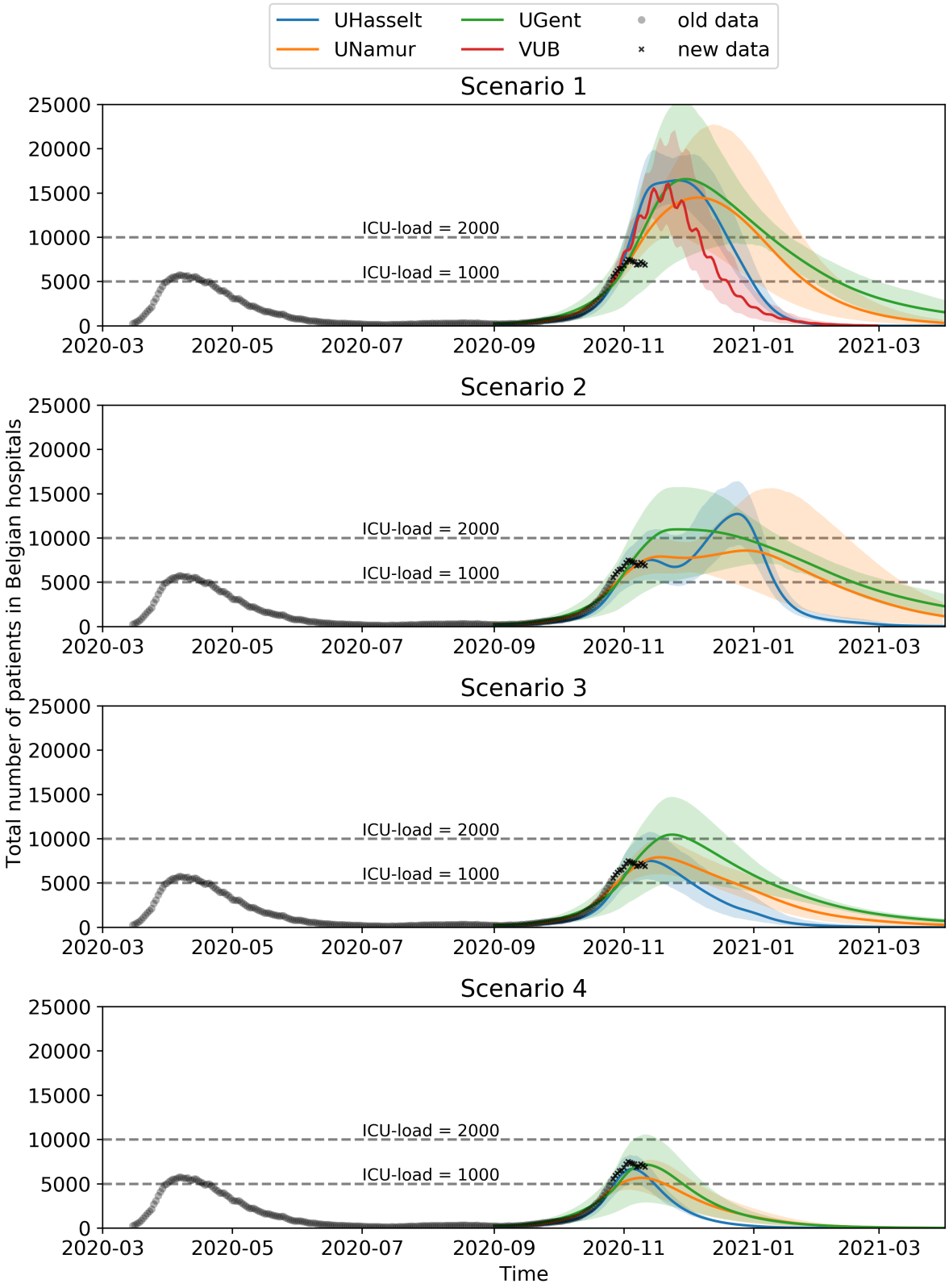

Figure 2: Long-term predictions of the hospital load: mean value with 95% prediction interval. The dashed lines indicate the number of available ICU beds for COVID-19 patients (1000: normal capacity and 2000: increased capacity). The VUB-model is only used for predictions in Scenario 1: a continuation of the situation as indicated by the currently available data. Note that it takes some time before changes in contact behaviour are manifested in the data.

