

# A modified SEIR model to predict the COVID-19 outbreak in Spain and Italy: Simulating control scenarios and multi-scale epidemics

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## ABSTRACT

After the spread of the SARS-CoV-2 epidemic out of China, evolution in the pandemic worldwide shows dramatic differences among countries. In Europe, the situation of Italy first and later Spain has generated great concern, and despite other countries show better prospects, large uncertainties yet remain on the future evolution and the efficacy of containment, mitigation, or attack strategies. This Manuscript was originally written in the last days of March as a way to report on the first current wave of the pandemic. The results were updated several times for March and also for the month of July. Here we applied a modified SEIR compartmental model accounting for the spread of infection during the latent period, in which we also incorporate effects of varying proportions of containment. We fit data to reported infected populations at the beginning of the first peak of the pandemic to account for the uncertainties in case reporting and study the scenario projections for the individual regions (CCAA). The aim of this model it's to evaluate the confinement rate at the first stages of the epidemic outbreak in order to assess the scenarios that minimize the incidence but also the mortality. Results indicate that with data for March 23, the epidemics follow an evolution similar to the isolation of 1,5 percent of the population, and if there were no effects of intervention actions it might reach a maximum of over 1.4M infected around April 27. The effect on the epidemics of the ongoing partial confinement measures is yet unknown (an update of results with data until March 31st is included), but increasing the isolation around ten times more could drastically reduce the peak to over 100k cases by early April, while each day of delay in taking this hard containment scenario represents a 90 percent increase of the infected population at the peak. Dynamics at the sub aggregated levels of CCAA show epidemics at the different levels of progression with the most worrying situation in Madrid and Catalonia. Increasing alpha values up to 10 times, in addition to a drastic reduction in clinical cases, would also more than a half the number of deaths. Updates for March 31st simulations indicate a substantial reduction in burden is underway. A similar approach conducted for Italy pre- and post-intervention also begins to suggest a substantial reduction in both infected and deaths has been achieved, showing the efficacy of drastic social distancing interventions. By last we show the real evolution of the pandemic up to the end of May and the beginning of July in order to calculate the real confinement rate from data to compare with the scenarios formulated at March.

## 1. Introduction

Epidemiological reports for the current situation of COVID-19 out of China indicate Europe was one of the centers of the pandemic in the month of May, and that nearly 200 countries/regions worldwide have reported cases [1]. Particularly in Italy and Spain, a large outbreak of SARS-CoV-2 infection occurred in the month of March 2020. Given the lack of previous exposure to this virus, future predictions of both the levels of virus spread in the global naive population and the acquired herd immunity cannot be properly anticipated. Data on the last similar pandemic one century ago remains limited for obvious reasons, despite aftermath reports exist [2]. Policymakers in the most affected countries face a difficult situation when trying to balance between draconian public health actions and keeping the economy alive, as the impact on the health of severe economic measures is also well-known [3]. The fact that the 1918 Spanish flu pandemic had a second deadly epidemic wave,

presumably caused by mutations in the H1N1 viral strain [4], has also stimulated a vivid debate on whether actions to take now should take into account this uncertain future. Under this scenario, optimal action on the COVID-19 pandemic is hard to fathom. And more so, the extent of pre-symptomatic and asymptomatic infections is not narrowly constrained (e.g. up to 86 percent [5]). In China, regions as well as local governments, including Hubei, tightened preventive measures to curb the spreading of COVID-19 since Jan. 2020 [6]. Many cities in Hubei province were locked down and many measures were implemented, such as tracing close contacts, quarantining infected cases, promoting social consensus on self-protection (e.g. wearing a face mask in the public area, minimum social distances). However, in other areas, the extent and efficacy of the so-called confinement or self-isolation are doubtful, and Facebook data on mobile location and movement showed yet massive people displacements under semi-confinement measures. At a time when the success of large-scale social distancing interventions is critical, access to accurate

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information to ascertain mobility is lacking [7]. Similarly, credible serology tests that could show whether someone has had the infection and recovered are not yet massively deployed, thereby assessment of SARS-CoV-2 prevalence in the population is not established [8].

We followed the approach of Peng et al. [6] and implemented a modified SEIR model that accounts for the spread of infection during the latent period. This novel capacity to significantly spread during the latent period is a distinctive feature of the current SARS-CoV-2 epidemic if compared to SARS in 2003. Therefore, many classical models such as SIR[9–11], SEIR [11] and SEIJR [12] are not appropriate to describe the outbreak of SARS-CoV-2 in China and elsewhere. Thanks to new data on the average latent period and average time of treatment, this time delay process can be successfully incorporated in a novel dynamical system framework to describe these unique dynamics. It has been discussed that at times of ongoing epidemics, and due to errors and under-reporting, accumulated numbers of diagnosed cases and even the number of deaths might reflect more reliably the extent of epidemic progression than the daily reported new cases. Alternately, and as in Chen 2020 [9] and Peng et al. [6] we also employ the accumulated numbers in time as variables, as it was done also for modeling MERS-CoV in the recent past [13]. According with some studies [14] many of the first cases in China (before January 1, 2020), were linked to the Huanan Seafood Wholesale Market, as compared with 8.6% of the subsequent cases. The mean incubation period was 5.2 days, with the 95th percentile of the distribution at 12.5 days. In its early stages, the epidemic doubled in size every 7.4 days. With a mean serial interval of 7.5 days, the basic reproductive number was estimated to be 2.2. On the basis of this information, there is evidence that human-to-human transmission has occurred among close contacts since the middle of December 2019. Isolating key segments of populations (e.g. vulnerable populations, workers providing essential services, or territory with too fast-growing incidences) to protect them from an uncontrolled epidemic progression, is under vivid discussion as the real extent of viral spread in the population is not well known. Both the limited diagnostic capacity and the lack of clear strategies and mechanisms to quarantine infectious individuals, stand as two of the main limitations to control disease spread. Countries such as South Korea [15,16] and Taiwan [17,18] rapidly deployed aggressive contact tracing and quarantine systems [14], understanding that early deployment of resources to try to control initial seeding foci, often not only balances public health criteria but also economics. Given the differences in public health strategies and the varying capacity of the national health systems in each country to tackle the extent of the infection in the population, the growing proportions of undiagnosed infected that eventually show up, are seen to exert elevated stress on the already saturated health's system capacities. It is therefore relevant to accurately evaluate the effects of the social distancing actions imposed by governments, such as the individual or territory isolation and interruption of labor activity and/or intra and inter-urban transportation. Such strong provisions of isolation for suspected cases and infection due to contact with undiagnosed individuals are also taken into account in our modeling approach. This same SEIR model has been utilized to compare the effects of the lock-down of Hubei province on the transmission dynamics in Wuhan and Beijing [6]. Many works have been done to evaluate different aspects of COVID-19 dynamics. In Mohammad et al. [19] authors use a dynamical model based on the fractional derivative of nonlinear equations that describe the outbreak of COVID-19 according to the available infection data in the press. They simulate the available total cases reported and based on the data they use to show graphical illustrations of the numerical solutions of all parameters of the model being handled under different situations. The results of the model contribute to the ongoing research to reduce the spreading of the virus and infection cases but the complexity of the model can be very high.

The model formulated by Khan and Atangana [20] describes a mathematical model for CVID-19 putting the eye in the details of interaction among the bats and unknown hosts, then among the peoples and the reservoir of the infection (seafood market). In this work, the

seafood market is considered the main source of infection. They assume the purchasing of items from the seafood market can infect either asymptotically or symptomatically. They consider the available infection cases for January 21, 2020, till January 28, 2020. This model is centered on the very early stages of the pandemic and tries to solve the source of this worldwide infectious disease. This model is based on a previous work by Singh et al. [21] where the authors analyze the epidemiological model to describe computer viruses with an arbitrary order derivative having a non-singular kernel.

Gao et al. [22] investigate to find the optimal values of a mathematical model that reproduces the transfer of 2019 –nCoV from the reservoir to people. This model, named Bats-Hosts-Reservoir-People coronavirus (BHRPC) model, is based on bats as essential animal reservoirs. They simulate the spreading under the optimal parameters. Whereas the obtained results show the effectiveness of the theoretical method considered for the governing system, the results also present much shed light on the dynamic behavior of the Bats-Hosts-Reservoir-People transmission network coronavirus model. As in the previous case, in this paper authors concentrate on the virus spillover from the animal reservoir more than on the human to human transmission of the virus.

Since the beginning of the pandemic, many efforts have been made by the scientific community to assess the possible impact of the pandemic to analyze strategies to mitigate its effect on the population [23]. In this sense, several approaches have been proposed. From machine learning techniques to understand the spreading and improve the forecasting of the infection [24], to classic modeling approaches [25,26] based on differential equations as previously mentioned. All of these efforts are not in vain since different model configurations tackle/approach different aspects of the same problem. different aspects of the same problem.

In this work, we present a simple and easy-to-implement mathematical model that allows us to easily evaluate the best population confinement strategy during the initial stages of an outbreak. This allows us to know the impact that this strategy has on the final size of the outbreak and number of deaths. To do this, we focus on the first COVID-19 wave that spanned from early February to mid-July in Europe. We only use the data from the first wave of the pandemic due to there is a high discrepancy in the way this data was reported after July. For Spain, this problem is notable, mainly for the recovered cases but also for the reported cases.

The manuscript is organized as follows: in Section 2, we describe the dynamic model and datasets used to simulate the evolution of the outbreak of SARS-CoV-2 in Spain and its administrative regions (CCAA), as well as in Italy, we also describe the methods used for the model optimization and the main parameters. The effect on the epidemic curves of the efficacy of the different intervention measures aggregated for Spain is presented in Section 3.1. Section 3.2 provides estimates of the future number of diagnosed people, fatalities, and recovered individuals for each CCAA prediction as of March 23 and the main active foci in Section 3.3. Section 3.4 addresses model uncertainties and limitations of our study, and we add results for Italy pre- and post-interventions in Section 3.5. We also discuss the efficacy of possible actions in each case and territory in terms of health burden and report and provide an update of the situation up to March 31 and May 30 for Spain and for the case of Italy we provide a first actualization of the model for March 31 and a second, covering until July 4.

