ICUBAM (Intensive Care Unit Bed Availability Monitoring) Intensive care unit bed availability monitoring and analysis in the Grand Est region of France during the COVID-19 epidemic

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TITLE

`ICUBAM` (Intensive Care Unit Bed Availability Monitoring) – Surveillance de la disponibilité des lits dans les unités de soins intensifs et analyse de la région Grand Est durant l'épidémie de la COVID-19

ABSTRACT

Reliable information is an essential component of responding to a sudden and large disease outbreak such as COVID-19, particularly with respect to critical care beds (CCBs) availability. This article presents: i) the development and construction of `ICUBAM`, a tool that collects in real-time and visualizes information on CCB availability entered directly by intensivists; ii) an analysis and interpretation of the data collected over a 6-week period during the first wave of the epidemic in the hard-hit Grand Est region of France; iii) an analysis and interpretation of the data collected during the first wave of the epidemic in the Grand Est region; iv) the development of a medium and long term prediction using SEIR models, and a short term statistical model to predict the number of CCBs.
Data ingested by `ICUBAM` were used to anticipate CCB shortages and predict future admissions. Most importantly, we demonstrate the importance of having a cross-functional team involving statisticians computer scientists and physicists working both with first-line medical responders and local health agencies and the importance of leveraging appropriate data. This allowed us to quickly implement effective tools to models the COVID-19 epidemic's evolution and assist in critical decision-making processes.

Keywords: *COVID, SEIR model, visualization.*

RÉSUMÉ

La fiabilité des informations est un élément essentiel de la réponse à une épidémie soudaine et de grande ampleur telle que la COVID-19, notamment en ce qui concerne la disponibilité des lits de soins intensifs. Cet article présente : i) le développement et la construction de `ICUBAM`, un outil qui recueille en temps réel et visualise les informations sur la disponibilité des lits de soins intensifs saisies directement par les urgentistes ; ii) une analyse et une interprétation des données recueillies pendant une période de 6 semaines au cours de la première vague de l'épidémie dans la région du Grand Est, durement touchée par l'épidémie ; iii) une analyse et une interprétation des données recueillies au cours de la première vague de l'épidémie dans la région du Grand Est ; iv) le développement d'une prédiction à moyen et long terme à l'aide de modèles SEIR, et d'un modèle statistique à court terme pour prédire le nombre de lits de soins intensifs.
Les données ingérées par `ICUBAM` ont été utilisées pour anticiper les pénuries de lits de soins intensifs et prédire les admissions futures. Plus important encore, nous montrons l'importance d'avoir une équipe interdisciplinaire comprenant des statisticiens, des informaticiens et des physiciens travaillant à la fois avec les intervenants médicaux de première ligne et les agences de santé locales, ainsi que l'importance d'exploiter les données adaptées. Cela nous a permis de mettre rapidement en place des outils efficaces pour modéliser l'évolution de l'épidémie de COVID-19 et aider aux processus critiques de prise de décision.

Mots-clés : *COVID, modèle SEIR, visualisation.*

At the beginnig of the COVID-19 crisis, ICUs were quickly overwhelmed and reliable information on the availability and location of ventilator-equipped critical care beds (CCBs) quickly became essential for efficient patient and resource dispatching. Predicting the future load of the various ICUs also became necessary to better anticipate transfers and bed openings.

A consortium including intensivists, computer scientists, statisticians and physicians developed `ICUBAM`[1] (Intensive Care Unit Bed Availability Monitor)[2], which allows a network of intensivists to provide information in real-time on the capacity of their unit. Analysis of the collected data is used to monitor the burden on ICUs during the pandemic, and allows for anticipating CCB needs as well as for modeling the epidemic's evolution.

This paper has three main contributions : In Section 1, we present the open-source `ICUBAM` tool and demonstrate how it can be used by intensivists at patient's bedside as well as by health authorities, to obtain reliable information on the availability of CCBs. In Section 2, using data from the *Grand Est région* from March 18th to April 30th, we present descriptive statistics and visualizations which monitor the burden in terms of admissions and availability of CCBs on ICUs during the pandemic. Finally, in Section 3, we propose a SEIR model to describe the course of the pandemic using `ICUBAM` data, and show that it has better descriptive and predictive performances for patient inflow (number of patients admitted to ICU) and outflow (number of deceased and discharged ICU patients) than models calibrated on public data only or even on both sources of data. We complement this medium-horizon modeling by a short-horizon analysis using simpler statistical models to predict daily bed requirements.

1. `ICUBAM` : a tool for bed availability monitoring

The `ICUBAM` application was built in response to the urgent need for intensivists to know real-time ICU bed availability. The first iteration was built in 3 days on the *Grand Est* region, and the system currently works as follows :

– Intensivists receive a text message 2 times per day (morning and evening) [3] requesting bed information and containing a link to a web-based form.

– Physicians enter data into the form (Fig. 1) and can also access the map (Fig. 2) with the number of beds currently available for each *région* and ICU, as well as the ICUs' contact information.

Data entry can be performed in less than 15 seconds. The variables in Figure 1 were chosen to ensure the relevance of the chosen statistics for both real-time use and downstream analysis. The 8 variables collected by `ICUBAM` allow study of the course of the pandemic on the ICU and are as follows : the number of free and occupied "COVID+" beds (in a COVID-19 floor), the number of free and occupied "COVID-" beds (in a non-COVID floor), the cumulative number of ICU-deceased COVID-19 patients, the cumulative number of ICU-discharged COVID-19 patients, the cumulative number of patients not accepted for entry due to lack of available CCBs and the cumulative number of patients transferred out of the ICU for capacity reasons (most often to other regions by medical trains).

The first French lockdown began on March 17th, 2020, and `ICUBAM` began operation on March 25 in the *Grand Est région*. `ICUBAM` was quickly adopted by 95% (40 out of 42) of hospitals in the *Grand Est région* and provided much-needed visibility to professionals on bed availability in their area. Within 2 weeks, ICUBAM covered one third of ICU beds : 130 ICU wards in 40 *départements* which represents more than 2, 000 ICU beds.

1. https ://icubam.github.io/about/
2. See Appendix A for a more thorough description of the genesis of `ICUBAM`.
3. In practice, doctors enter the latest data from their unit in the form in real time, *i.e.* as soon as there is a change.