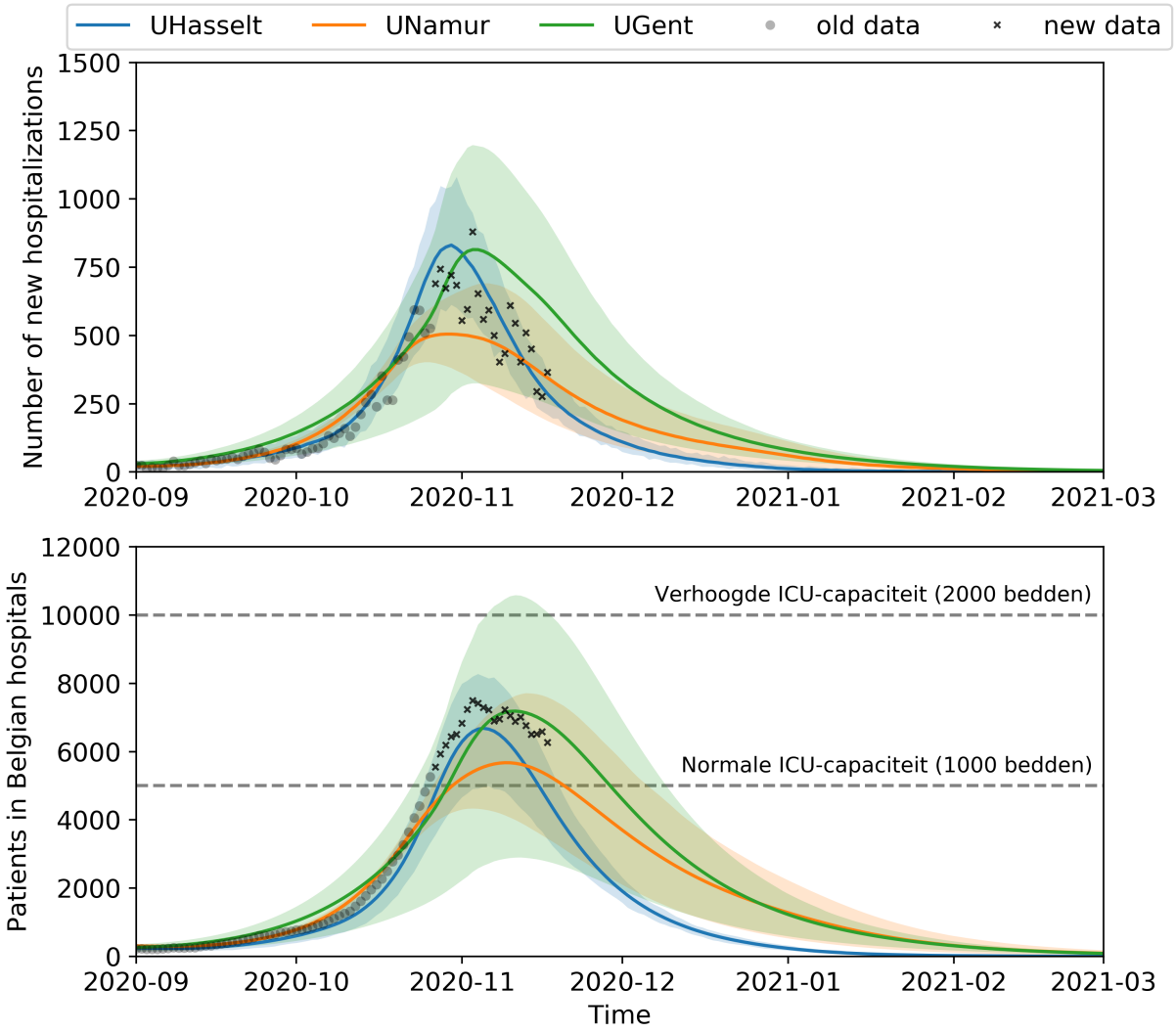

Figure 3: Zoom of Scenario 4 on the period September 2020 - March 2021, for number of new hospitalisations (top) and hospital load (bottom).