## 2. Model and data description

We used a generalized SEIR modeling framework similar to Peng et al. [6], which enables the testing of control interventions [27]. Compared with statistical methods mathematical modeling based on dynamical equations can often provide essential information on the epidemic dynamics. This is particularly true when basic epidemiological parameters are unknown or largely uncertain and more mechanistic understanding is needed, such as for the current COVID-19 disease. The population is assumed constant due to the rapid disease spread, i.e. the births and natural death have the same value. The recovery rate and death rate are

**Table 1**  
Main model parameters description.

Parameter	Description
$\alpha$	Protection rate
$\beta$	Infection rate
$\gamma$	Incubation rate
$\delta$	Quarantine rate
$\lambda$	Recovery rate
$k$	Mortality rate by the virus
$\mu$	Natural death and birth rate
$\tau$	Length of the protection

time-dependant. The model also assumes that susceptible individuals ( $S$ ) are contagious upon coming into contact with infected ( $I$ ) individuals not detected. It is assumed, however, that the infected are all quarantined ( $Q$ ) and that they do not have contact with susceptible individuals. In turn, the susceptible population can be protected by confinement by moving to the protected population compartment ( $C$ ). This assumption on  $Q$  means that hospital infections are not considered under this framework, therefore resulting in a potential underestimation of the real contagion extent. However, we chose this option in an attempt to be conservative and our results should be interpreted as the current best-case scenario. It is assumed also that the protected population does not have contact with the infected individuals and therefore cannot be infected. The COVID-19 dynamics is modeled by the following equations system:

$$\begin{aligned} \frac{dS}{dt} &= \mu N_T + \tau C(t) - \alpha S(t) - \beta \frac{S(t)I(t)}{N_T} - \mu S(t), \\ \frac{dE}{dt} &= -\gamma E(t) + \beta \frac{S(t)I(t)}{N_T} - \mu E(t), \\ \frac{dI}{dt} &= \gamma E(t) - \delta I(t) - \mu S(t) - \mu I(t), \\ \frac{dQ}{dt} &= \delta I(t) - \lambda(t)Q(t) - k(t)Q(t) - \mu Q(t), \\ \frac{dR}{dt} &= \lambda(t)Q(t) - \mu R(t), \\ \frac{dD}{dt} &= k(t)Q(t), \\ \frac{dC}{dt} &= \alpha S(t) - \mu C(t) - \tau C(t), \end{aligned} \quad (1)$$

where  $S(t)$  is the susceptible population,  $C(t)$  is the confined susceptible population,  $E(t)$  is the exposed population,  $I(t)$  is the infectious population,  $Q(t)$  is the population under Quarantine (infected reported cases),  $R(t)$  is the recovered population and  $D(t)$  is the dead population by the virus.

The main parameters of the model are the protection rate ( $\alpha$ ), the infection rate ( $\beta$ ), the incubation rate ( $\gamma$ ), the quarantine rate ( $\delta$ ), the natural death and birth rate( $\mu$ ) ( $1/(80 * 365)$ ), the recovery rate ( $\lambda(t)$ ), the mortality rate by the virus ( $k(t)$ ) and finally,  $\tau$  is the length of the protection by confinement ( $1/30$ ) The  $\alpha$  parameters represent the rate of people being protected from infected populations at time  $t$  and it is used to model the different actions of control of the epidemic by isolation of a healthy population.

The parameters  $\lambda(t)$  and  $k(t)$  are time-dependent following the approach of [28] and for simplicity are modeled as shown next in Eq. (2)

$$\begin{aligned} k(t) &= k_0 \exp(-k_1 t), \\ \lambda(t) &= \lambda_0 (1 - \exp(-\lambda_1 t)), \end{aligned} \quad (2)$$

where  $k_0, k_1, \lambda_0$  and  $\lambda_1$  are the fitted coefficients. The model parameters and their meaning are summarized in Table 1.

The data for fitting the model to Spain was obtained from public data sources [29,30] and correspond to the reported cases, recovery cases, and deaths. Data is available for the entire country as well as for individual CCAA. Data for Italy is retrieved from the World Health Organization [31].

The model was fitted in a non-linear approach by calculating the normalized least-squares error of the model approximation and the infected reported cases. The optimization algorithm used was trust-region-reflective with a maximum number of iterations of 500 and a step size of  $6.4e-7$ . The error for the model fitted for all Spain was  $3e-3 \pm 0.6e-4$  ( $ci = 95\%$ ).The fitted parameters are summarized in Table 2.

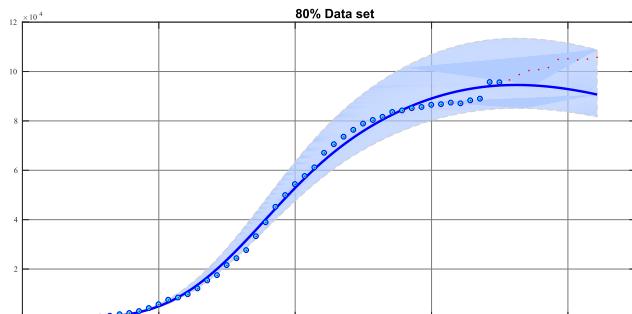
The ordinary differential equation (ODE) system was solved by using a nonlinear data-fitting approach that minimizes a least-squares error function, by using the lsqcurvefit function of the Matlab optimization toolbox. The problem to minimize is shown in

$$\min_x \|F(x, x_{data}) - y_{data}\|_2^2 = \min_x \sum_i^N (F(x, x_{data}), y_{data})^2 \quad (3)$$

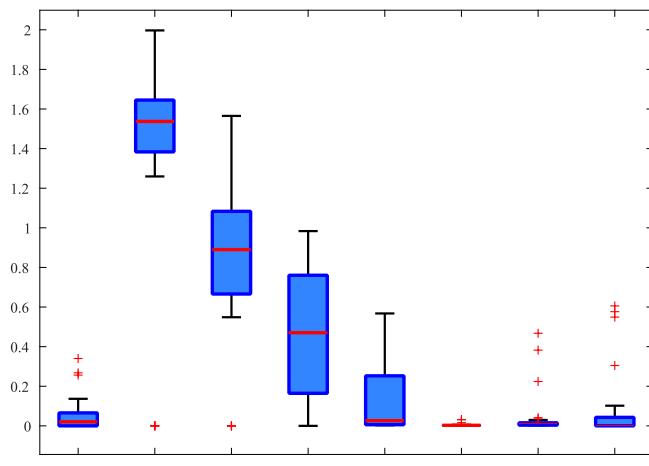
where given an input data,  $x_{data}(Q, R \text{ and } D)$ , provided by the integration

**Table 2**  
Model fitted parameters for the 17 AA CC in Spain and for all Spain up to March 21.

Community	$\alpha$	$\beta$	$\gamma$	$\delta$	$\lambda_0$	$\lambda_1$	$k_0$	$k_1$
Andalucía	0,015	1,073	0,776	0,610	0,062	0,017	0,171	0,970
Aragón	0,000	1,118	0,262	0,458	0,013	0,007	0,014	0,064
Asturias	0,001	1,438	0,264	0,623	0,023	0,076	0,017	1,709
Illes Balears	0,025	1,022	0,256	0,101	0,042	0,019	0,020	0,082
Canarias	0,007	1,257	0,182	0,335	0,035	0,030	0,005	0,002
Cantabria	0,016	1,086	0,217	0,010	0,014	0,607	0,004	0,012
Castilla-La Mancha	0,000	1,339	0,571	0,750	0,027	0,044	0,015	0,000
Castilla y León	0,015	1,124	0,575	0,467	0,059	0,027	0,045	0,219
Catalunya	0,015	1,359	1,138	0,760	0,159	0,006	0,651	0,859
C. Valenciana	0,015	1,155	0,862	0,674	0,090	0,007	0,447	1,267
Extremadura	0,025	1,017	0,272	0,203	0,026	0,013	0,028	0,080
Galicia	0,021	1,835	0,915	0,892	0,076	0,004	0,003	0,000
Madrid	0,015	1,227	0,939	0,613	0,274	0,011	0,016	0,000
Murcia	0,025	1,871	0,908	1,090	0,019	0,006	0,001	0,037
Navarra	0,002	1,012	0,681	0,686	0,048	0,002	0,003	0,000
Euskadi	0,000	1,081	0,564	0,626	0,137	0,010	0,015	0,048
La Rioja	0,000	1,745	0,241	1,269	0,016	0,029	0,003	0,005
Spain	0,015	1,288	0,870	0,585	0,057	0,026	0,070	0,144



(a)



(b)

**Fig. 1.** Model uncertainties (a) dynamics obtained by adding new values to the time series and (b) the fitted parameters variation.

of the ODE system 1  $y_{data}$  is the observed output (Active reported cases, Recovered and Deaths) sourced from public repositories. Confirmed cases may include presumptive positive cases and probable cases.

The ODE system 1 was integrated by using a 4<sup>th</sup> order Runge–Kutta method. These kind of methods are easy to implement and very stable.

For straightforward dynamical systems, this method can converge fast if we use an integration step in the order 1e3. Although from the computational point of view this method is expensive compared to simpler methods such as Euler's, the error of approximation is considerably less. On the other hand, this type of method has greater stability, especially when applied to non-linear systems [32]. The fitted parameters are the confinement rate, the infection rate, the incubation rate, the quarantine rate, the coefficients that determine the recovery rate and the coefficients and that determine the mortality rate. Thus, the optimization problem described in Eq. 3 is subject to the constraints specified by the vectors  $lb = [0; 0; 0; 0; 0; 0; 0]$  and  $ub = [1; 2; 2; 2; 1; 1; 1]$ , lower limit and upper limit, respectively. The algorithm chosen to minimize the problem was a trust-region because this type of algorithm is especially useful for solving non-linear optimization constrained problems.

