Quantitative Assessment of Natural Ventilation in an Elementary School Classroom in the Context of COVID-19 and Its Impact in Airborne Transmission

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Abstract: The importance of Indoor Air Quality (IAQ) has been highlighted by the COVID-19 pandemic, particularly due to the possibility of long-distance airborne transmission. Consequently, assessment of ventilation rates and estimation of infection risk has become a matter of the utmost importance. In this paper, a naturally ventilated elementary school classroom is studied, where carbon dioxide (CO₂) concentrations were measured during five months. Ventilation rates are calculated via a fully-mixed box model and the airborne risk of infection for SARS-CoV-2 is assessed. Risk results are found to steadily decline from winter to spring. Furthermore, analytical simulations for different scenarios are conducted. It is shown that periodic ventilation significantly reduces the transmission risk, even if it occurs only during very reduced time spans. The results show that periodic ventilation is a useful strategy for reducing the risk of any airborne transmitted disease. It is particularly well-suited for naturally ventilated environments in cold weathers, as it allows for a compromise between IAQ and thermal comfort, and does not require any modification to existing buildings.

Keywords: SARS-CoV-2; COVID-19; ventilation rate; airborne transmission; Wells-Riley; natural ventilation

1. Introduction

The SARS-CoV-2 pandemic (COVID-19 disease) has had a tremendous global impact. More than six million people have died, there have been massive economic losses, and health systems from around the world have been strained beyond their limits [1].

By now it is well established that SARS-CoV-2 is of airborne transmission, through liquid droplets expelled by infected individuals when breathing, sneezing or coughing. Transmission can either happen through close contact, via larger droplets that follow ballistic trajectories and end up falling, or through smaller aerosolized droplets, which can remain suspended and travel long distances with air drafts [2]. The latter is called the long-range airborne route and has put Indoor Air Quality (IAQ) under the spotlight. In particular, ventilation becomes of paramount importance, as it is the main way of diluting and removing the suspended pathogen from indoor spaces. Moreover, several prominent researchers have insisted in the need for a paradigm shift in how IAQ is conceived, even after the pandemic recedes [3]. For example, risk evaluation has been suggested to become a design method for ventilation systems [4].

Several tools are available for studying indoors ventilation and airborne transmission risk. Perfectly mixed box models have been extensively used for estimating ventilation rates [5–9] and simple models for quantitatively assessing airborne transmission risk, such
as the Wells-Riley approach, have been around for more than 50 years [10,11]. In the context of the pandemic the interest in these models has increased. New approaches and interesting modifications have been proposed and have enabled the use of these models for risk assessment in public buildings and transport [12–16]. In particular, there has been substantial interest in studying primary school buildings, as they hold stable populations which stay inside for considerable amounts of time [12,17]. Furthermore, an important concern regarding school buildings around the world is that many of them lack mechanical ventilation systems, and instead rely on natural ventilation. For these buildings, high ventilation rates during winter might be incompatible with thermal comfort, so the transmission risk could be higher.

Many studies have focused on evaluating IAQ in classrooms through measuring carbon dioxide (CO₂). For example, in [18] IAQ was described in 19 Spanish classrooms through CO₂ measurements. In [19], an aware-raising intervention for improving natural ventilation in school classrooms in Switzerland was evaluated by measuring CO₂ concentrations. Ref. [20] estimated ventilation rates through measuring CO₂ concentrations in five Serbian schools. Ref. [21] evaluated IAQ in ten Australian school classrooms. Indoors temperature, relative humidity, CO₂ concentration and particulate matter concentrations (PM2.5 and PM10) were monitored, and the ventilation rate was calculated from the CO₂ measurements. Measured values were compared to different threshold references, but no risk assessment methods were used. Ref. [22] presented an experimental campaign comprising 17 CO₂ sensors, placed in a representative naturally ventilated primary school classroom. The effectiveness of different ventilation strategies was assessed and practical details regarding CO₂ sensors placement were discussed. The authors concluded that continuous ventilation is needed, instead of intermittent strategies, in order to achieve acceptable air quality. Furthermore, the importance of cross ventilation was highlighted. It should be mentioned that the authors assessed their results in terms of CO₂ concentrations, but did not estimate the airborne transmission risk. This and other studies have mainly focused on either evaluating ventilation rates or airborne contagion risk, but generally do not compare both nor quantitatively analyse recommendations for risk reduction. In [23] the results of a measurement campaign performed during one week in 20 classrooms of four primary schools in Scotland were presented. Indoor temperature, relative humidity and CO₂ concentration were measured for in each classroom (one sensor per room), which were either naturally (manual operation of windows) or mechanically ventilated. The ventilation rate was computed from the CO₂ measurements and it was concluded to be higher in mechanically ventilated classrooms. In [24] the authors analysed the airborne infection risk of COVID-19 in 20 naturally ventilated university classrooms. For doing so, CO₂ concentrations were monitored in seven classrooms. The measured data was also complemented with previous experimental campaigns reported in the literature. Based on a box model and the Wells-Riley equation, the authors estimated the infection risk in each classroom for a one-hour exposure time under different conditions such as activity level or use of masks.