Conclusions

This updated report shows at the same time the limitations and the power of a long-term modelling exercise. We can predict (albeit with a given uncertainty) the evolution of the virus spread given a certain scenario, but we cannot predict which scenario will become reality. However, by presenting different scenarios, we offer the opportunity for preparedness to a range of uncertain futures.

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Appendix: modelling details

Table 1: Main properties, assumptions and limitations of each model. The complete model descriptions can be found below.

	UHasselt	UGent
model type	stochastic	deterministic
	compartmental	compartmental
properties	age-structured	age-structured
	discrete-time	continuous-time
	no re-importations	no re-importations
	mechanistic	mechanistic
assumptions	asymptomatic individuals 50% less infectious	children 50 % susceptible
	deaths in hospitals only	deaths in hospitals only
	age-dependent probability of being asymptomatic & developing severe symptoms	mildly infected self-quarantine
	UNamur	**VUB**
model type	deterministic	deterministic
	compartmental	time-series
properties	age-structured	non-age-structured
	continuous-time	discrete-time
	re-importations from travellers	no re-importations
	mechanistic	grey box
assumptions	estimated infectiousness per severity	homogeneous hospitalization probability
	separated deaths from nursing homes and hospital	homogeneous population
	age-dependent probability of being asymptomatic & developing severe symptoms	death in hospitals only

UHasselt stochastic compartmental model

We use a stochastic discrete age-structured compartmental model (Abrams et al., 2020) calibrated on high-level hospitalization data (Sciensano), serial serological survey data (Herzog et al., 2020) and Belgian mortality data (Sciensano). More specifically, the stochastic model predicts (stochastic realisations of) the daily number of new hospitalizations per age group (i.e., 10 year age groups). The modeling approach depends on assumptions with regard to the transmission process which inevitably implies an underestimation of the level of uncertainty. As the model-based long-term predictions rely on changes in social contact behaviour following the exit strategy initiated May 4, 2020, we present such predictions under various scenarios which aim at giving some insights in the future course of the epidemic without being able to assign a probability to each scenario related to the likelihood of a given scenario to become reality. We do account for the current resurgence of COVID-19 in the selection and presentation of plausible scenarios. In this model we are not explicitly accounting for re-importation of the pathogen in the population