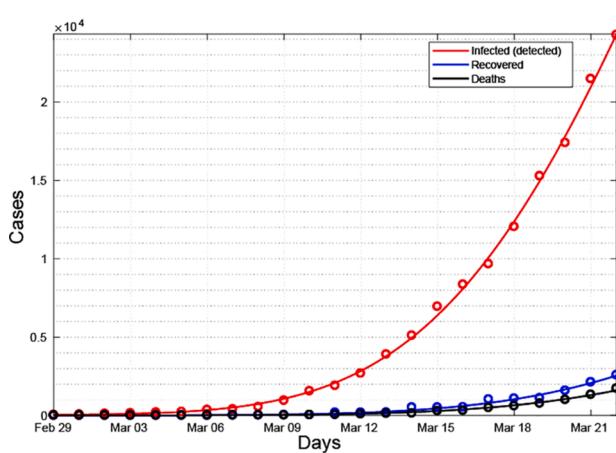
To obtain a representative measure of the optimal set of parameters, 500 iterations of the method were performed taking initial values for the parameters, randomly within a uniform distribution. The same algorithm was run using incremental data set sizes (from 10 points to 50 points, the equivalent of 80% of the data set). This procedure was carried out point by point 100 times with stochastic initial conditions in order not to always fall into the same local minimum. Fig. 1 shows a measure of the uncertainties of the fit using both a data set of 80% of the total values and how the remaining values (not used in the training of the model), were correctly predicted. The mean error is of the order of  $3e^{-3} \pm 6e^{-4}$  (CI95%) [27].

### 3. Results

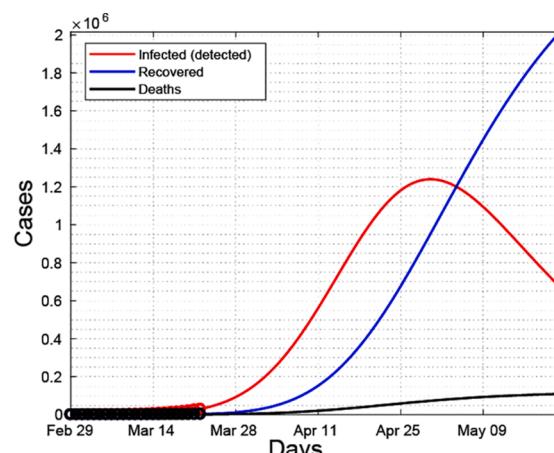
#### 3.1. Epidemic curves for Spain and the 17 Autonomous Communities (CCAA)

The model fitting to data aggregated for Spain on reported infected population up to March 23 yields a good approximation to the exponential curve, as well as to the reported evolution in deaths and recovered (Fig. 2). The model was fitted from day 1 of the epidemic at the end of February because the initial protection rate is assumed to be 0.

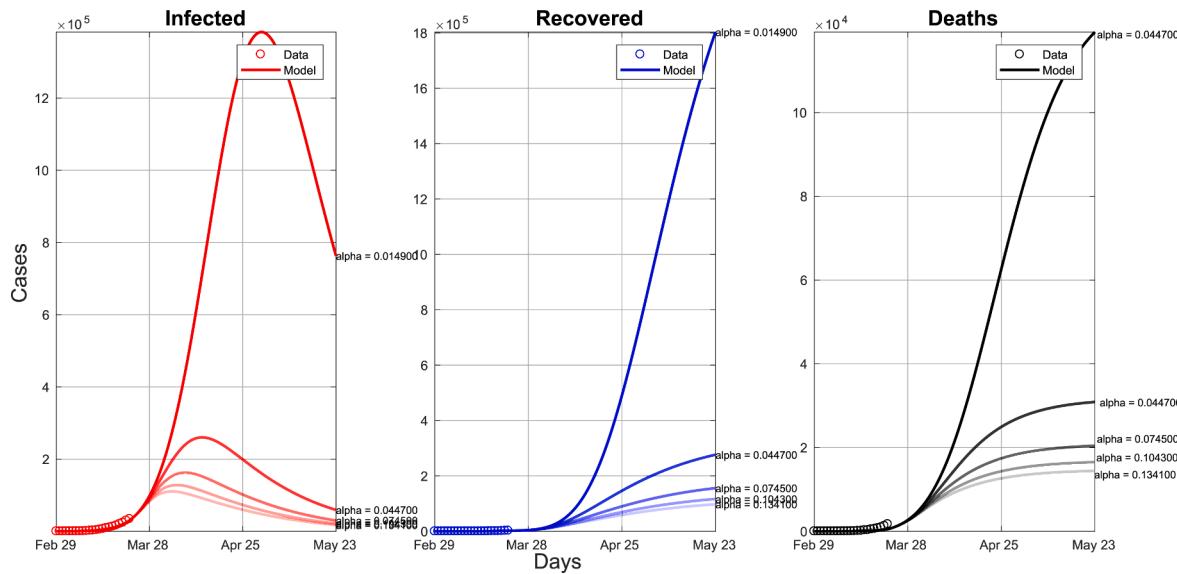
Progression of infected, deaths, and recovered track very approximately observations. With data up to March 22, the model predicts the first peak in cases around the end of April or early days in May with an error of the approximation of less than 5%. The current scenario may already include to some extent the effects of the partial "confinement" measures imposed on March 13, therefore it is likely that total projected infections would be much higher should these restrictions not exist. More than 1.6million people would have been recovered from SARS-CoV-2 infection by mid-May and total deaths for the entire country at



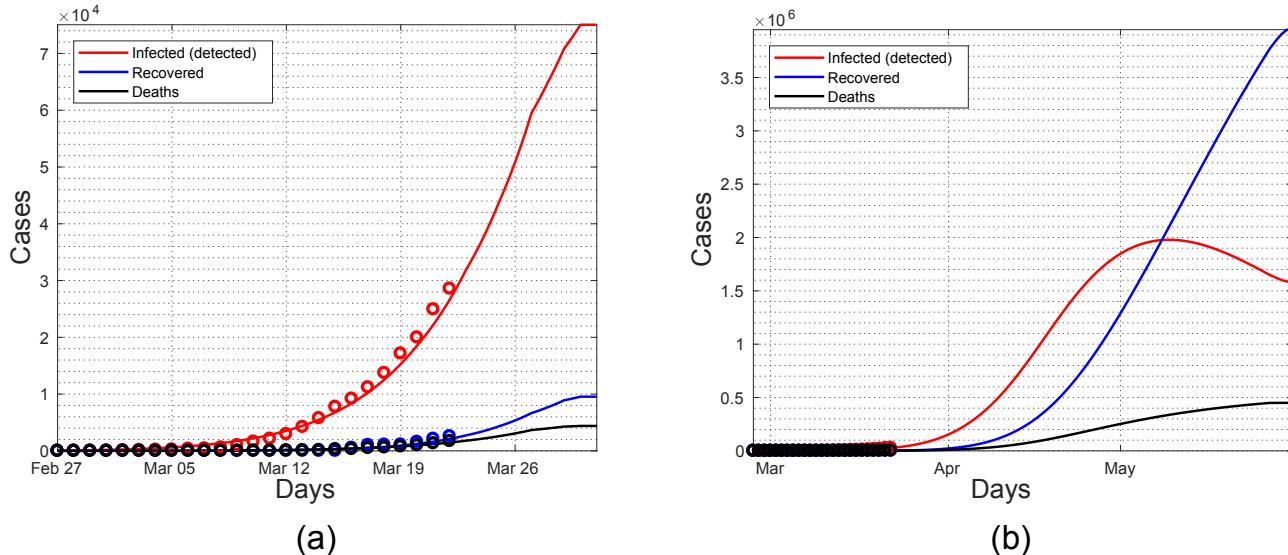
(a)



**Fig. 2.** Fitting of the population model implemented on a global scale up to March 23 (all Spain).



**Fig. 3.** Control scenarios for the global model up to March 23 (all Spain).



**Fig. 4.** Aggregated CCAA model fitting up to March 23 for Spain.

that time would rise over 100 thousand people (Fig. 3).

### 3.2. Evolution of SARS-CoV-2 in the 17 autonomous regions (CCAA)

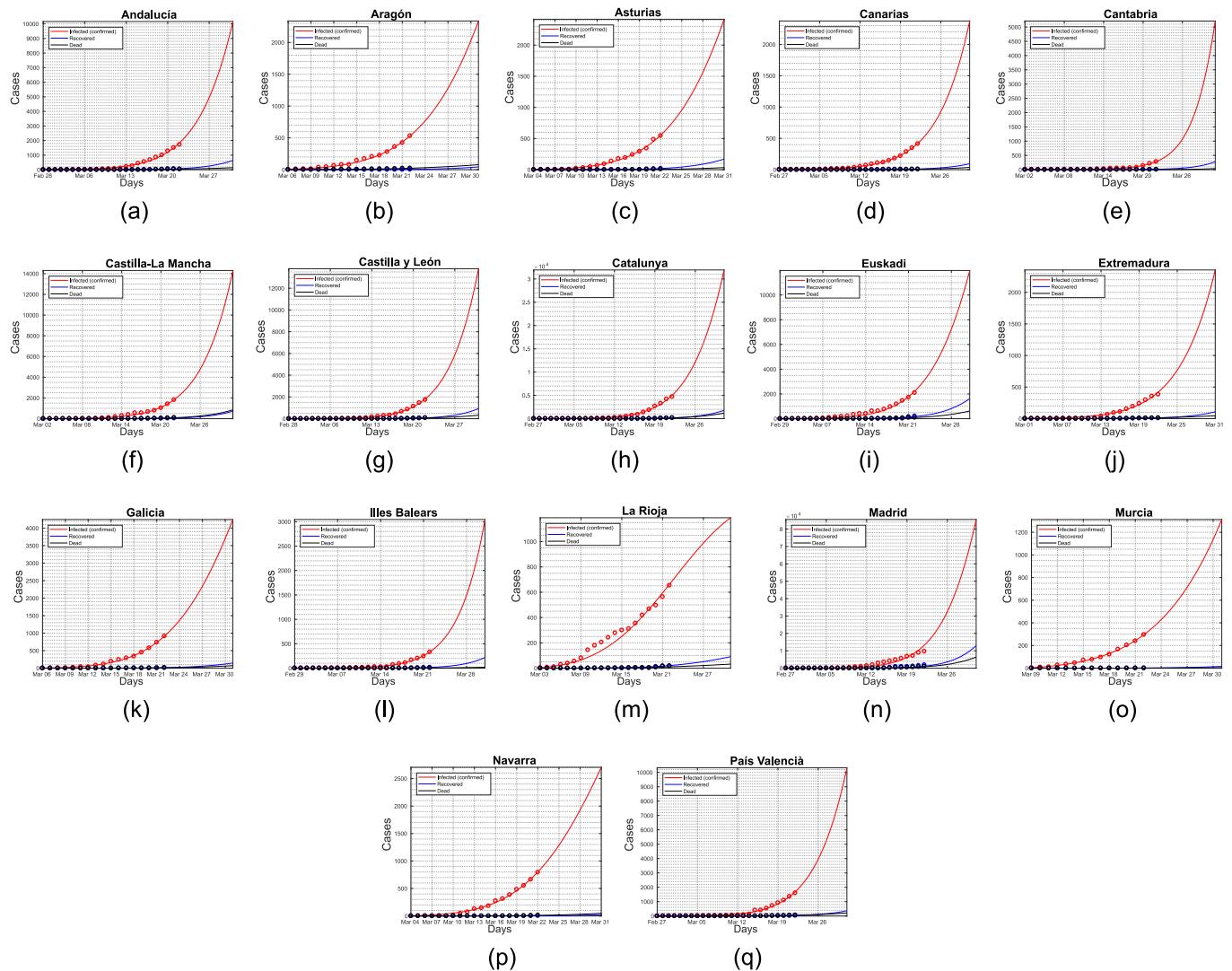
To approach the degree of colonization of the virus at smaller levels of aggregation than the entire country, we applied the same model framework to each of the 17 individual CCAA. The former was an attempt to model the epidemics spatially and approach scale-derived differences with country aggregated data (e.g. municipality-level data is not yet available). Results on July 2020 are shown in Fig. 5 and display varying developmental stages of the COVID-19 epidemic outbreak, thereby recovering the different demographic topologies for the variety of CCAA and Fig. 6 shows the extended fitting to have a better understanding of different development stages at the community level.

