COMORBUSS, a bio-social agent model for disease propagation

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Introdutction

Social inequalities, which translate into unequal access to basic infrastructure and care, can lead to **increased prevalence in more vulnerable communities** during a pandemic [1]. Effective interventions must consider these social heterogeneities and take into account social behavior in communities in order to protect vulnerable or highly exposed groups and suppress the infection wave as a whole. In order to take these into account in the evaluation and design of intervention policies, we developed a **highly modular and configurable software for stochastic agent-based simulations called COMORBUSS** (COmmunitary Malady Observer of Reproduction and Behavior via Universal Stochastic Simulations). We model in detail the **infrastructure of a city and perform a stochastic evolution of agent behavior** based on the individual characterization of the agents and their social roles.

Community Model

COMORBUSS is based on the interaction of two core parts, the disease model and the community model. In the community model we use demographic data from a real city and **organically construct a representation of that community in the simulation**. Information like **densities** (population density, services density, etc) **and periods** (service visitation periods, work periods, etc) are made **as close as possible to the real population**. We seek the average epidemiological behaviour and the associate variance for a city with a given demography and dynamics. This is done by simulating multiple realizations of a stochastic model for the disease propagation in this active community. In order to eliminate biases introduced by a single societal network, we generate for each random seed a new community **preserving the average characteristics and behavior**.

Disease Model

Each agent is characterized by its age, which determines the agent's **susceptibility, probability of developing symptoms and probability of dying** from the disease. When a susceptible agent encounters an infectious one (pre-symptomatic, asymptomatic, mildly or severely symptomatic), **it has a probability of becoming exposed**. After an incubation period, this agent becomes pre-symptomatic, and after an activation period, its state is converted to either asymptomatic, mildly or severely symptomatic. **The distribution of these states is estimated empirically from actual statistics** [3, 4]. After a random period, agents are converted to recovered (or deceased).

Simulation Parameters

Population Parameters

≫ `population_ages`: Number of citzens by age goup;
≫ `population_graph`: Samples of households structures (number of persons and respective ages);
≫ `persons_per_home`: Mean number of persons per household;

Services Parameters

For each service modeled:
≫ `number`: Number of instances of this service in the city;
≫ `hours`: Openning and closing hours;
≫ `days`: Days of the week service opens;
≫ `visitation_period`: Mean time between visitations for each particle in the population;
≫ `isolation_visit_frac`: Factor to reduce visitations if an particle is in isolation;
≫ `net_par`: Configurations for the dynamic encounters network inside service;
≫ `workers`: Parameters to select workers and it's schedules, location inside service, etc;
≫ `inf_prob_weight`: Factor to apply to the probability of infections in this service;

Disease Parameters

≫ `inf_probability`: Probability of an infection given an encounter between an S and a I particle;
≫ `inf_prob_sympt` and `inf_severe_sympt_prob`: Probability by age goup of an infected particle to develop symptoms and severe symptoms;
≫ `inf_severe_death_prob`: Probability of an infection to end in death of the particle;
≫ `inf_duration` and `inf_severe_duration`: Mean time a particle stays infectious for normal and severe infections;
≫ `inf_incubation`: Mean time in the exposed state (incubation);
≫ `susceptibility`: Susceptibility to an infection by age group;

Interventions Parameters

≫ `isol_pct_time_series`: A daily percentage of citzens that stayed at home;
≫ `quarantines`: Configurations relative to quarantines and hospitalizations of severe particles;
≫ `diagnostics`: Configurations relative to available diagnostics to the population;

Figure 1. COMORBUSS' most relevant parameters.

References

[1] Lara E. Coelho et al. "Prevalence and predictors of anti-SARS-CoV-2 serology in a highly vulnerable population of Rio de Janeiro: A population-based serosurvey". 2022.

[2] Juliano Genari et al. "Quantifying protocols for safe school activities". 2022.

[3] Natalie M. Linton et al. "Incubation Period and Other Epidemiological Characteristics of 2019 Novel Coronavirus Infections with Right Truncation: A Statistical Analysis of Publicly Available Case Data". 2020.

[4] Robert Verity et al. "Estimates of the severity of coronavirus disease 2019: a model-based analysis". June 2020.

Schools Interventions Results

NPI	Description
Reduced Workload	Schools function with shifts of two hours instead of four hours.
Alternating Groups	Schools function with reduced class sizes, and in particular classes are separated into 2 groups having in-person activities on alternate days.
Use of Mask	Low quality: $p_m = 0.5$; N95 or PFF2: $p_m = 0.05$; Good quality: $p_m = 0.3$; Teachers and staff with N95.
Active Monitoring	Schools function under the following measures: • Symptomatic people are tested; • If a case is found in a classroom, their activies are suspended for 14 days; • Students are tested and isolated (14 days) when they are symptomatic or a family member is confirmed positive; • Teachers which had contact with a classroom in which there were confirmed cases are tested and suspended for 14 days in the case of positive result; • School is closed for one week if there are two cases in distinct classes within a week.

Figure 2. **NPIs description.** Icons distinguish the non-pharmaceutical interventions evaluated in this study. In mask-related scenarios, the mask penetration factor pm is uniform for all individuals, except for teachers wearing PFF2 masks.