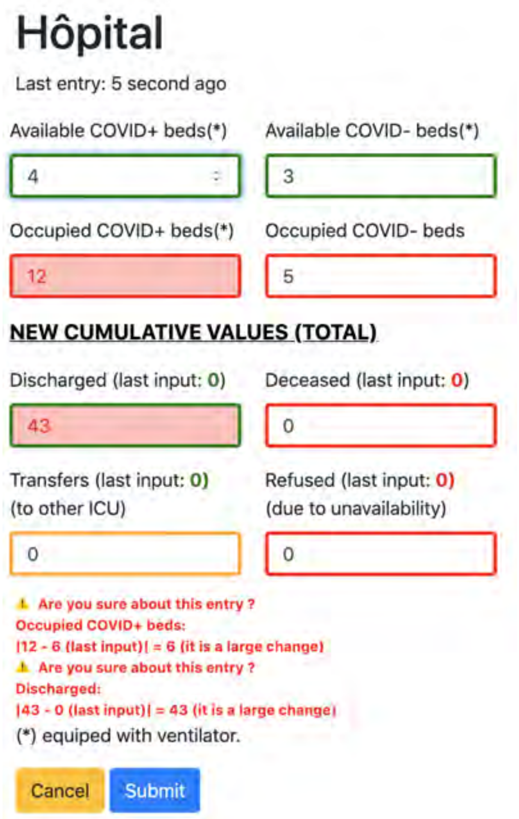

FIGURE 1 – *The form used by physicians to enter data into ICUBAM. Large or inconsistent entries trigger warnings. Previous values are pre-filled to encourage consistency.*

Authenticated accesses to map information are provided to regional health authorities. More details concerning the front and back-end of `ICUBAM` are provided in Appendix B.

2. Visualization of data collected in the *région Grand Est* from 18th March to 29th of April

We can observe the evolution of the epidemic in the *Grand Est région* by following the evolution in admissions. Daily COVID-19 ICU admissions are presented in Figure 3. The number of patients entering is defined by

$$E_j = \Delta(N_j^{\text{occ.}}) + N_j^{\text{death}} + N_j^{\text{discharged}} + N_j^{\text{transfer}}$$

where N_j is the quantity N on day j, and $\Delta(N_j)$ represents the change in quantity N between day j and day $(j-1)$. The number of patients refused due to CCB shortages is not taken into account as they are often rerouted to an in-*région* ICU. Since April 1st, a decrease in the daily number of patients entering the ICU of the *Grand Est* is visible for all *départements*. This is most likely due to the lockdown measures put in place on March 17th, which suggests a two-week delay (mean duration between time from contamination to hospital admission) in system response to confinement measures (Zhu et al., 2020).

We can observe the saturation of ICUs following the evolving demand and supply of CCBs. Figure 4 demonstrates the impressive increase in CCB capacity, going from a nominal capacity of 501 beds to 1056 beds in 12 days i.e. 211% of nominal capacity. Nevertheless, this sudden increase in capacity

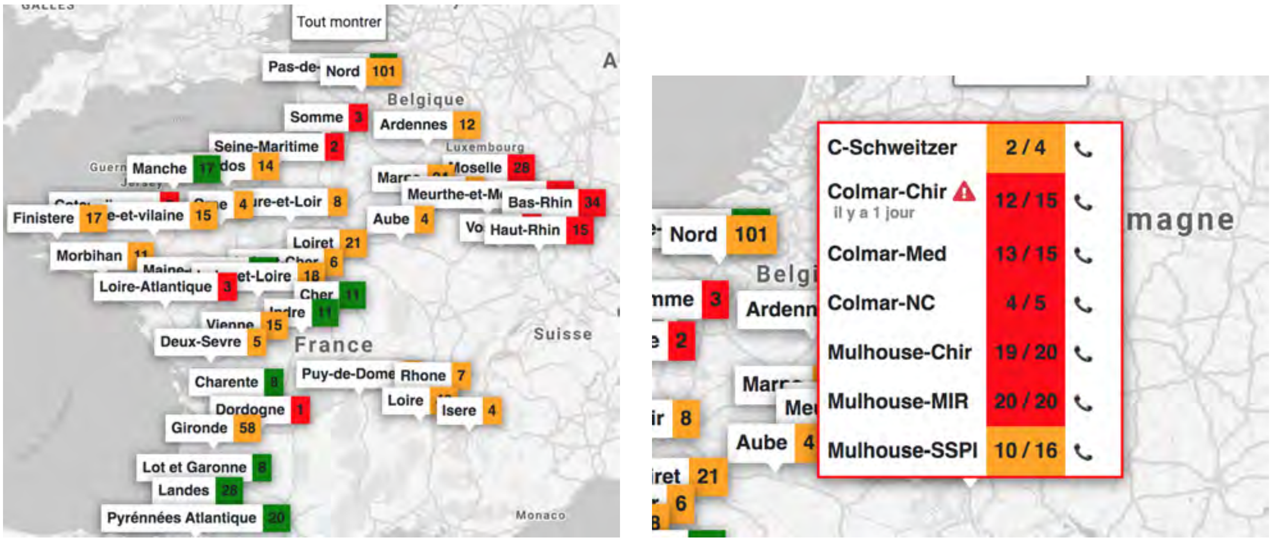

FIGURE 2 – ***Left :*** *Map of available beds in France - April 18. Red indicates that more than 80% of the beds are occupied, orange between 50 and 80% and green less than 50% ;* ***Right :*** *Number of beds occupied versus total number of beds in a département's ICUs. The numbers reflect the last values indicated by the ICU. If the last input was more than a day ago, a warning is displayed to make it clear that the reported number might not be up to date.*

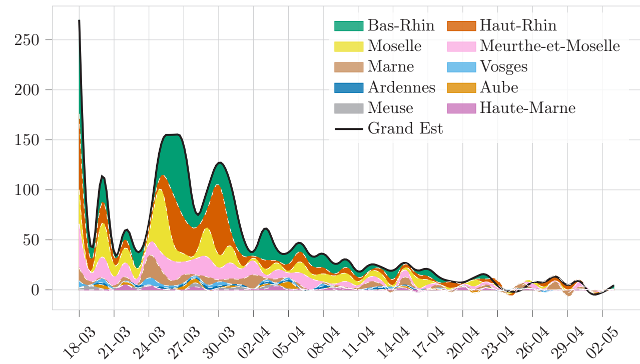

FIGURE 3 – *Daily number of COVID-19 ICU admissions for each département over the study period. Remark : the first value is disproportionate because it accounts for all patients of the period before the start of our data (March 18).*

was not enough to satisfy the need for CCBs, and almost 600 patients had to be transferred out of *région* to avoid surpassing the available CCB capacities. After the pandemic's apex, the decrease in the number of occupied CCBs is observable, but evolves slowly. COVID-19 CCB bed use went from 250 to 500 in 6 days (from 2020/03/18 to 2020/03/24), however the decrease from 750 to 500 has taken a total of 24 days (from 2020/03/30 to 2020/04/23), 4 times slower than the rate of admissions. This slow rate of discharges means that the system was still over-saturated.