The largest increases of infected “in absolute terms- to the month of may were expected according to the CCAA curves, in the coming weeks for Madrid, Catalunya, Castilla La Mancha, País Valencià, Castilla León and Andalucía. All the former displays -under the current scenario evolution- peak cases occurring from late April to early May.

To compare Fig. 2 above with the effect of community disaggregation on the evolution of reported cases for Spain, simulations were performed individually and results aggregated together as shown in Fig. 4. Results are comparable despite they show relatively larger values for total infected than those arising from the simulations on the country's total cases.

#### 3.2.1. Control scenarios for Spain

The situation in Spain is at April 2020 yet very severe, based on public data until March 25. To this end, we tested the potential effects of intervention strategies to control and reduce social contacts. Effects of the adopted policies on March, 14 are not yet known or they can barely begin to show up as substantial changes in the epidemic curve at this date (see Appendix for an update to March 31). To help in the evaluation, we generated different scenarios with varying values of  $\alpha$ , to simulate the effects of social protection. Increases in  $\alpha$  were structured in scenarios representing up to 10 times larger values than in that obtained from observations up to March 23. The results of these scenarios are summarised in Fig. 3. A drastic decrease in the resulting number of cases



**Fig. 5.** Model fitting for the 17 CCAA of Spain up to March 23.

can be seen, if we increase the actual daily protection rate around ten times.

Results with the current epidemic evolution for Spain, show that over 1,400,000 quarantined infections would be reported by the end of April, with an estimated burden of over 100,000 deaths. A four times increase in the levels of the protected population would represent a huge gain in the number of both clinically diagnosed infections and casualties (Fig. 3). A decrease to around 200,000 infected is achieved and a reduction to below 50,000 deaths. Much larger reductions in both infected and deaths can be achieved if much stricter measures result in more drastic reductions in the number of effective contacts. Best case scenario simulated with ten times the efficacy of the observed  $\alpha$  on March, 23, can result in a more recent arrival to a peak of around 100,000 cases (around early April) and with a decrease in casualties to around 30,000.

### 3.3. Evolution of the main active foci (Barcelona and Madrid)

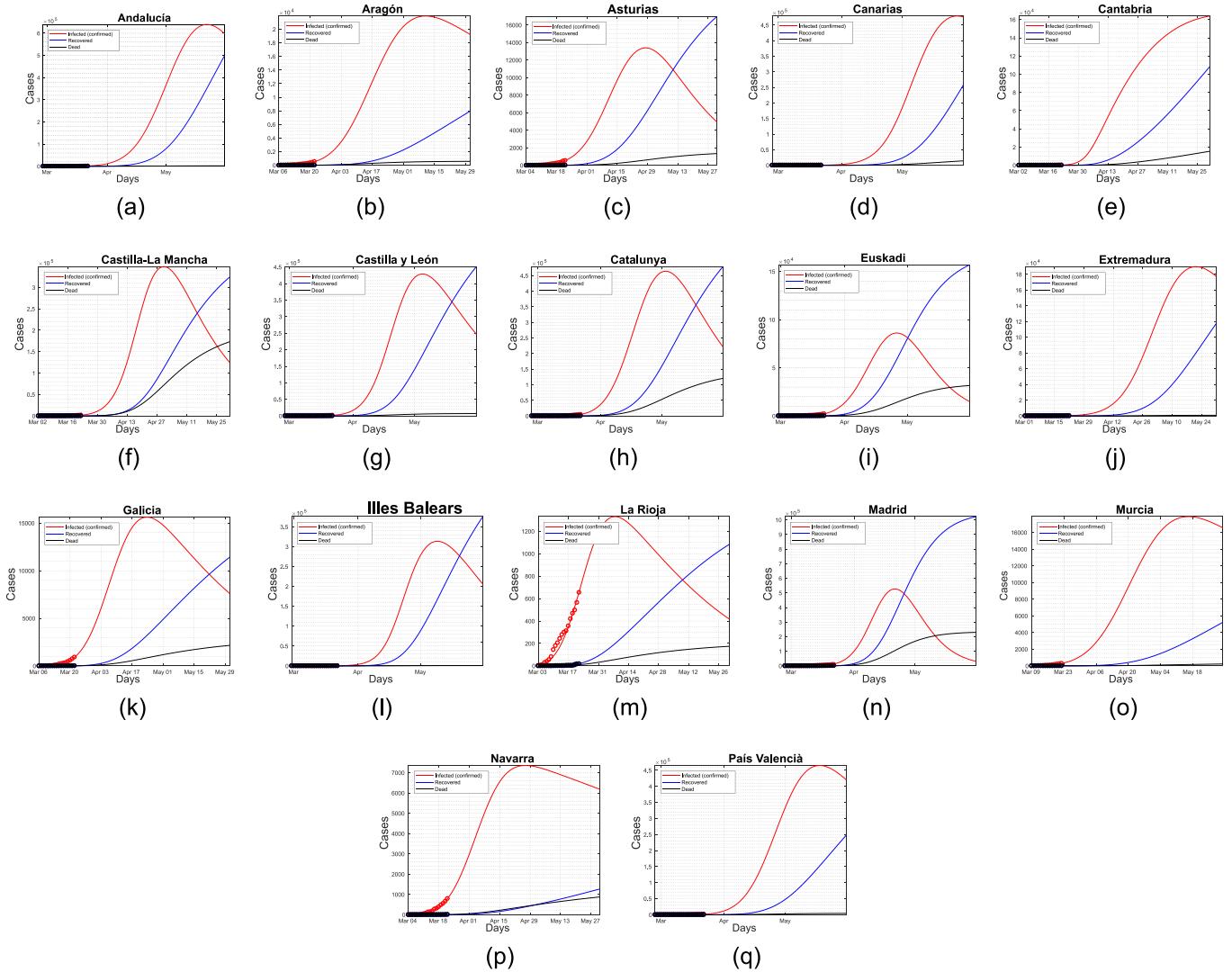
Active discussion on the convenience of imposing stricter measures is underway on March 22, with the overall effect of yet acting on the more active COVID-19 foci being under large debate. Given the large associated uncertainties and enormous public health and economic costs, timely actions at this point might represent large gains or losses. To aid in this respect, we simulated the effect of imposing stricter measures of

social distancing also on two of the most active foci, namely Madrid and Catalunya. Madrid was the CCAA where the initial outbreak evolved more rapidly and on March 23, it concentrates over 30 percent of total cases and a large majority of deaths. Similarly, Catalunya is now showing a significant increase in new infected and both areas share similar populations albeit Madrid has in comparison, higher population density.

Results are shown in Fig. 7 for Madrid and in Fig. 8 for Catalunya, respectively. Similar conclusions on the large effect of imposing stricter epidemic containment measures can be seen in both regions, even if imposed at the current stage of the epidemic development.

### 3.4. Model uncertainties

Because the strength of this type of model, both to adjust and to predict future dynamics, depends on the accuracy in case reporting, it is important to analyze the uncertainties in the adjustment and evaluate the degree of variation of the parameter estimates. To get a better idea of its performance, the model was fitted with a successively longer data series, adding a new day to the data window with which the fitting was computed. The shortest time series used was of 5 days from February 29 to March 3 and the longest covered up to March 31. The temporal span of the time series used can seriously affect the value of the fitted parameters. This is especially true at the beginning of the epidemic when



**Fig. 6.** Model extended fitting for the 17 CCAA of Spain up to March 23.

the relationship between infected, dead, and recovered is not entirely clear. For example, if the number of confirmed cases is small, it is difficult to ascertain whether the quarantine has been rigorously applied or not. Also, such under-representation would suggest that the number of infectious people is much larger than the number of confirmed cases. Results of the different dynamics and the parameter space can be seen in Fig. 1. Those parameters most affected are the ones directly related to the infection rate and the recovery rate, as well as the protection rate  $\alpha$ .

