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

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Disclaimer

Introduction: four predictive models

This report contains predictions from four different models describing the spread of SARS-CoV-2 (COVID-19) in Belgium. Each models 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 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 used models (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.

Below, we present predictions for the following 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).

For all scenarios, we implemented complete school closures during the holidays periods of the (extended) autumn (2 – 11 November), Christmas (21 December – 3 January) and spring (15 – 21 February).

Number of new hospitalizations

All models predict that if contact behaviour is not changed with respect to the level preceding 19 October (Scenario 1), a peak in hospitalizations will be reached between November and mid-way December, whose maximum might be up to 3 times higher than the one of the first wave in March 2020 (Figure 1). If contact behaviour is reduced during only one month (Scenario 2), the peak number of hospitalizations is predicted to be lower but spread over a longer period than under Scenario 1. A continuation of the reduced contact behaviour for six months (Scenario 3), as well as an even more stringent transmission reduction similar to the March-April 2020 lockdown (Scenario 4) both lead to a lower peak number of hospitalizations.
Anyhow, even in the best-case scenario, all models indicate that it is unlikely that we will not surpass the peak number of hospitalizations during the first wave.

Hospital load

If contact behaviour is not changed with respect to the level before 19 October (Scenario 1), all models predict that the increased maximal ICU-load of 2000 beds will be exceeded in the first half of November (Figure 2). In case of a reduced contact behaviour during one month (Scenario 2), this overshoot will be lower and spread over a longer period, but remains very likely. The probability of exceeding the maximal load decreases in case of continued contact reduction (Scenario 3) and a more stringent transmission reduction (Scenario 4). Regardless of the scenario, all models predict that the normal ICU-load of 1000 beds will be most likely exceeded.