These region-wide evolutions are present in all individual *départements* as illustrated in Figure 5. A dot is placed to indicate the first date on which the nominal capacity was exceeded. The *Bas-Rhin* stands out, with a number of occupied beds which increased sharply on March 27. The number of people transferred was also significant at the time and started to decrease from March 30 (not represented here).

As the epidemic evolved in the *Grand Est* region, different *départements* evolved differently in terms of CCB availability and demand. The different evolution in terms of bed occupancy and demand of

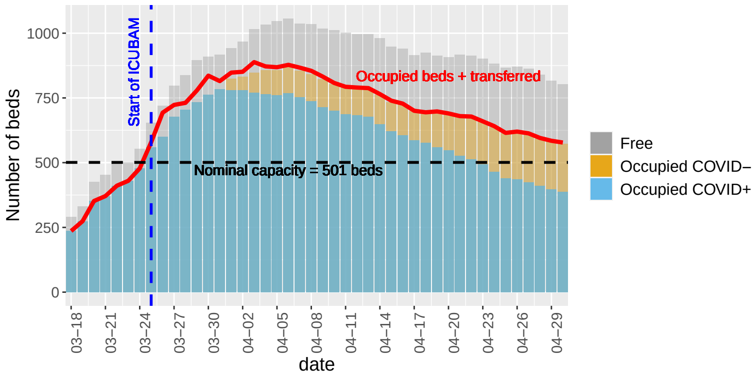

FIGURE 4 – *Number of beds occupied by COVID-19+ patients, non-COVID-19 patients, and total number of free ICU beds (regardless of COVID-19 status). The red curve represents the number of occupied beds plus the number of patients transferred to another region. Note that data before March 25th does not contain the number of transferred patients.*

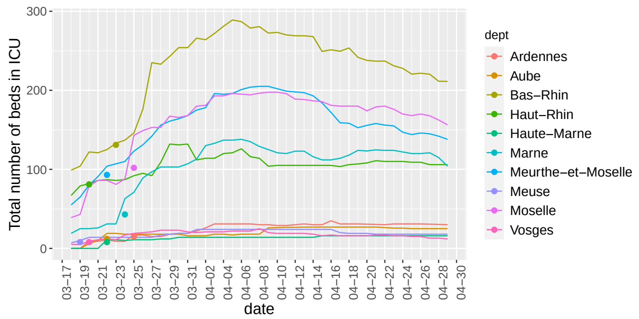

FIGURE 5 – *Evolution of the number of COVID+ CCBs for each département. The point indicates the first date on which the normal capacity is exceeded. Not all département have the same base population, but smaller département do not host many ICU beds.*

each *département* can also be compared using a correspondence analysis (Husson et al., 2017; Lê et al., 2008).

Figure 6 highlights groups of *départments* with different profiles : *départements* such as *Haut-Rhin* (and to a lesser extent *Meurthe-et-Moselle*) had many occupied CCBs at the beginning of the epidemic (i.e. dates in red from March 18th to 26th), while *départements* (*Ardennes*, *Aube*, *Haute-Marne*, *Marne*) had relatively more occupied CCBs at the end of the period relative to the beginning. Finally, *Meurthe-et-Moselle* and *Vosges départements* had reduced their CCBs occupation earlier than other *départements*.

3. Modeling CCB availability

A key objective during the initial surge of patients is to properly allocate resources in a predictive rather than reactive manner, which requires predicting the number of critical care beds needed for each region. We therefore propose modeling the spread of the current pandemic using ordinary differential equations (ODEs) that are appropriate to describe the number of patients in ICUs and the number of cumulative deaths, as well as to provide a medium and long term prediction of CCB use. Simple statistical models were also considered for short-term prediction of the number of released CCBs. The aim is to show how ICUBAM data can be used to feed predictive models to anticipate CCB shortages and predict future admissions.

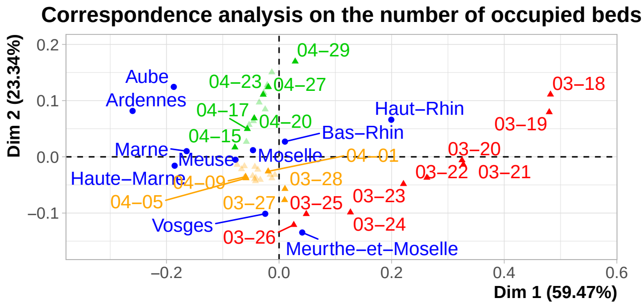

FIGURE 6 – *Correspondence analysis on the number of occupied beds per département and per day. This graphic presents both correspondences between dates, as well as départements, brought into the same plot. Some labels are not drawn.*

3.1. Modeling the evolution of the pandemic with SIR and SEIR models

A large number of epidemiological models are available to describe the epidemic spread and the flows between the different states, either with the simplest SIR type model (susceptible, infected, recovered), or with more complex models, such as SEIR models (susceptible, exposed/incubation state, infected, recovered/deceased (see, e.g., Hethcote, 2000; Allen, 2017). These models can be made more complex to take into account the specifics of the particular epidemic and the available data. Many teams around the world are using official data to model the evolution of the pandemic at different scales in different countries. One can mention the resource center John Hopkins University (2020), the work of Lavielle (2020) which gives very good adjustments for the evolution of the pandemic at the scale of each country, and on French data, a study on the pre and post lockdown periods (Di Domenico et al., 2020).