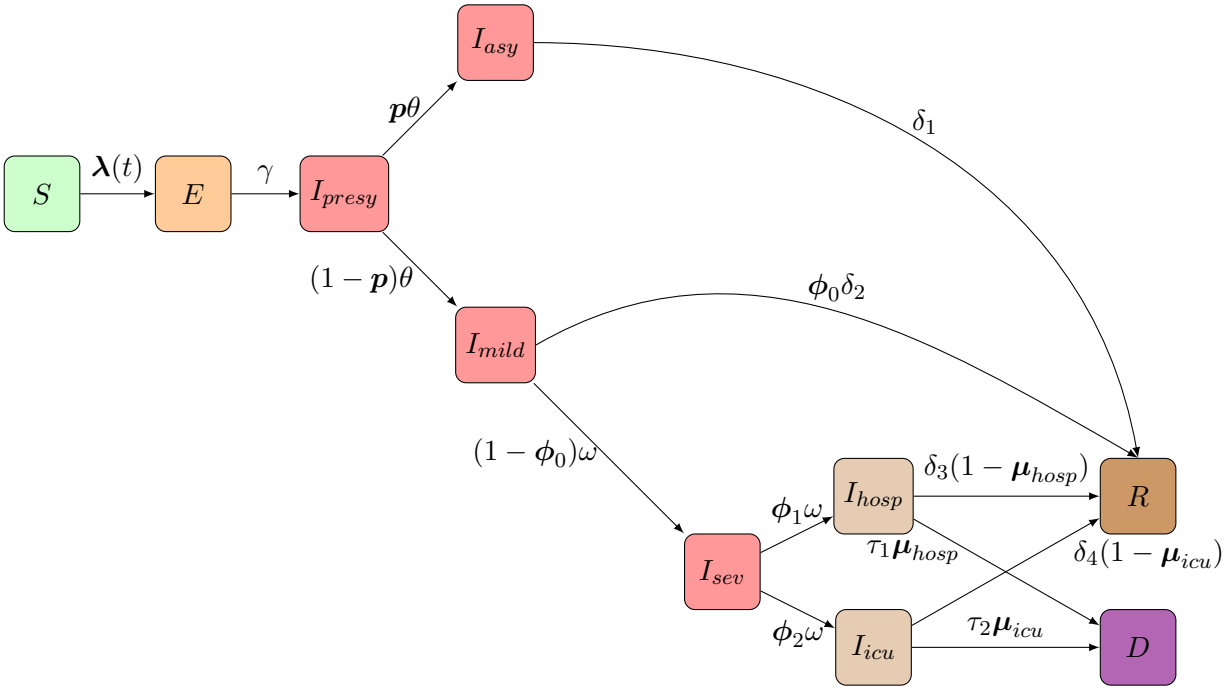

Figure 4: Schematic overview of the flows of individuals in the compartmental model: Following SARS-CoV-2/COVID-19 infection susceptible individuals (S) move to an exposed state (E) and after a latent period individuals further progress to a pre-symptomatic state (I_{presym}) in which they can infect others. Consequently, individuals stay either completely symptom-free (I_{asym}) or develop mild symptoms (I_{mild}). Asymptomatic individuals will recover over time. Upon having mild symptoms, persons either recover (R) or require hospitalization (going from I_{sev} to I_{hosp} or I_{icu}) prior to recovery (R) or death (D).

UGent deterministic compartmental model

We extend the classical SEIRD model to incorporate more expert knowledge on SARS-CoV-2 (Alleman et al., 2020). The model accounts for pre-symptomatic and asymptomatic transmission, as these have been shown to be important contributors to SARS-CoV-2 spread. Furthermore, the susceptibility to SARS-CoV-2, the severity of the disease and the susceptibility to a sub-clinical infection depend on the age of the individual. Our model takes hospitals explicitly in account and distinguishes between regular hospital wards (Cohort) and intensive care units (ICUs). From the pooled dataset of two Ghent (Belgium) hospitals, we computed age-stratified mortalities in both hospital wards. We used age-stratified social contact rates from a study by Willem et al. (2012) to model age-specific social mixing. These social contact data are available at home, in the workplace, in schools, on public transport, during leisure activities and during other activities. Community mobility data from Google are used as weights for the contributions of social contacts. In this way, the model can be used to simulate discrete government policies. We calibrated the model to the daily Belgian hospitalizations between March 15th, 2020 and March 23rd, 2020 and found the reproduction number to be $R_0 = 2.83$, in line with the global consensus range of $R_0 = [2, 4]$. A flowchart of the model and its compartments is available in Figure 5. As previously mentioned, the model is age-stratified and simulates the disease dynamics in nine age-bins of 10 years.