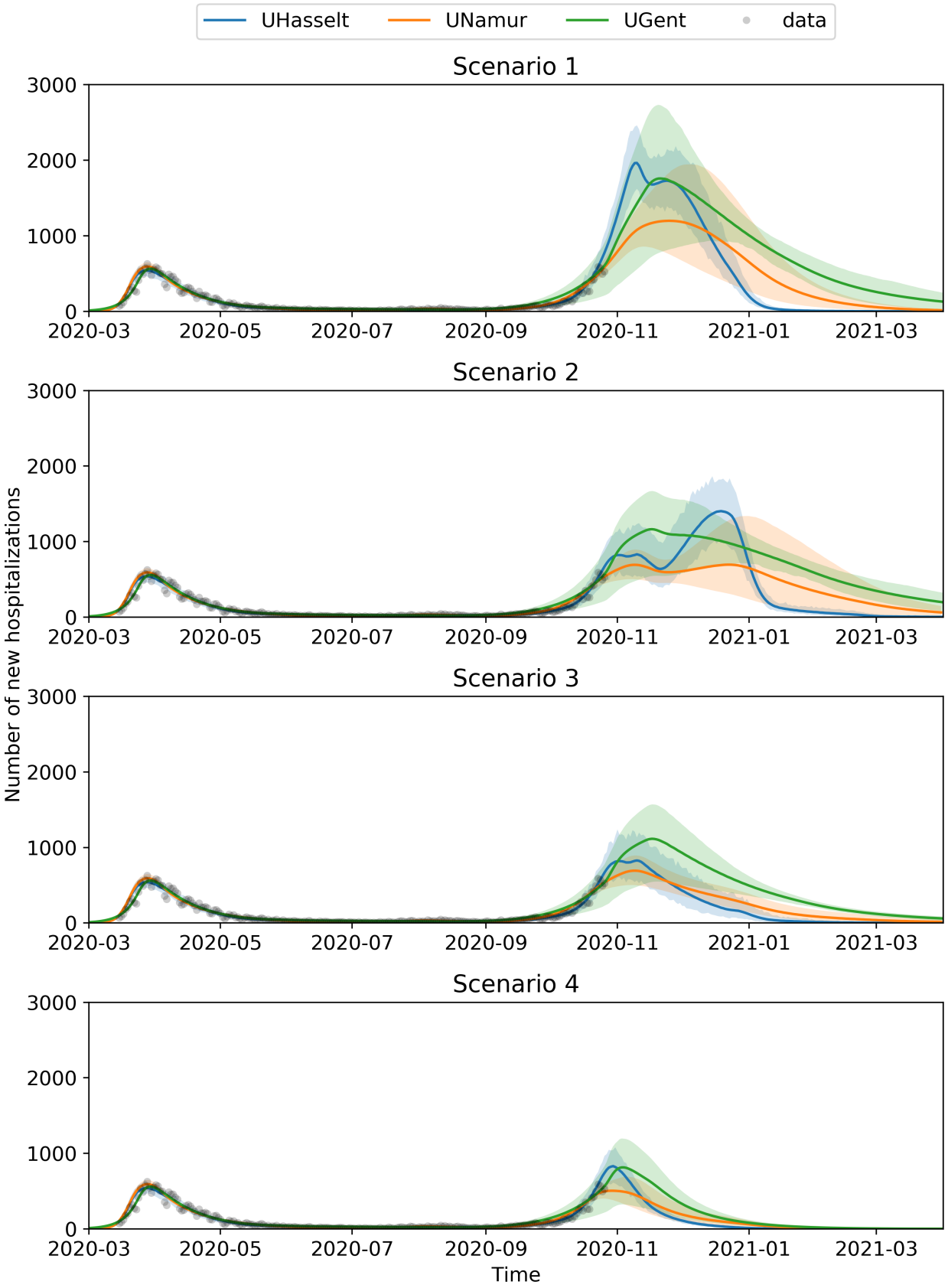

Figure 1: Long-term prediction of the number of new hospitalizations for the different scenarios and models: mean value with 95% prediction interval.