For the *Grand Est* region, we have also found that it is possible to give a good account of the evolution of the epidemic based on public data, in each *département*, with classical models of the SIR or SEIR type. Another possibility is to combine public data with `ICUBAM` data (although the various sources are not always easy to align as illustrated in Appendix C). Nevertheless, we have obtained accurate descriptions and predictions of the number of patients in intensive care as described by `ICUBAM` data by modeling the underlying pandemic with a model calibrated on public data (Santé Publique France, 2020) for the number of hospitalized, discharged and deceased patients, and on `ICUBAM` data for CCB occupation. Indeed, the number of hospitalized patients is an additional element of data which is important to leverage. We may expect that the global dynamics of the number of hospitalized patients will constrain in the fits the one of the ICU patients. Somewhat surprisingly, a model using only `ICUBAM` data gives as good results as more complex models based on both datasets. This also means that as good or better results are obtained with a smaller number of parameters, which suggests better predictive power for the purely `ICUBAM`-based model. For this reason, the `ICUBAM`-only results are presented here.

Figure 7 illustrates the model used. It is a simple SEIR model which assumes that the different *départements* are independent (the data are collected after lockdown), and uses the number of patients admitted to ICUs and the number of exits (discharged and deceased patients), but considers a lengthy time-to-exit by adding a period before exiting ($ICU_1 \rightarrow ICU_2 \rightarrow$ exit) to account for the time of recovery (or death). The ICU compartment is divided in ICU_1 and ICU_2 to take into account short or long time in ICU before exit. More details are given in Appendix D. The model parameters are calibrated in order to have the best agreement between the observed data and the model outcome (with a maximum likelihood criterion). The proposed family of models have predictive capabilities as shown in Figure 8 and in Figure 14 in Appendix D. The modeling allows us to see a global trajectory and the coherence of the observations in relation to the evolution of the pandemic. For example, for the *Meuse département* in Figure 14 the observations 'catch up' with the model's predictions.

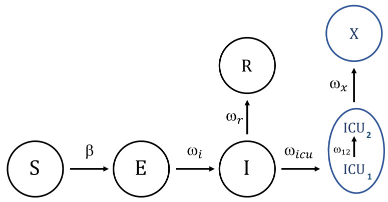

FIGURE 7 – *Flow shart of the SEIR type model with incubation compartment. In blue, the parts corresponding to the* `ICUBAM` *data on which the model is calibrated : number of patients in ICU, cumulative number of patients leaving the ICU (X for eXit, discharged and deceased patients).*

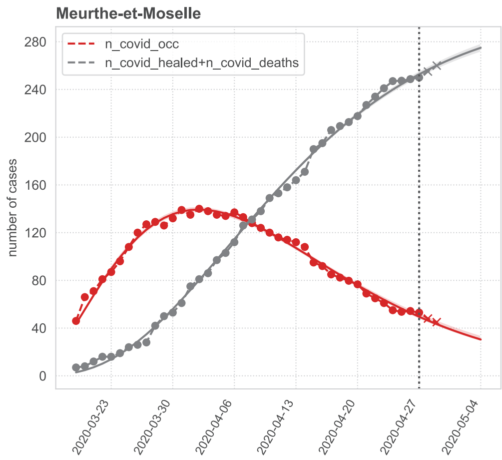

FIGURE 8 – *Fit a SEIR model for département Meurthe-et-Moselle using data up to the 27 of April (vertical dotted line ; data : circles) and with prediction for the following days (crosses : data on 28 and 29 of April). Model 'susceptible/exposed/infected/ICU/exit', with recovery (or death) period. Red : number of patients currently in ICU. Grey : cumulative number of patients either deceased or discharged from intensive care units.*

However, predicting the number of released CCBs faces several problems. Models of the SIR type are well suited to account for the current number of patients in intensive care and the cumulative number of discharged and deceased patients. The number of released CCBs is calculated as the difference between the change in each of these numbers between two consecutive days. For large numbers, the differences will vary greatly for small variations in the estimated quantities. For a fit calibrated on data up to 26 April, for example, a number of CCBs released during the two following days, 27 and 28 of April, is predicted which is correct for the *départements Haut-Rhin* (9, observed 6), *Marne* (7 or 8, observed 10), *Moselle* (13 or 14, observed 11), but gives a large difference for the *Bas-Rhin* and *Meurthe-et-Moselle*. This can be understood by looking at figure 14 : the predicted trajectory deviates slightly from the data, with the formation of quasi plateau that a SIR model cannot account for. A more refined modeling of the dynamics of the evolution of the patients' condition — resulting in a wide distribution of ICU residence times, as discussed below — could be incorporated into the model.

3.2. Modeling the number of beds released with statistical models

To get short-term (per day) and refined prediction of the number of released CCBs (either due to death or discharge), we consider disconnecting the prediction of the number of admissions, which depends on the evolution of the pandemic, to the prediction of the number of beds released.

Several types of statistical models that leveraged number of ICU admissions in the preceding days as explanatory features were used : Regression models with variable selection, random forests, but also the simple average of the number of ICU admissions between 1 and 20 days before the date for which the release is predicted. This latter simple method comes from the observation that the distribution of the number of days with invasive mechanical ventilation times is not significantly different from a Uniform distribution (see figure 9). Note that the data is obtained from a single hospital with a hundred of patients and should be refined. As a benchmark, the naive method that predicts the number of critical care beds released by the last observation of the number of critical care beds released was added.

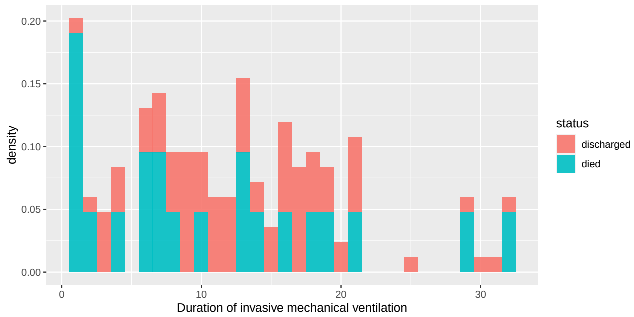

FIGURE 9 – *Duration of invasive mechanical ventilation before death or discharge.*

To evaluate the models, all data until a date (called “Last training day” in Table 1) are considered as a train data set and then the predictions is evaluated on a test data set corresponding to the 2 days after. Table 1 gives the mean absolute error of prediction of the number of beds that would be released the next two days for each *département* when the models are trained using data until the last training day (1st column). It turns out that the average method gives the smallest errors (2.03) and improves significantly upon the last observation carried forward method (day before).