### 3.5. The case of Italy

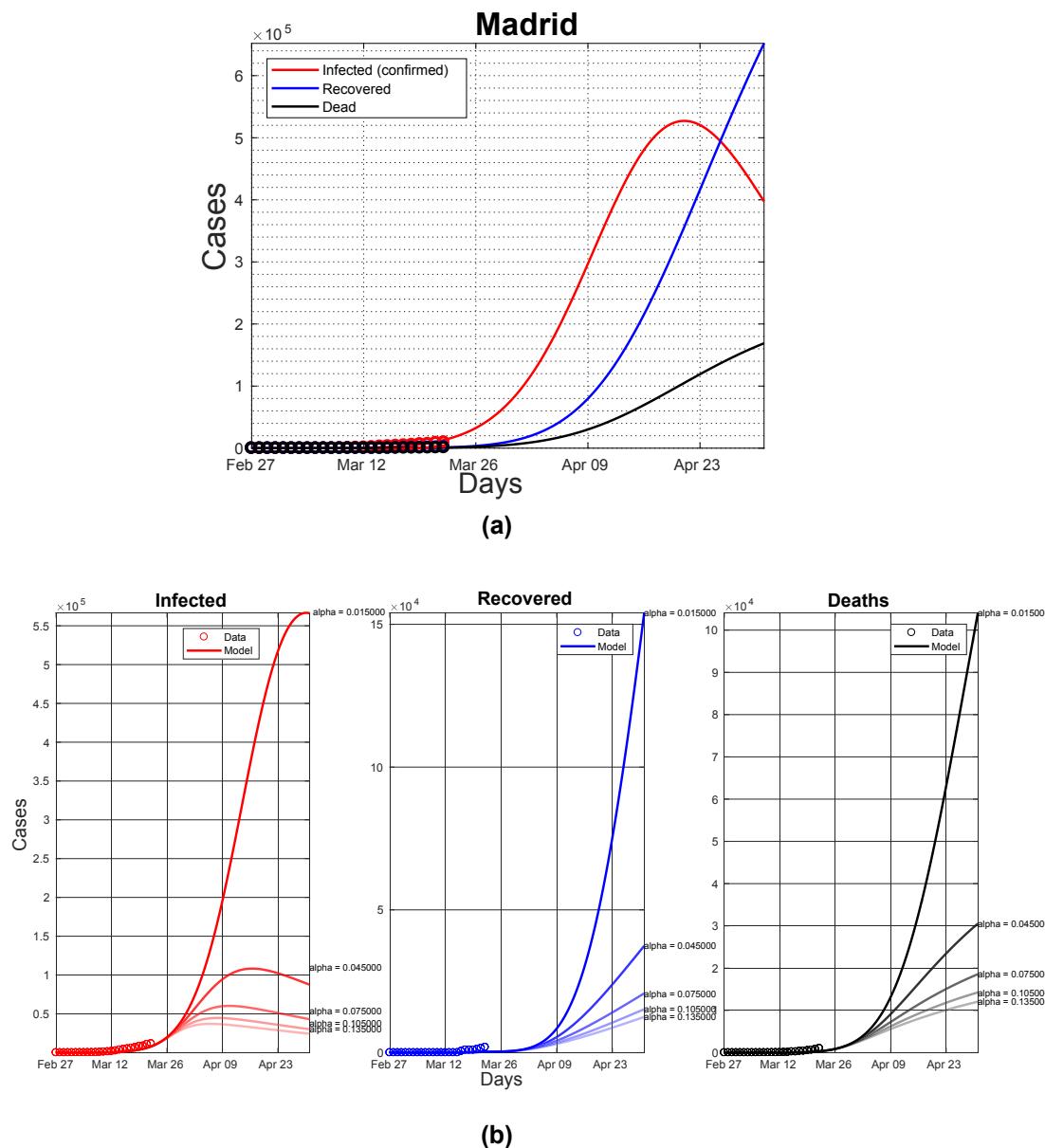
To see the performance of applying the same model framework in the other European country with more quarantine cases to date, we fitted the model to the COVID-19 epidemic in Italy. This way, as the situation in Italy precedes that of Spain by around one week, evaluation of control scenarios can be done at a more advanced stage of confinement measures. As the first cases in Italy were reported at the end of February, two different sets of fittings were performed to compare the confinement restrictions imposed by the Italian authorities on March 10th. The NMSE in this case was  $2.7e-3^{+3.6e-4}$  ( $ci = 95\%$ ) and the parameters for each case are summarized in Table 3.

Fig. 9 displays model results for the two different scenarios. The bottom panel shows the effect of different measures of confinement since day 1 in a hypothetical control scenario. These dynamics are the

result of increasing the fitted  $\alpha$  until approx 1% daily. This is a significant increase having into account the initial value of the protection rate.

### 4. Discussion

Current estimates of future trends in new infections in the weeks after March 23 largely compromise the capacity of the Spanish health system, as it happened for Italy. This is especially critical in particular for intensive care units from the end of March [33]. Our projections for the forthcoming evolution in the COVID-19 epidemic curve for Spain show a pessimistic scenario unless current social distancing measures are effective (see Appendix for an update as of March 31. With the estimates at hand, over 1.4 million people would be clinically diagnosed at the disease maximum and over 100.000 resulting in deaths. Imposing stricter measures under the current uncertainties seems a logical preventive option given the considerable gains in terms of infection and casualties, even at moderate increases in alpha. Assessment of total country changes through aggregated and CCAA disaggregated data estimates, provides similar dynamical evolution despite different absolute values. Discrepancies to larger values might partly come from the heterogeneous population landscape in the different CCAA (e.g. cities with high population density), as opposed to the homogeneous contact assumption in the aggregated model estimates. Gaining extra time for exerting alternative interventions, such as temporary increases in public



**Fig. 7.** Extended fitting for Madrid up to March 23.

health responses, or increasing the capacity of massively screening the population to gain an accurate value of the real prevalence of SARS-CoV-2, or to develop disease treatment strategies seem a logical conclusion. While two of the most populated CCAA (namely Catalunya with roughly 7.7M people and Madrid Community, with 6.7M people) are already in the lead in terms of epidemic progression, other similarly populated regions lag only a few days entering a similar slope in their respective epidemic growths. The largest population density in Madrid compared to other CCAA together with its more advanced epidemic progression cast urgent attention on the evolution of this highly active epidemic focus. Those regions where the outbreak was initiated earlier (e.g. Madrid, Catalunya, Euskadi, and Navarra) or appear to have more connectivity to the initial foci and largest population density tend to show earlier peaks. Those regions yet in the early stages of the exponential increase are those where strong initial social isolation measures (therefore protection of the population), would have the largest effects in resulting infected (Fig. 5).

The projected rise in the number of infections shown in Fig. 2 is very sensitive to the latest data used, as these data are the ones governing the

changes in trends, therefore errors in reporting or other large uncertainties associated with these values may dramatically alter the outcome in terms of the number of infected and associated mortality. For the curve to happen as shown, the simulation assumes the initial conditions hold, therefore if that were not the case and measures were lifted before the epidemic reaches  $R_0 \approx 1$ , infections might rise again. Improvements can be achieved with more complete integration of time-delay coordinates in classical SEIR models [6]. This way, both the incubation period and the period before recovery, as well as the precise role of the asymptomatic population, can be better represented at times when this information is highly uncertain. A substantial gain in the epidemic projection in the form of reduced infections in the population would already be achieved with a four-times rise in the efficacy of the control situation we had around March 9–16. This was the time when social distancing/confinement was imposed (March 13). Time will show to which extent current measures manage to increase the value of alpha. Application of strict containment measures clearly shows a drastic effect on the epidemic progression and a substantial reduction in both infected and to a lesser extent, deaths (Fig. 3).

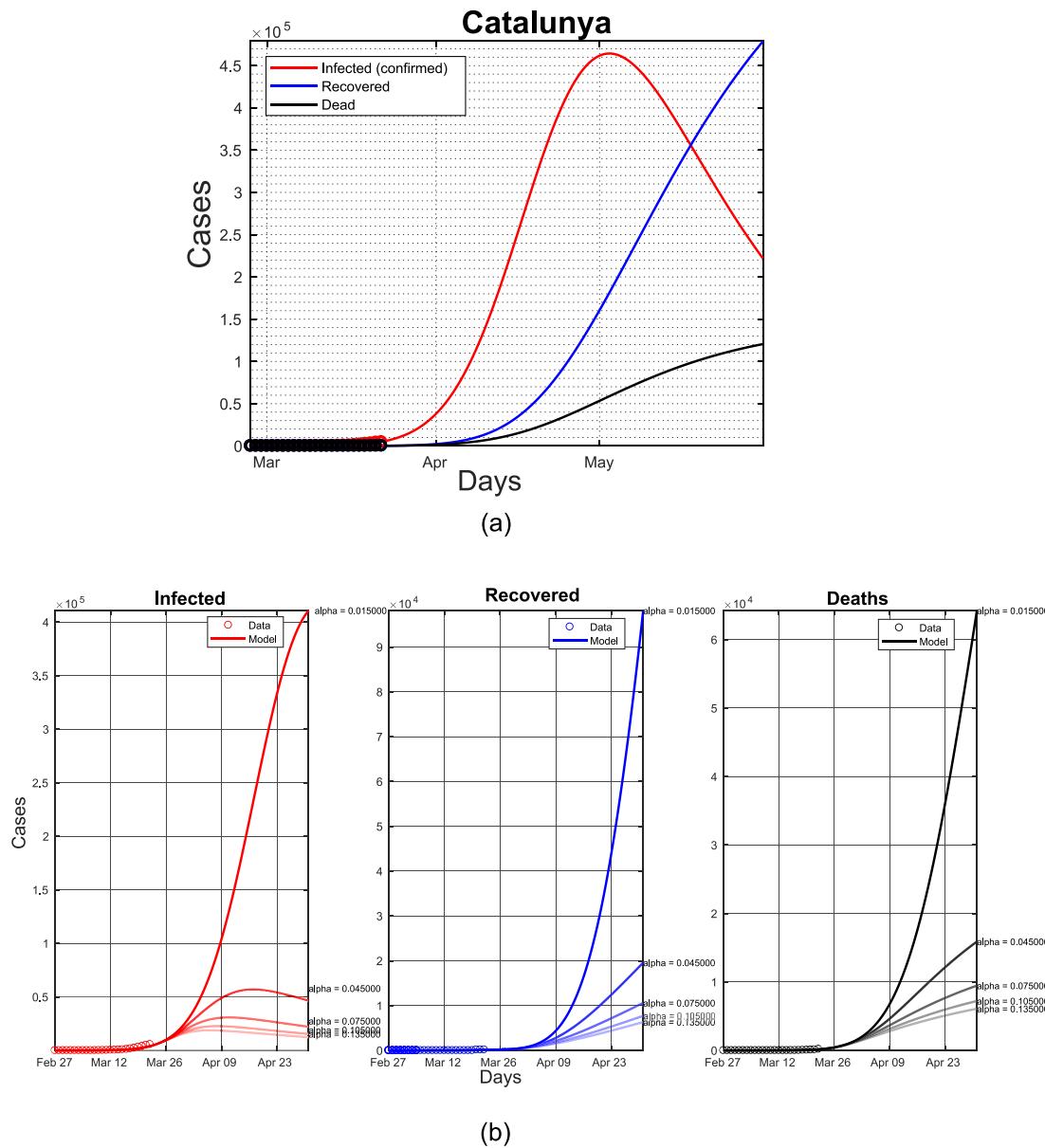


Fig. 8. Extended fitting for Catalunya up to March 23.