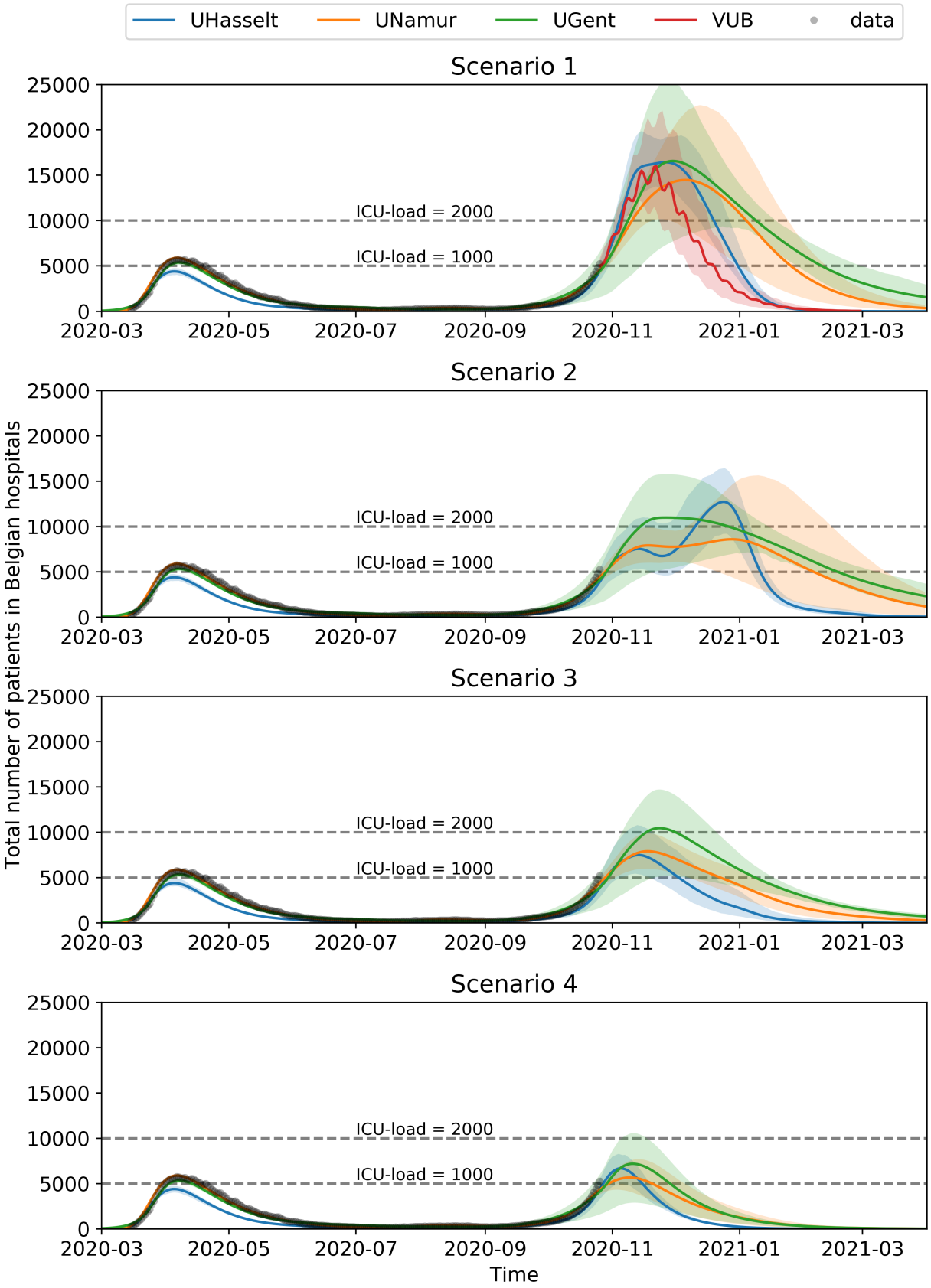

Figure 2: Long-term predictions of the hospital load: mean value with 95% prediction interval. The dashed lines indicate the number of available ICU beds for COVID-19 patients (1000: normal capacity and 2000: increased capacity). The VUB-model is only used for predictions in Scenario 1: a continuation 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.

Conclusions

The consideration of different models for generating long-term predictions allows to capture model uncertainty, related to different model types, properties, assumptions and structures. However, despite the discrepancy between the assumptions underlying the four models, their predictions are consistent in the sense that they indicate the same trends. Moreover, also the predicted numbers are very much in line with each other, especially taking into consideration the difficulty of predicting an inherently uncertain future. We cannot but emphasize the importance of taking the provided uncertainty into account when making statements about the further epidemic progression, preparing for what is still to come and taking decisions that have a societal impact. Moreover, one always should keep in mind the assumptions and limitations intrinsic to all models: it are always simplifications of reality. Finally, the model predictions are only valid under the given scenarios and the unpredictability of human behaviour adds up to the general uncertainty. The latter source of uncertainty is, for instance, not present in weather models, and those already present considerable uncertainty in their predictions.

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References

Abrams et al. (2020). *Modeling the early phase of the Belgian COVID-19 epidemic using a stochastic compartmental model and studying its implied future trajectories.* medRxiv

Alleman et al. (2020). *A deterministic, age-stratified, extended SEIRD model for assessing the effect of non-pharmaceutical interventions on sars-cov-2 spread in belgium.* medRxiv

Franco (2020). *Covid-19 Belgium: Extended SEIR-QD model with nursery homes and long-term scenarios-based forecasts from school opening.* medRxiv

Herzog et al. (2020). *Seroprevalence of IgG antibodies against SARS coronavirus 2 in Belgium – a prospective cross-sectional nationwide study of residual samples.* medRxiv.