Table 1 – *Mean absolute error of prediction between observed values and predicted values given by four models : linear model (lm), random forests (RF), the average of inputs between D-1 and D-20 and the entry observed the day before ; models learned with data from the 18 of March until the last training day (1st column) and predict for the 2 days after.*

Last training day	lm	RF	average	day before
2020-04-28	1.19	1.49	1.35	3.44
2020-04-27	1.81	1.77	2.19	3.71
2020-04-26	3.19	2.57	2.18	2.78
2020-04-25	3.65	3.22	2.61	2.30
2020-04-24	3.54	3.23	2.44	4.65
2020-04-23	3.72	2.27	1.80	2.85
2020-04-22	2.64	1.77	2.22	3.52
2020-04-21	2.04	1.17	1.49	2.75
Mean	2.72	2.19	2.03	3.25

For the prediction at D+5, the method with the average remains the best since the mean of the error (last row of the table) would be 8.76 for linear model, 5.44 for random forest, 3.53 for the average and 9.30 for the last day.

The number of exits for May 1 and 2 are predicted and given in Table 2.

Table 2 – *Prediction of the number of exits (sum of deaths and discharged) for May 1st and 2nd obtained with the linear model (lm), random forests (RF) and the average of the ICU admissions between D-1 and D-20 ; the models learned with the data until April 30.*

	lm	RF	average
Ardennes	0	1	1
Aube	0	1	0
Bas-Rhin	1	3	2
Haut-Rhin	4	5	5
Haute-Marne	1	1	1
Marne	2	4	3
Meurthe-et-Moselle	1	2	4
Meuse	0	1	0
Moselle	3	4	5
Vosges	0	1	0

4. Conclusion

4.1. Quality data, a flexible process and an inter-disciplinary team

The great strength and particularity of `ICUBAM` is to be supported by an inter-disciplinary team of intensivists, engineers, researchers, statisticians, computer scientists and physicists who, together, designed and built the entire pipeline, from data collection to analysis, and communication of results in real-time to meet operational needs in an emergency context.

Data quality is a key challenge in the management of this crisis and the flexibility of the data collection as well as the direct contact with stakeholders to get and exploit important information (such as time spent in critical care) is essential.

Nevertheless, `ICUBAM` data, although granular, provide only a partial view of the pandemic as data were only collected for critical care beds. In addition, the strength of this tool is to collect data directly from the intensivists but it also implies that the data are necessarily limited : only the data that is immediately useful for intensivists are entered, and it is obviously not possible to increase their workload by asking them to enter more information — the lightweight interaction with our systems was key in having be used by so many ICUs.

The customized nature of `ICUBAM` also allowed it to be easily adapted as new needs arose (addition of a non-COVID ICU map, displaying age of the data, live plotting for physicians and health agencies).

4.2. Impact of ICUBAM

From direct discussions with intensivists from the *Grand Est* region, `ICUBAM` has aided in disseminating information along two important axes : First, horizontally amongst other intensivists of the *Grand Est* region. `ICUBAM` quickly gained traction amongst these front-line physicians by creating both visibility of the situation in nearby ICU wards, but also by creating an important information connection between private and public-sector ICUs to easily share their availability in a unified platform.

Secondly, `ICUBAM` has proven to be a useful tool for sharing information vertically from the physician-level, and up through authorities. This distribution of information from `ICUBAM` hopefully contributed to the balance between demand and availability of critical care beds in the *Grand Est* region.

From a public and clinical health perspective, better understanding of the epidemic's mechanisms and better planning of resource needs and triage of critical care patients can have a substantial impact on patient care and possibly save lives. We hope that `ICUBAM` can be useful to assist the decision-making process by providing a framework to collect and analyze detailed and reliable data, and that the analyses provided herein give some insights on how COVID-19 can quickly overload even a well-structured health system.

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Author contributions

The authorship of this article is in alphabetical order. The contributions are as follows :

- Project design and organisation : GDA, JJ, AK and OT
- Creation of the `ICUBAM` interface : GDA, AK, VI, OT
- System : GDA, SG, RP, FQ, PGM, VR, OT, RY
- Data processing : GDA, VI, AK, FL, RY
- Descriptive statistics : GDA, FH, JJ, AK, VI, FL
- Modeling : LBG, FH, JJ, AK, JPN
- Writing : GDA, FH, JJ, AK, JPN

Ethics

The ethics board from french intensive care society gave ethical approval for the paper and project.

In accordance with the Common Inria's legal department guarantees that project is in accordance with the General Data Protection Regulation and that data are transferred to the Ministry of health.

Code availability

`ICUBAM` is open-source and is available on GitHub https://github.com/icubam/icubam/. Documentation for installation is available at https://docs.icubam.net/en/latest/. All source code used for analysis and modeling is available at https://github.com/icubam/predicu.
Code for statistical analysis and modelling is written in R (R Core Team, 2020).
Code for the SIR type modeling is written in Python (Python Core Team, 2015). To compute the credible regions (see the Appendix) we made use of the PyMC3 package for Python (Salvatier et al., 2016) (https://docs.pymc.io/).

The instance of ICUBAM used in this paper ran on Inria servers.

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Appendix

A. Genesis of `ICUBAM`

The project is the result of a personal initiative by Antoine Kimmoun M.D., and intensivist from the *Grand Est région* of France who identified the urgent need to visualize occupied COVID-19 CCBs in a real-time manner. He started to develop a prototype on March 18, 2020 to collect the data on the availability of beds by placing phone calls and centralizing the information in a spreadsheet. `ICUBAM` development began on Sunday March 22, 2020 after a meeting between Antoine and team of engineers and researchers from Polytechnique, Inria, and elsewhere. On Wednesday March 25, 2020, we launched `ICUBAM` in the *Grand Est région* in agreement with the ARS (the French Regional Health Agency). Other regions quickly started using `ICUBAM` (Center Val-de-Loire, Brittany, AURA, New Aquitaine, etc.). In April 2020, `ICUBAM` was currently used by 130 ICUs in 40 *départements*, which represents more than 2,000 COVID-19 CCBs.

B. `ICUBAM` open-source software

B.1. User flow

The user's journey on `ICUBAM` has been thought with physicians to ease their way through finding quickly bed availability nearby, under the particular stress constraints witnessed in pandemic times.