At the peak of COVID-19 restrictions on April 8, 2020, up to **1.5 billion students across 188 countries were affected by the suspension of physical attendance** in schools. Schools were among the first services to reopen as vaccination campaigns advanced. With the emergence of new variants and infection waves, the question was to find safe protocols for the continuation of school activities. **We needed to understand how reliable these protocols are under different levels of vaccination coverage.** We investigated the impact of face-to-face classes under different protocols (see Figure 2) and quantify the surplus number of infected individuals in a city [2].

First, we used the **pandemic surveillance data from the city of Maragoji-AL** to calibrate a baseline scenario (with closed schools). Then, we simulate counterfactual scenarios with schools open under different protocols, to assess the impact of physical school attendance in classrooms with poor air circulation (Figure 3). We find that:

1. Resuming school activities with people only wearing **low-quality masks** leads to a near **fivefold city-wide increase in the number of cases** even if all staff is vaccinated;
2. Resuming activities with students wearing **good-quality masks and staff wearing N95s leads to about a threefold increase**;
3. Combining high-quality masks and active monitoring, activities may be carried out safely even with low vaccination coverage. These results highlight **the effectiveness of good mask-wearing**. Classes can be carried out safely, provided the correct set of measures are implemented.

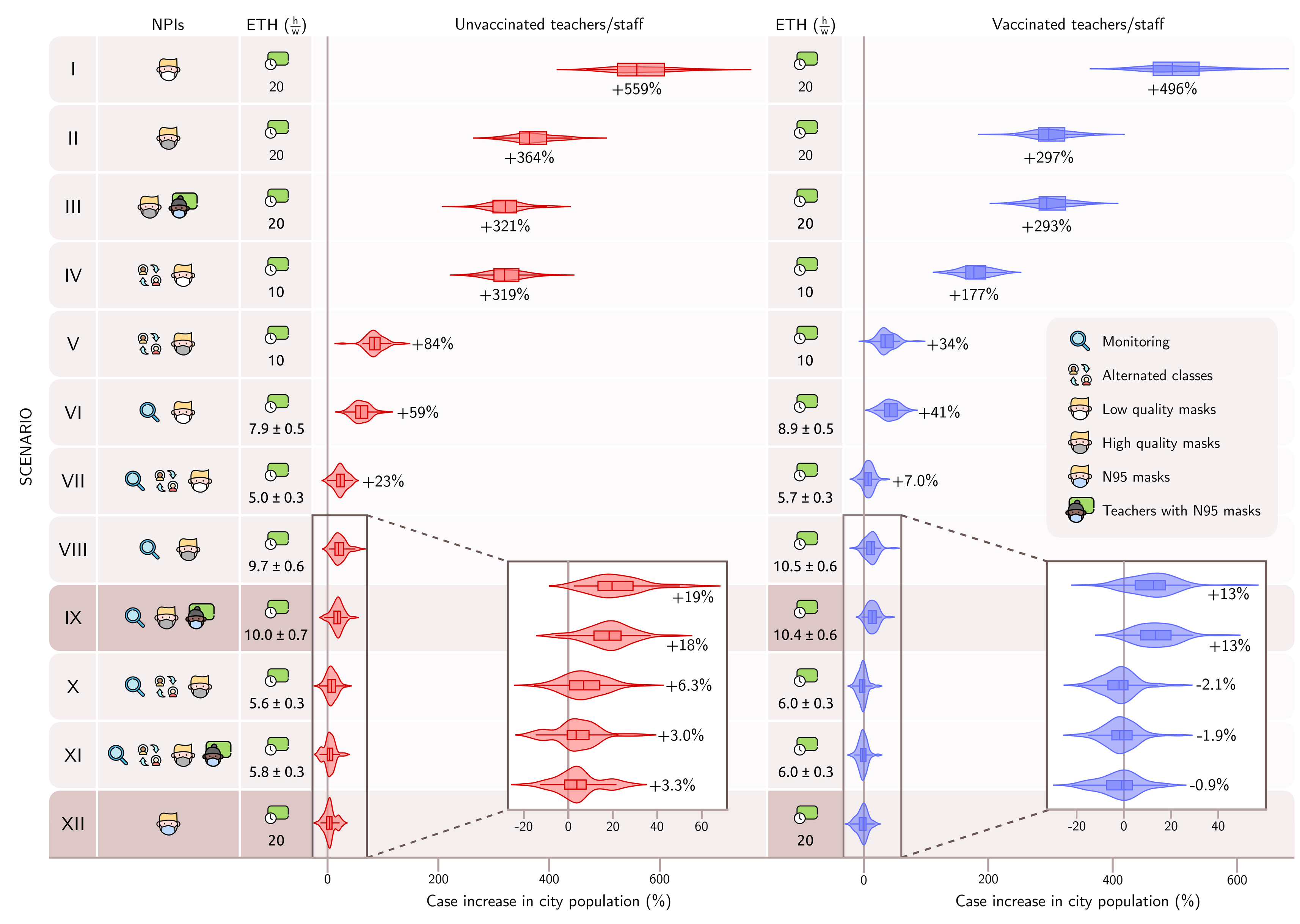

Figure 3. Combination of **NPIs measures in comparison to the baseline model**.

Applications and Future Work

Possible future topics to be explored using COMORBUSS:

- Improve **design of vaccination trials**;
- Design data and simulation assisted **interventions for future pandemics**;
- Study **causal links** between social interventions and disease evolution;
- Extend model to diseases with **different infection vectors**.

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