Faes et al. (2020). *Time between symptom onset, hospitalization and recovery or death: a statistical analysis of different time-delay distributions in Belgian COVID-19 patients.* medRxiv.

Willem et al. (2012). *A nice day for an infection? Weather conditions and social contact patterns relevant to influenza transmission.* PloS one.

Barbé K. et al. (2020). *Sars-Cov2 hospitalization model: Time series approach.* Technical note ICDS300420.

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

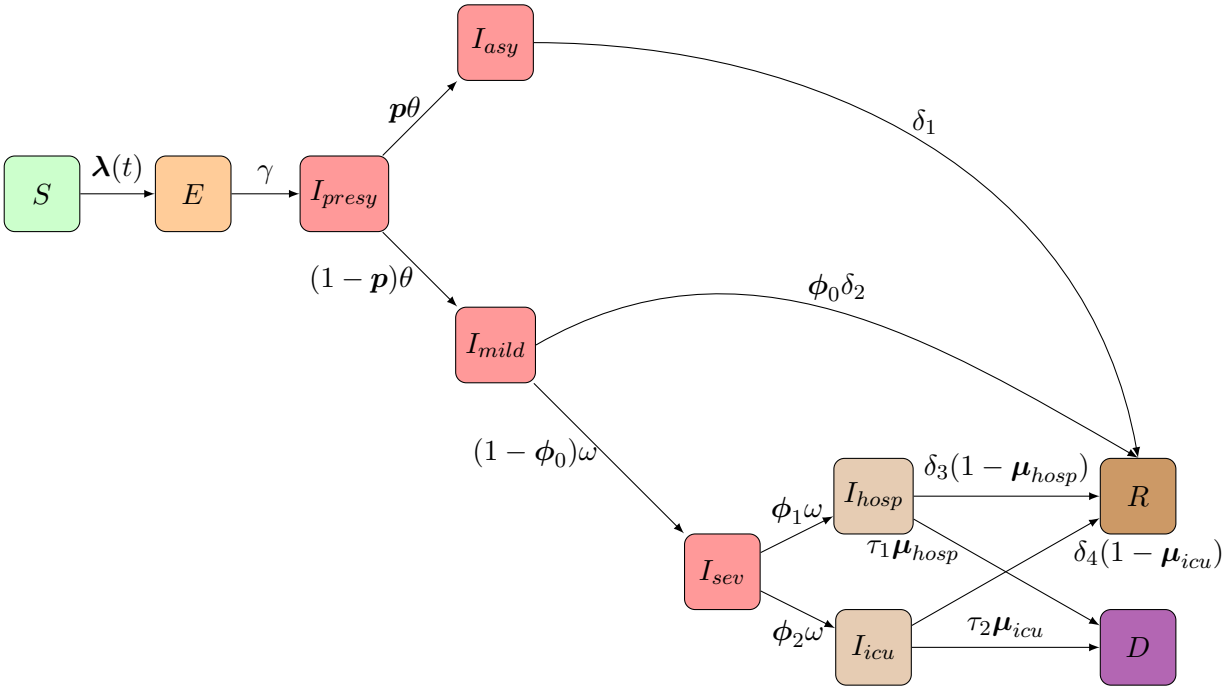

Figure 3: Schematic overview of the flows of individuals in the compartmental model: Following SARS-CoV-2/COVID-19 infection susceptible individuals (S) move to an exposed state (E) and after a latent period individuals further progress to a pre-symptomatic state (I_{presym}) in which they can infect 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 4. As previously mentioned, the model is age-stratified and simulates the disease dynamics in nine age-bins of 10 years.