It starts with a text message (usually SMS, but other means are also supported) sent to the user on a regular schedule. This message contains as token, that is generated specifically for a given user of a given ICU. `ICUBAM` also supports automatic refreshing of tokens periodically.

This link containing the token is needed to access the availability form in which the user can easily enter the 8 counts described in this document. To prevent typos, big changes in number from an update of those counts to the other triggers a warning, inviting the user to double check the values.

Having entered the current state of bed availability in their ICU, the users are eventually redirected to the map page, where color codes and warning signs helps the physician narrowing down his search of bed availability to nearby ICUs.

The user's journey ends up with one or several call to some ICUs, directly from the map.

B.2. Architecture

`ICUBAM` is divided into four web services : communication with the database, the web interface for physicians, a back office web interface for administrators and a message scheduler service.

B.3. Dashboards

A dashboard (Fig. 10) is available for some users with granted access through the `ICUBAM` backoffice, which is a web interface to manage `ICUBAM`'s ecosystem. It contains summary statistics (Fig. 11) and some of the plots presented in this document.

B.4. Data

Note that the data collected for this study is done so by an instance of `ICUBAM` hosted by Inria and not part of the open-source software. External developers as well as external deployments of `ICUBAM` have no access whatsoever to this data, but do own their own data. This separation between data and software guarantees both data security and reproducibility of the `ICUBAM` service outside of the French context.

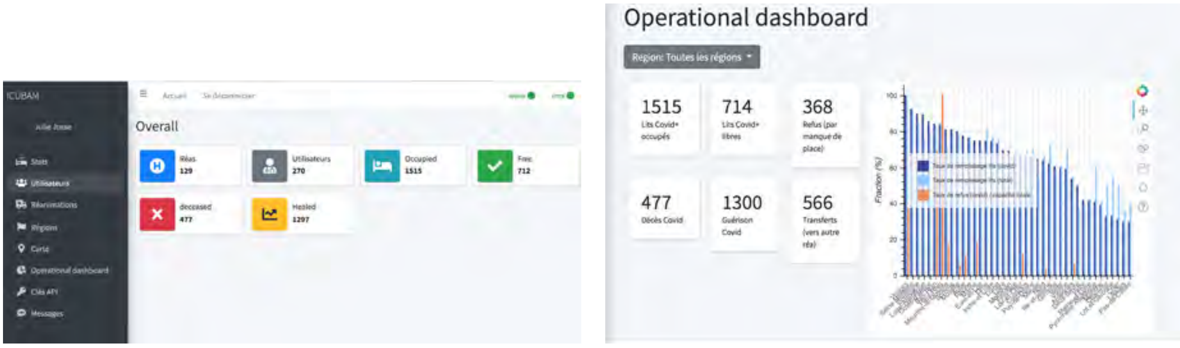

FIGURE 10 – *Dashboard for medical doctors : Excerpt from the April 18 dashboard.*

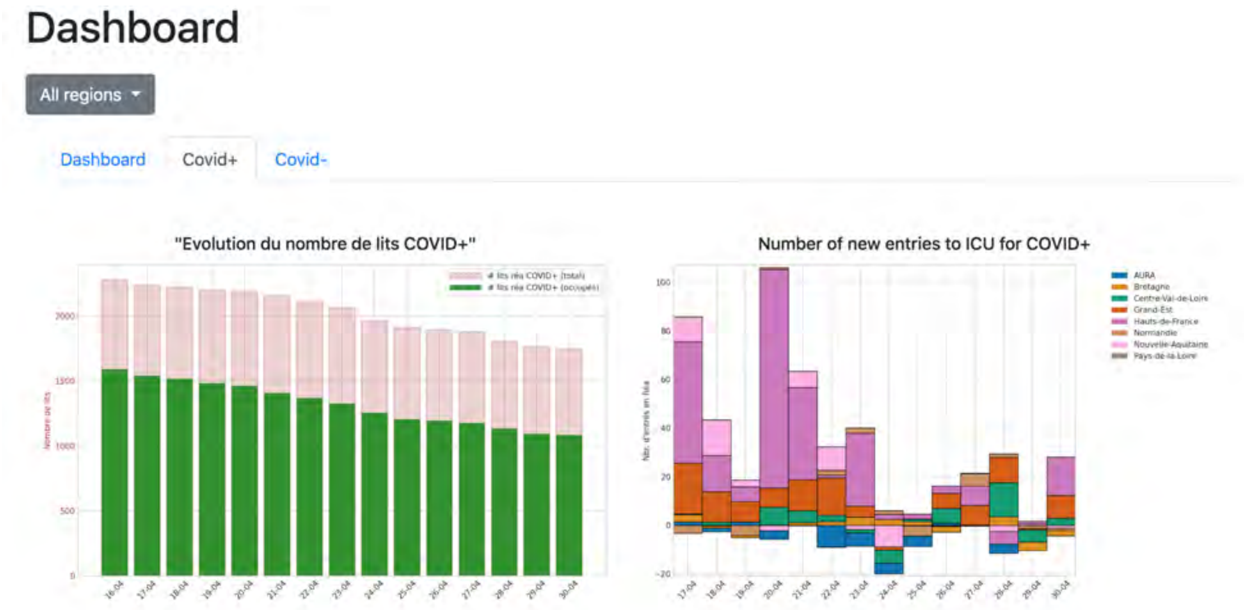

FIGURE 11 – *Dashboard for medical doctors : Excerpt from the April 30 dashboard.*

C. Comparison between `ICUBAM` and official public data

The analysis of `ICUBAM` data and the use of public data (Santé Publique France, 2020) has also highlighted the difficulty of comparing the data collected, which often represent different realities. For example, `ICUBAM`'s scope only covers resuscitation beds equipped with a ventilator, whereas very often critical care beds include equipped or not with ventilators. However, this implies that the number of ICU patients should be larger in the public data case, which is not always the case, as can be seen in the bottom panel of figure 13.