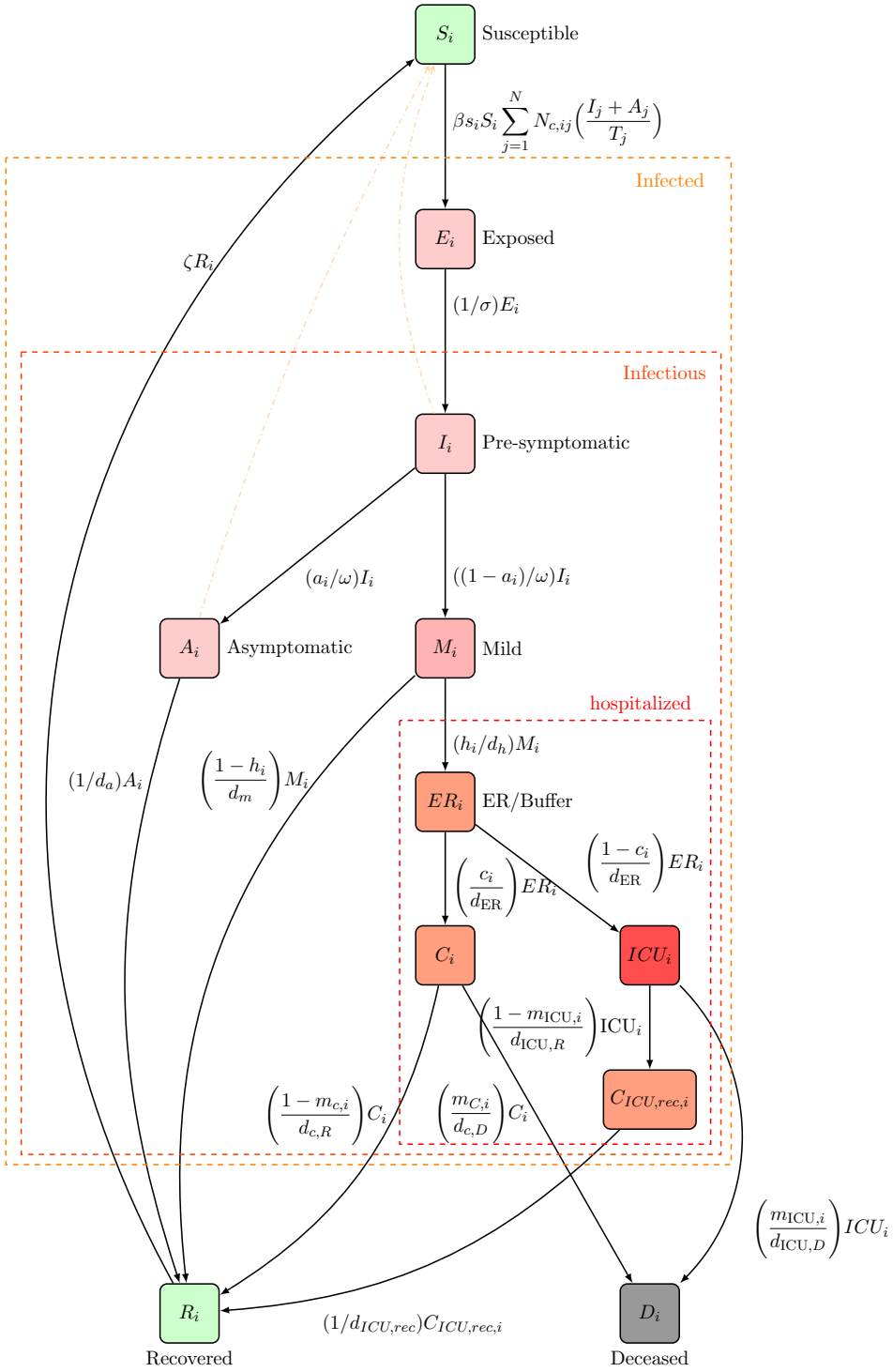

Figure 5: Extended SEIRD dynamics used in this study. Nodes represent model states, edges denote transfers.

UNamur deterministic compartmental model

The model initially developed at UNamur is a continuous age-structured compartmental model based on differential equations, calibrated on public Sciensano data on hospitalization, mortality and serology from blood donors. Transmission between age classes is computed using social contact data at different places (home, work and transport, school, leisure and others). The model has 65 estimated parameters with probability distribution given by an MCMC method. Nursing homes are considered in a specific way as 2000 isolated entities with random infection and variable hospitalization policy during the first wave. Continuous care improvement from the first wave is taken into consideration. The model specifically accounts for the under-reporting in new hospitalizations due to transfers of patients from a non-COVID unit. The recent update of the model takes also potential re-importations during the holidays season into account. Technical details can be found in Franco (2020).