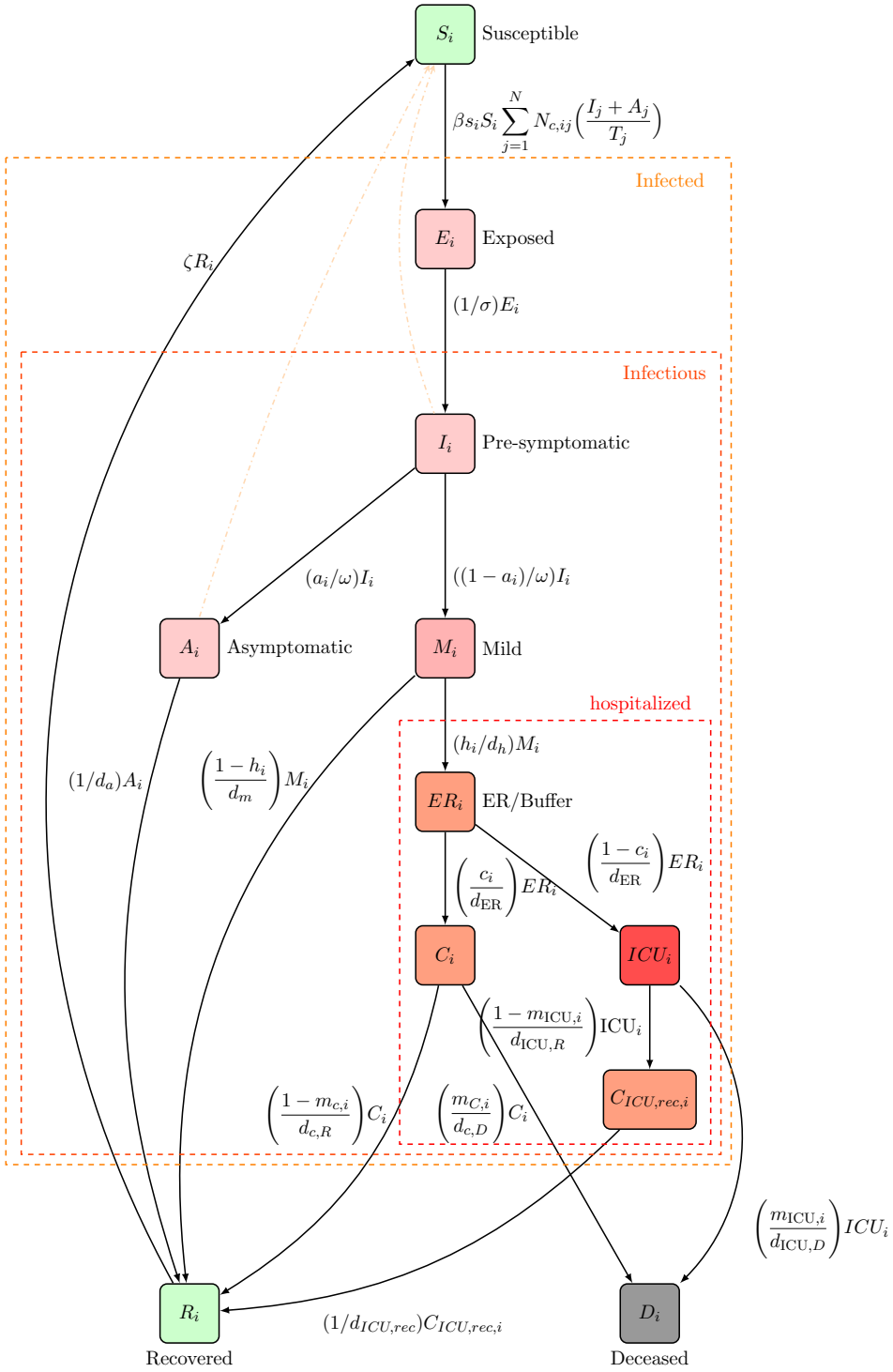

Figure 4: Extended SEIRD dynamics used in this study. Nodes represent model states, edges denote transfers.

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).