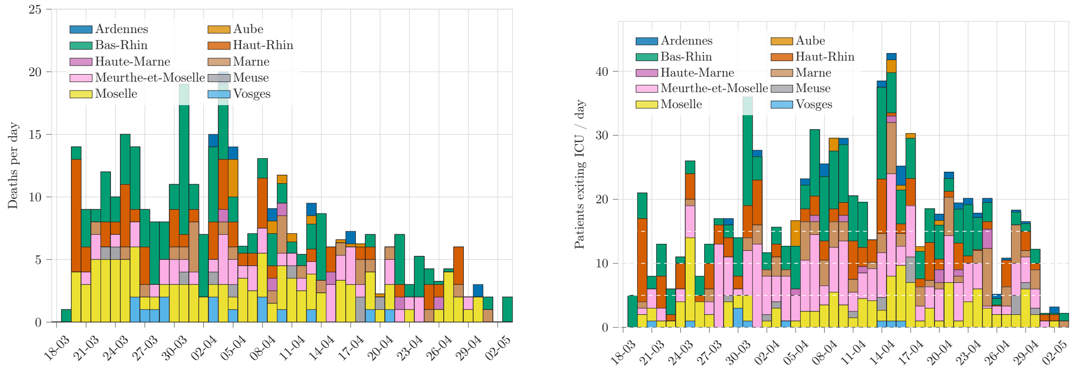

FIGURE 12 – ***Left*** *: total number of patients (COVID or not) hospitalized on 29th of April in each département, based on official public data (source* Santé Publique France *(2020)). The slope of the regression line was calculated by excluding the Haut-Rhin (outlier) and the intercept was set at* 0 *(a null population implying a null number of hospitalized patients).* ***Right*** *: comparison between official public data and* `ICUBAM` *data on the number of ICU cases.*

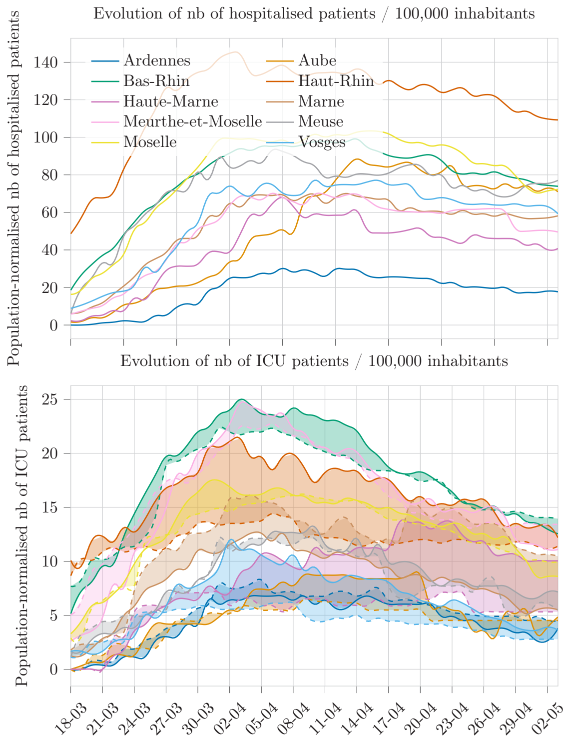

FIGURE 13 – ***Top*** *: Time evolution of the number of hospitalized patients (official public data* Santé Publique France *(2020)).* ***Bottom*** *: comparison of the evolution of the number of ICU patients according to the official public data* Santé Publique France *(2020) (dotted lines) and the* `ICUBAM` *data (continuous lines).*

The discrepancy in the number of patients in resuscitation at the time of reporting between the `ICUBAM` data and the public data is also visible in figure 13. We have observed that the data from `ICUBAM` could be ‘ahead’ from some sources of information (sometimes by two days) indicating that they better represent the reality of the day.

D. SEIR model calibrated on the ICUBAM Grand Est data

Modeling approach The ICUBAM data give access, for each day t, to the number of patients occupying an ICU bed, noted here $C(t)$ ('C' for Critical Care), the number of transfers taking place on that day t, and the number of refusals that day t. We also know the number of deceased patients, and the number of discharged cases cumulated on day t. We only consider the total number of beds released, $X(t)$ ('X' for eXit) (deaths + discharged cases). One writes ordinary differential equations (ODEs) describing the underlying contagion dynamics. In a given *département*, with population size N, at each time there is a number $S(t)$ of susceptible individuals ($S(t_0) = N$), $I(t)$ of infected individuals (denoting $\Delta A(t)$ the variation of a quantity A between day t and day $t+1$) :

$$\begin{aligned}
\Delta S(t) &= -\beta \frac{I(t)S(t)}{N} \\
\Delta I(t) &= \beta \frac{I(t)S(t)}{N} - \omega_{ic} I(t) - \omega_{ir} I(t) \\
\Delta C(t) &= \omega_{ic} I(t) - \omega_{cx} C(t) \\
\Delta X(t) &= \omega_{cx} C(t)
\end{aligned}$$

The model used for the figures takes into account an incubation phase (exposed state, SEIR model) and a long exit time, obtained by adding one sub ICU compartment :

$$\begin{aligned}
\Delta S(t) &= -\beta \frac{E_t S_t}{N}; \\
\Delta E(t) &= +\beta \frac{E_t S_t}{N} - \omega_{ei} E_t \\
\Delta I(t) &= \omega_{ei} E_t - \omega_{ic} I_t - \omega_{ir} I_t \\
\Delta C_1(t) &= \omega_{ic} I_t - \omega_{cc} C_{1t} \\
\Delta C_2(t) &= \omega_{cc} C_{1t} - \omega_{cx} C_{2t} \\
\Delta X(t) &= \omega_{cx} C_{2t}
\end{aligned}$$

Here the total number of ICU patients is $C_t = C_{1t} + C_{2t}$.

Importantly, in the above models we do not consider the refused and transferred patients. One difficulty is that the outcome of these critical care patients initially admitted and thereafter transferred by medical train were unknown. Thus, the models implicitly take into account the local critical care bed capacity. Future work will explore how to incorporate these flows of patients into the modelling approach.

We calibrate all the model parameters in order to have the best agreement between the observed data and the model outcome (with a maximum likelihood criterion, assuming Gaussian noise), the observations being the number of critical care patients and the total number of deceased and discharged alive patients, along the study period.

Since the data do not cover the full epidemic period, we initialize the model by going backward in time : for each *département*, we look for the date $t_0 < t_1$ such that one gets the best fit by assuming that the epidemic starts at time t_0.