**Table 3**  
Fitted model parameters for Italy up to March 31.

Escenario	$\alpha$	$\beta$	$\gamma$	$\delta$	$\lambda_0$	$\lambda_1$	$k_0$	$k_1$
Before control	0, 0001	1, 955	0, 200	0, 897	0, 052	0, 99	0, 059	0, 051
After Control	0, 025	1, 341	0, 712	0, 221	0, 035	0, 027	0, 020	0, 017

The control scenarios presented contemplate a significant increase in the percentage of the population under confinement, ranging from 1.3 percent daily to 13 percent daily. These percentages imply that after a week of starting this control, the percentage of protected susceptible population is 9.1% and 91%, respectively, from the start of the measurement. These numbers explain the drastic differences in the two dynamics observed and the huge gain in lowering the toll of infected.

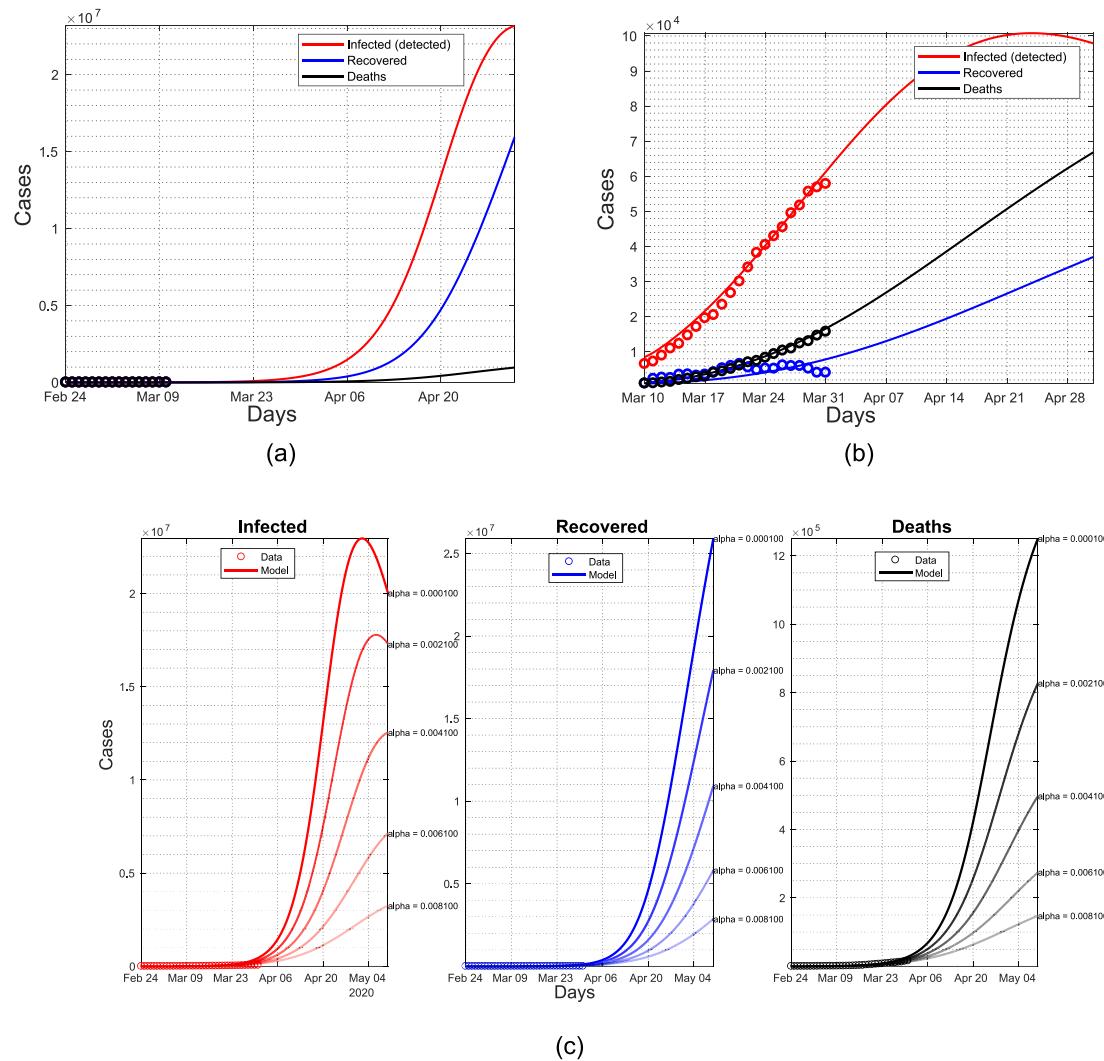
Update of the epidemic situation in Spain partially showing the effect of partial lockdown and the current values for alpha are shown in the Appendix as for March 31. Later we update the model for May 30 in the

case of Spain and its communities and until July 4 for Italy. This actualization suggests that the model first predictions and scenarios formulated are not to far from the reality.

## 5. Conclusions

The results presented in this study and the writing of this article were completed by mid-March and were later updated several times until the month of July. Therefore the references to 'now' should be seen as of March 2020. The Covid-19 pandemic is exerting unprecedented stress on the public health systems of many countries. Those at major risk now are Italy and Spain, and for them, the efficacy of the partial confinement or total lockdown effects are yet unknown. Under this situation, we implemented a modified SEIR compartmental model accounting for infection from undiagnosed individuals and for different levels of population isolation, to evaluate the effects of contacts reduction in the epidemic temporal dynamics.

In this manuscript, we present a simple model that allows us to evaluate confinement strategies for the initial stages of the pandemic. The scenarios are counterfactual since, in reality, the confinement



**Fig. 9.** Model fitting and control scenarios for Italy. (a) fitting before confinement restrictions (b) fitting after confinement restrictions and (c) Control scenarios.

strategies carried out by each community and by each country were very heterogeneous, but the results obtained suggest that the model accurately adjusts to reality and that the projections are reliable.

Among the advantages of the implemented model, it should be noted that despite the simplicity of the hypotheses, the adjustments obtained were accurate and the projections made do not differ much from those other more complex models. Also, the instantaneous increment of cumulative diagnosed people depends on the history of cumulative infected people, by which the latent period can be taken into consideration.

The results of the implemented control scenarios for March 23 show that drastic isolation of the susceptible population should be implemented as soon as possible. Even not so drastic increases in alpha (two or three times the current rate) imply also significant reductions in the incidence of cases. The adjustments made in different CCAA also serve to verify the efficacy of the isolation hypothesis for the most affected communities (Madrid and Catalunya). They also serve as a basis for timely action in those communities that do not yet have a significant number of cases that jeopardize their health systems.

Policymakers should weigh in the values and ethical considerations of employing now maximum strength in actions to help reduce the slope of the epidemic curve against the enormous associated economic cost. However, our study indicates that a three-week interruption of labor activities, thereby a drastic reduction in contacts, could end the current epidemic in around two months and drastically reduce both the burden of this disease and much lower the toll of lives.

Our results could also provide useful suggestions for the prevention and control of the COVID-19 outbreaks in different countries and locations such as Argentina and the USA lagging behind the current epidemic wave in Spain and Italy. These represent two very different scenarios. In the case of the USA, no radical control measure was initially implemented by the federal government and the epidemic seems to be in a phase of uncontrolled growth. In Argentina, the health authorities seem to have taken note of what is happening in Europe and more strict movement restrictions have been implemented, although it is difficult to determine the degree of commitment by the population.

However, our model does not consider space explicitly as we approached aggregated data. This lack of spatial granularity may affect the accuracy of simulations when the spread of infections in a territory reaches and takes off in a populated city. The former might alter results-producing more new cases than expected, exactly what the aggregation for CCAA data clearly shows. Spatial modeling should also be incorporated explicitly and an extension of this modeling approach to incorporate the movement of individuals should follow. Results should be interpreted with care as projections at these initial stages of the epidemic are very dependent on the quality of data, with small changes in observed values producing large variations in trends. However, even with this limitation in mind, the magnitude of positive increments in cases suggests these results are strong. Variable isolation strength measures can be tested with this model and inform governments of the most probable effects of their actions on the initial course of the COVID-

19 disease.

In general terms, the model is quite stable, as shown in the uncertainty analysis carried out. On the other hand, it can be seen in the successive updating of the parameters that the initial projections of the proposed model were not too far from the real data reported. This gives a special value to the work since it somehow justifies the previous discussion. Although the scenario is counterfactual and it is not possible to determine whether a more severe increase in the confinement rate would have reduced the number of cases if it can be said that the model did not depart too far from the initial projections.

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## CRediT authorship contribution statement

**Leonardo López:** Conceptualization, Methodology, Investigation,

Writing - original draft, Writing - review & editing, Formal analysis.

**Xavier Rodó:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision, Formal analysis, Funding acquisition, Project administration.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

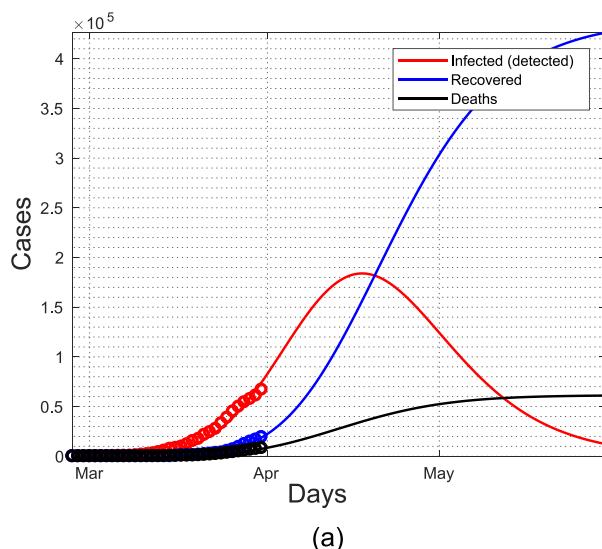
## Acknowledgments

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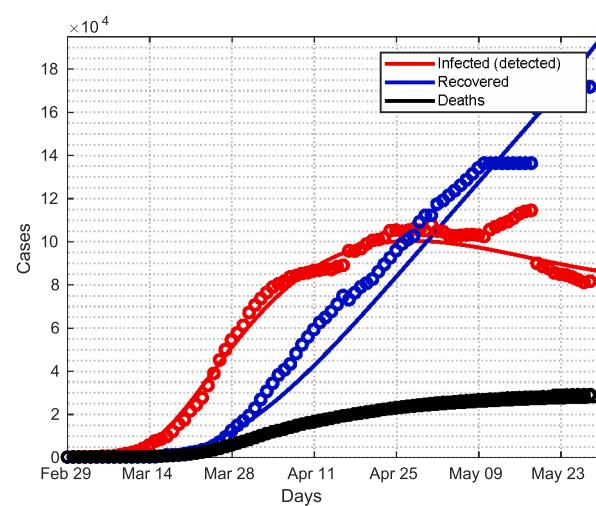
## Appendix A. Updated results for Spain