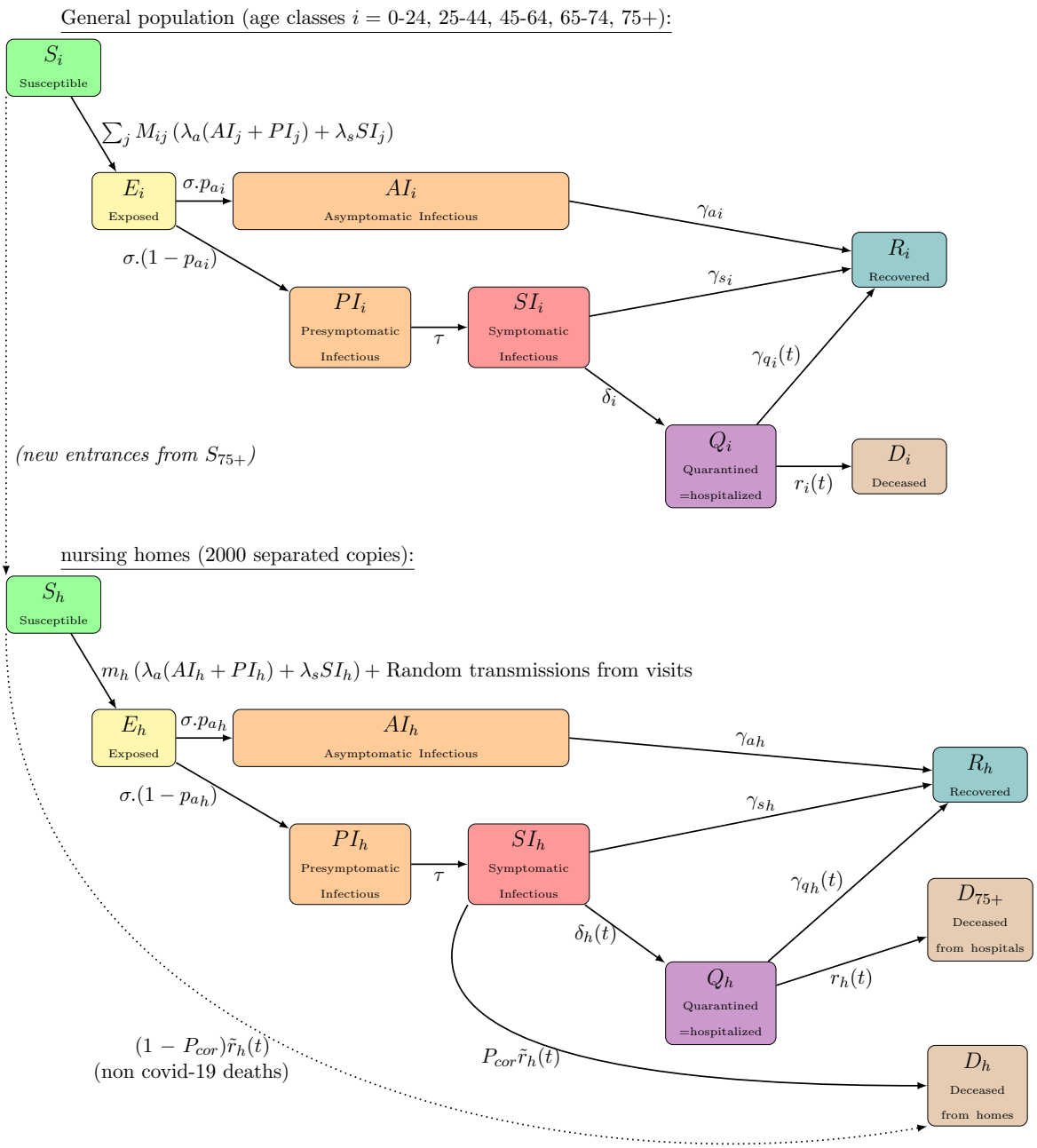

Figure 5: Schematic view of the UNamur compartmental model.

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.