Figures 14 present the results. In Figure 14 (right) we show the Bayesian *credible regions* (Kruschke, 2015) (see below). For the *Aube département*, there was clearly a data entry problem during the first two weeks, with an abrupt entry made at the time of the peak. Remarkably, the observations seem to 'catch up' with the model's prediction. Similarly, for the *Meuse département*, on the last dates the data 'come back' onto the model trajectory. Consideration should also be given to the decreasing quality of the data. Thus, for some *départements*, as the *Vosges*, we can observe an inconsistency in the data for the last few days, suggesting a non-entry of departures, while the number of patients

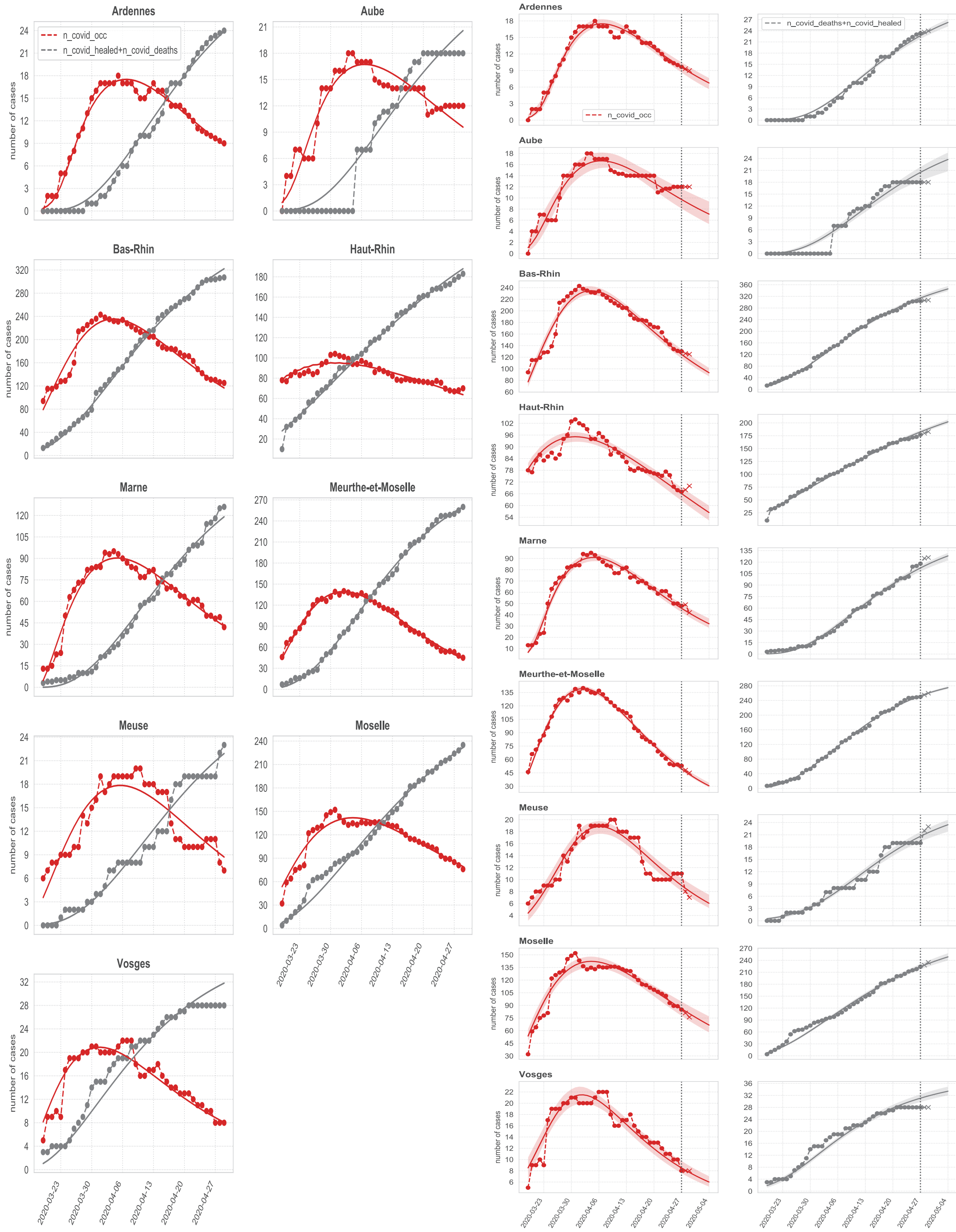

FIGURE 14 – Left : *Fits for ICU patients, and the number of (deaths + discharged cases), from the SEIR type model (see text). Model calibrated on* `ICUBAM` *data as of 29 April 2020.* **Right :** *Fits and predictions for ICU patients, model calibrated on* `ICUBAM` *data as of 27 April 2020 (vertical dotted line ; data : circles) and extrapolated for the 4 following days (crosses : data 28 and 29 of April).* **Red :** *patients currently in ICU.* **Black :** *cumulative number of patients either deceased or discharged from intensive care units.* **Colored zones (right panel) :** *95% credible regions (see text).*

in ICU is decreasing. The correct number of patients leaving the ICU is thus slightly increasing in the last days, in better agreement with the model predictions.

Credible regions The general idea is the following. Given the observed data, one computes the statistical ensemble of the most plausible scenarii (trajectories) from the Bayesian view point. Let us denote by $\mathcal{X}$ the observed data set $\{C_t, X_t, t = 1, ..., T\}$ and $\Omega = \{\beta, \omega_{ei}, \omega_{ic}, ..., \omega_{cx}\}$ the set of parameters. We are interested in the posterior $P(\Omega|\mathcal{X}) = P(\mathcal{X}|\Omega)p(\Omega)/P(\mathcal{X})$. The probability $P(\mathcal{X}|\Omega)$ is the result of the model assuming Gaussian noise. $p(\Omega)$ is the prior on the parameters, and we choose the uniform distribution for every parameter on $[0, 1]$. Given the observed data $\mathcal{X}$, one can then generate sets of parameters in order to cover 95% of the distribution (more precisely, we consider the 95% highest density region, see (Hyndman, 1996)). This is done with the Slice sampling algorithm (a Markov chain Monte Carlo algorithm method). For each one of these sets of parameters, one generates the associated trajectory $\widehat{\mathcal{X}}$. The envelope of these trajectories then defines the 95% credible region. For the variance of the Gaussian noise, we choose a time-independent but *département* specific value estimated from the data.