In this appendix, we show an update of the fitted model with the data reported up to March 31 first, and then we fit the model with data reported until May 30. By doing this we can compare the first model's predictions with the actual data reported at the end of the first epidemic wave. Fig. 10 shows the fitting and projections of the model with the new data. On the left panel, the results for March 31 are showed while in the right panel the model fitting until May 30 is showed. If we compare these results with those in the previous sections, the model now predicts an epidemic peak much lower than before. Also watching the update to May 30 we can see Eq. (2) that the peak it's a little lower than the first predictions but the result it's acceptable if we have into account the few data points used at the beginning of the fitting (less than 20 data-points). This may be mainly because of the Spanish government control measures imposed and a harder confinement restriction. The model parameters for March 31 are  $\alpha = 0.087, \beta = 1.305, \gamma = 1.044, \delta = 0.510, \lambda = [0.095, 0.017], k = [0.026, 0.022]$ , while for May 30 are  $\alpha = 0.092, \beta = 1.05, \gamma = 1.03, \delta = 0.610, \lambda = [0.093, 0.015], k = [0.02, 0.018]$ . A significant increase in the control rate is mostly evident from the first fitting but the change in general terms from March until May it's not that significant.

In Fig. 11 and to better understand the scenario of March 31 is showed in dashed lines in the context of the scenarios previously outlined in Fig. 3, the dynamics of the update until May 30 it's not showed in this figure due to the similarity of the previous dynamic in terms of the peak. The corresponding populations to the parameters indicated above are added as dashed lines for each panel (Reported, Recovered, and Deaths).

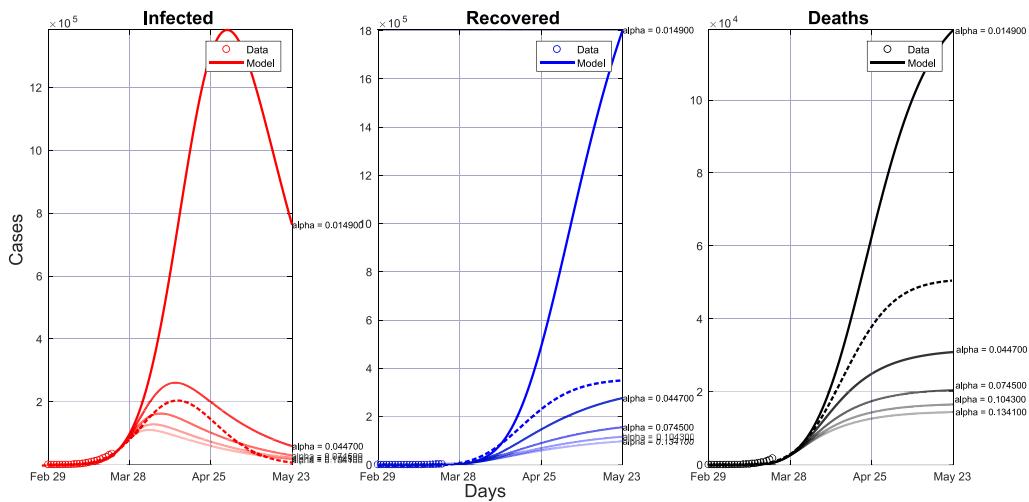


(a)



(b)

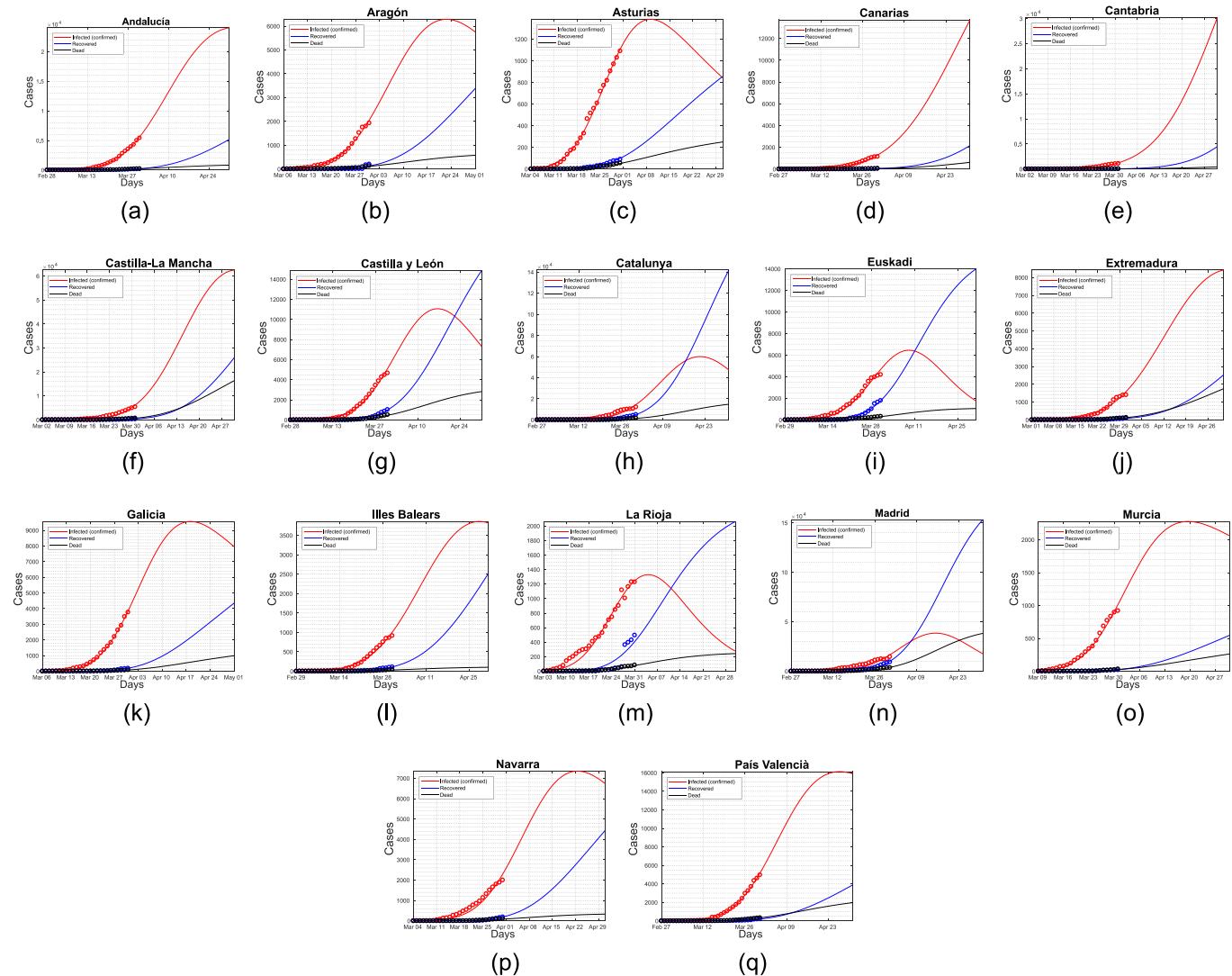
**Fig. 10.** Model fitting for Spain updated to March 31 (a) and model fitting for Spain updated to May 30 (b).



**Fig. 11.** Control scenarios for the global model (all Spain) with the predictions as for March 31st added as dashed lines.

## Appendix B. Updated scenario for each CCAA in Spain

In the same way than we did for Spain, in this section we show results of the model fitting with the data updated until March 31<sup>st</sup> and until the end of the first epidemic wave in May 30. In Fig. 12 the new fittings are showed and in Table 4 the fitted parameters are listed. Notice the closeness to the epidemic peak in some of the CCAA, a fact that can be real or be due to the yet low prevalence of the disease in parts of Spain. Fig. 13 the fittings until