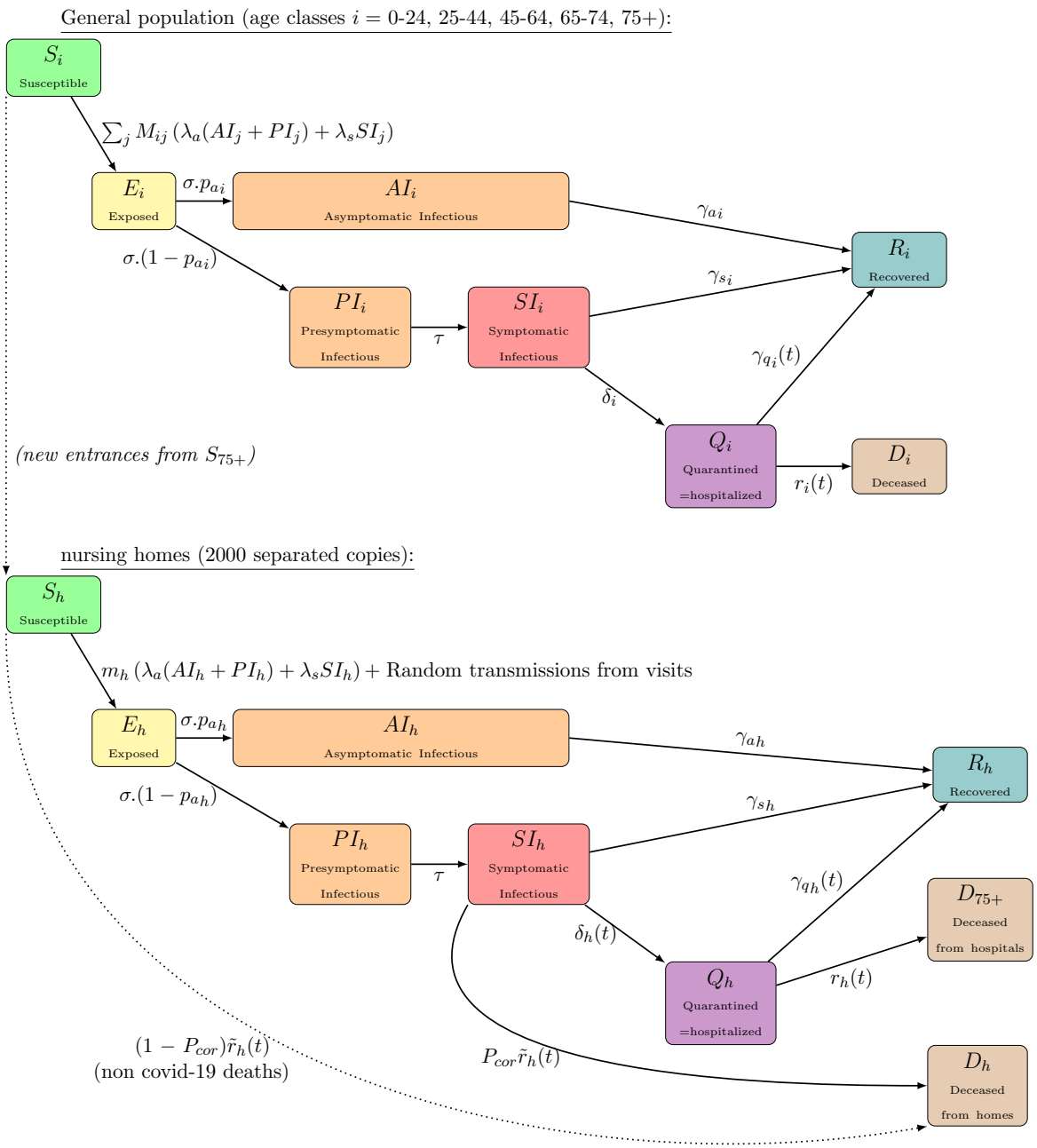

Figure 6: Schematic view of the UNamur compartmental model.

VUB time-series model

This analysis applies a time series approach wherein the log-number of events $\log(X_t)$ (with X_t the number of events of interest) is assumed to follow a first order auto-regressive process with a piecewise linear drift driven by a Gaussian cyclo-stationary process. The cyclo-stationarity is a priori set to a weekly periodicity to account for the weekend effect. The model choice is derived from a linearisation of the standard SEIR-model equations. The analysis uses the publicly available national data daily distributed by Sciensano. Forecasts are obtained by transforming the time series parameters to the parameters of the SEIR model equations proceeded by solving the SEIR differential equations numerically through a standard Runge-Kutta 4/5 numerical scheme. Currently the model applies 23 parameters and 7 knot points.

The model is data-driven which serves as a prediction model with limited possibility of scenario simulations. The uncertainty analysis relies on the assumed Gaussian cyclo-stationary noise process. The weekend-effect is modelled non-parametrically by analysis of the periodogram of the model residuals w.r.t $\log(X_t)$. The Fourier coefficient corresponding to a weekly periodicity is used in the residual's spectral density.