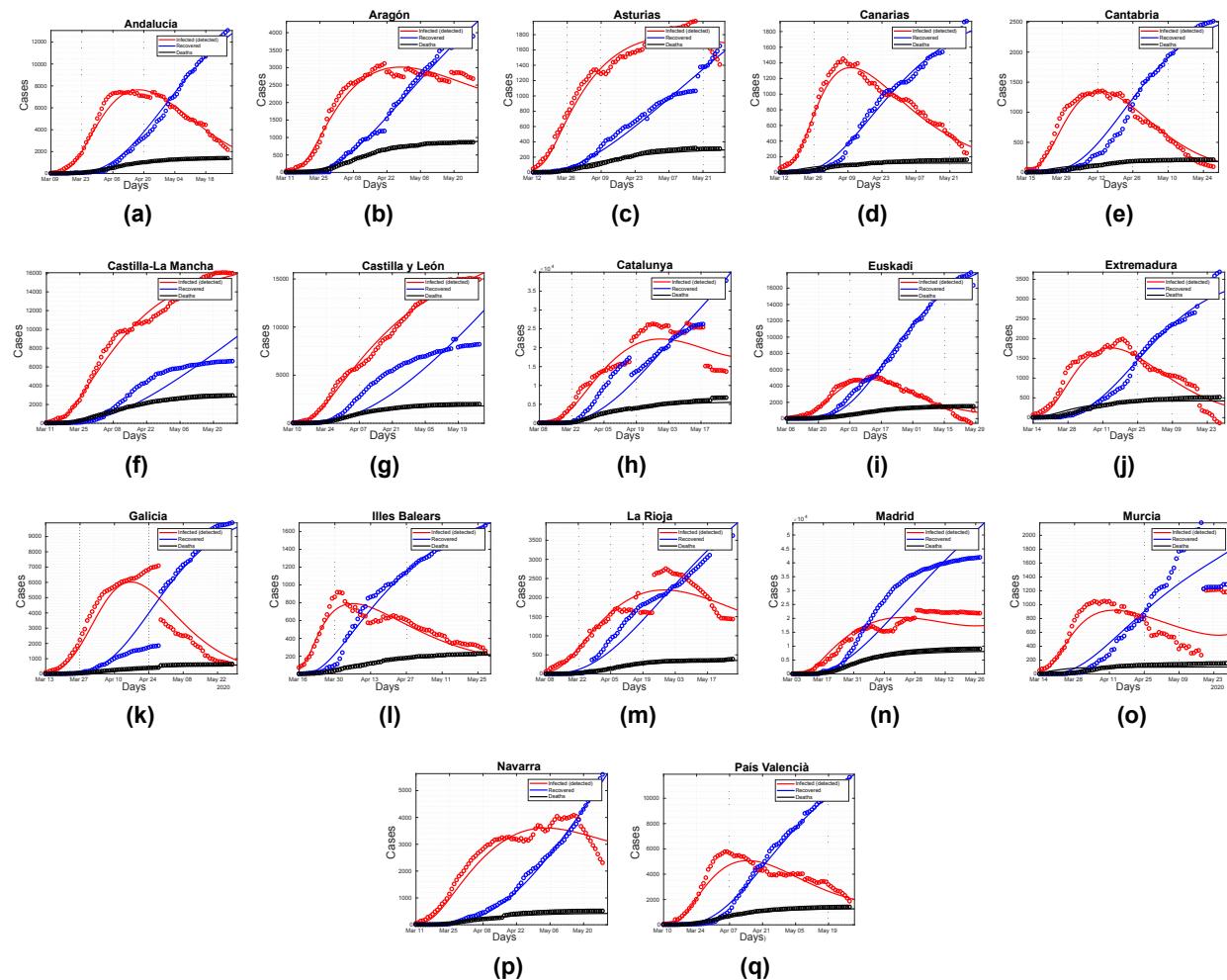


**Fig. 12.** Model extended fitting for the 17 CCAA of Spain until March 31.

**Table 4**

Model fitted parameters for the 17 AA CC in Spain and for all Spain up to March 31.

Community	$\alpha$	$\beta$	$\gamma$	$\delta$	$\lambda_0$	$\lambda_1$	$k_0$	$k_1$
Andalucía	0.015	1.133	0.357	0.279	0.071	0.005	0.008	0.040
Aragón	0.005	1.419	0.809	0.906	0.088	0.001	0.024	0.071
Asturias	0.017	1.700	0.884	0.858	0.128	0.005	0.003	0.001
Illes Balears	0.021	1.022	0.256	0.101	0.042	0.019	0.020	0.082
Canarias	0.022	0.854	0.189	0.075	0.076	0.003	0.005	0.015
Cantabria	0.016	1.086	0.217	0.010	0.014	0.607	0.004	0.012
Castilla-La Mancha	0.017	1.637	0.870	0.811	0.079	0.006	0.015	0.000
Castilla y León	0.025	1.225	0.550	0.338	0.268	0.002	0.012	0.003
Catalunya	0.018	1.523	0.750	0.532	0.433	0.002	0.010	0.002
Pais Valencià	0.025	1.263	0.509	0.372	0.080	0.003	0.013	0.013
Extremadura	0.017	1.017	0.272	0.203	0.026	0.013	0.028	0.080
Galicia	0.011	1.835	0.915	0.892	0.076	0.004	0.003	0.000
Madrid	0.025	1.624	0.993	0.681	0.430	0.006	0.026	0.001
Murcia	0.020	1.871	0.908	1.090	0.019	0.006	0.001	0.037
Navarra	0.025	1.770	0.884	0.909	0.029	0.004	0.003	0.001
Euskadi	0.025	1.667	0.829	0.712	0.189	0.007	0.011	0.004
La Rioja	0.025	2.000	1.000	1.174	0.326	0.001	0.003	0.000

**Fig. 13.** Model fitting for the 17 CCAA of Spain until May 30.

**Table 5**

Model fitted parameters for the 17 AA CC in Spain and for all Spain up to May 30.

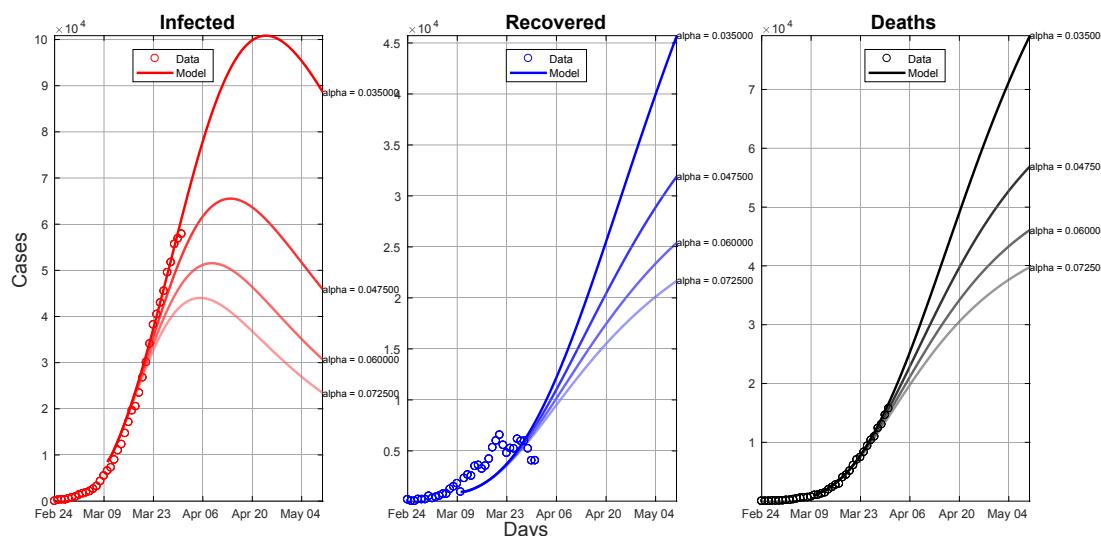
Community	$\alpha$	$\beta$	$\gamma$	$\delta$	$\lambda_0$	$\lambda_1$	$k_0$	$k_1$
Andalucía	0.054	0.928	0.927	0.148	1.144	0.001	0.024	0.050
Aragón	0.005	1.000	1.000	0.095	0.025	0.094	0.023	0.036
Asturias	0.018	0.913	0.839	0.269	0.015	1.847	0.011	0.029
Illes Balears	0.002	0.526	0.817	0.484	0.046	0.306	0.011	0.019
Canarias	0.019	0.757	0.867	0.143	0.053	0.023	0.010	0.045
Cantabria	0.029	0.629	0.955	0.145	1.962	0.001	0.010	0.032
Castilla-La Mancha	0.034	1.000	1.000	0.224	0.012	2.000	0.030	0.045
Castilla y León	0.012	1.000	1.000	0.334	0.016	2.000	0.031	0.054
Catalunya	0.017	0.959	1.000	0.311	0.029	2.000	0.030	0.040
País Valenciá	0.034	1.000	1.000	0.205	0.066	0.028	0.018	0.032
Extremadura	0.016	0.540	0.633	0.264	1.946	0.001	0.023	0.041
Galicia	0.021	0.814	0.470	0.272	1.605	0.001	0.100	0.103
Madrid	0.031	1.000	1.000	0.243	0.041	2.000	0.036	0.034
Murcia	0.016	0.803	0.716	0.416	0.039	0.081	0.359	0.334
Navarra	0.018	0.846	0.989	0.185	0.156	0.004	0.013	0.039
Euskadi	0.030	0.744	1.000	0.128	1.908	0.001	0.014	0.018
La Rioja	0.025	0.751	0.407	0.523	0.030	2.000	0.013	0.035

May 30, the end of the first epidemic wave, are showed and in [Table 5](#) the fitted parameters for this update are listed. As can be seen, there is a great discrepancy in the reported data for some communities that are certainly not reflected not only in the adjustments at the CCAA level but also at the level of the whole of Spain. This uncertainty in the data makes it difficult to adjust the model, but even taking this aspect into account, the adjustments are quite good and the updated results are not too far from the initial results, especially at the national level.

### Appendix C. Updated results for Italy: increasing the initial protection rate

With the purpose of making an hypothetical evaluation of the impact of a more severe protection rate for Italy we perform several control scenarios since March when the control measures were completely implemented were run where the alpha value was gradually increasing from 3.5% daily up to the post-control scenario assumption of 7.2% daily. Results can be seen in [Fig. 14](#).

Also and to compare these early projections with the real data reported at the end of the first wave, we fit the model with data reported until July 4 since on that date the end of the first wave is clear. In [Fig. 15](#) the results of the adjustment obtained for the first wave of the pandemic in Italy can be observed. As can be seen, the first approximation of the model was quite successful. This can be seen especially in the final size of the peak of reported cases. On the other hand, the adjusted parameters do not vary significantly from those reported in [Table 3](#)). For July 4 the mean fitted parameters are:  $\alpha = 0.035$ ,  $\beta = 1.10$ ,  $\gamma = 0.712$ ,  $\delta = 0.25$ ,  $\lambda_0 = 0.023$ ,  $\lambda_1 = 0.013$ ,  $k_0 = 0.020$ , and  $k_1 = 0.017$ .



**Fig. 14.** Control scenarios for Italy using as a starting point the parameters obtained with the post-control fitting ([Table 3](#)).

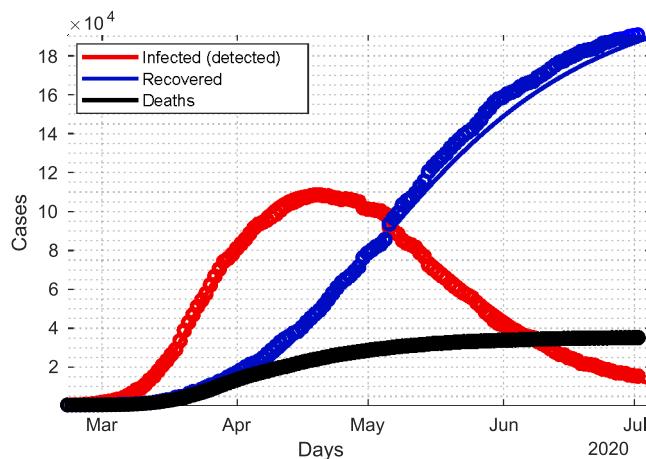


Fig. 15. Updated Italy model until July 4.

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