In this paper we focus on an Uruguayan naturally ventilated public school building. We quantitatively assess the ventilation rate and the transmission risk by measuring CO₂ concentrations and using a box model and a Wells-Riley approach. We present a novel and remarkably simple strategy for adjusting a CO₂ mass balance and compare risk results via a Rudnick-Milton [25] and a Gammaitoni-Nucci approach [26,27]. Finally, we show that periodic natural ventilation is a valuable and extremely efficient strategy for reducing airborne transmission risk, which does not require major building modifications.

2. Materials and Methods

2.1. Measurement Campaign

A measurement campaign was conducted in two elementary schools in Uruguay, both of which operate in the same building, one during the morning shift (between 8:00 and
12:00) and another one during the afternoon shift (between 13:00 and 17:00). The building has no central heating or ventilation systems and relies entirely on natural ventilation.

A single second grade classroom in the first floor of the school building was selected. It has a surface area of 6 m × 8 m and a height of 3.5 m, which yields a total net volume of 168 m³. It has four double casement windows facing west, which communicate directly to the school’s outside playground. On the opposite wall, facing east, there is a door and an awning window, which communicate with a central corridor. Figure 1 further defines the geometry of the classroom.

![Figure 1. Studied classroom. (a) shows the west wall and (b) shows the east wall. All dimensions are in m.](image)

The selected classroom has a nominal occupation of 30 children plus a teacher for both shifts. The populations are stable, that is, the students are always the same. There is a half hour break between 10:00 and 10:30 in the morning shift and between 15:15 and 15:45 in the afternoon shift.

Two different CO₂ concentration datasets were obtained. First, controlled tests were performed. These consisted of artificially generating CO₂ in the unoccupied classroom by mixing calcium bicarbonate with acetic acid in a bucket. The windows and the door were closed during generation and two ceiling fans were turned on to ensure the air was fully mixed. After a relatively high concentration was attained, CO₂ generation was stopped and the fans were turned off. Some windows and the door were opened, with different configurations for each test. The room was emptied and the decrease in CO₂ concentration was registered. For this test, two Aeroqual 500 monitors with calibrated 0–5000 ppm CO₂ heads were used (monitors AQ1 and AQ2) [28]. These registered a measurement every minute. Additionally, two AirCO₂ntrol 5000 CO₂ monitors were used (monitors AC1 and AC2) [29]. These were calibrated by comparison with the Aeroqual instruments and registered a measurement every 5 s.

The purpose of the controlled tests was twofold. Firstly, they were conducted to infer what ventilation rates could be expected. Secondly, they enabled assessing different ventilation patterns and associating them with specific ventilation rates.

The second dataset consisted of daily measurements (one per minute) in the classroom during normal school activities between August and December. In this case, monitors AQ1 and AQ2 were positioned at the front and back of the classroom, respectively. Monitor AQ1 was mounted on the side of the teacher’s desk and monitor AQ2 was positioned over a storage cabinet. Installing two monitors allowed for a primary evaluation of the perfect mix hypothesis, which will be introduced in the following section. This is rarely addressed in the available literature and, to the best of our knowledge, has not been previously evaluated in works dealing with ventilation and risk of airborne transmission.

Finally, a Davis Instruments Vantage Pro2 weather station was installed on the roof of the school during some months of the measurement campaign, in order to characterise the outdoors conditions.
2.2. Estimation of Ventilation Rates

The ventilation rate is a magnitude that expresses the net volumetric flow of reposition air $Q$ that enters a room. Said flow is usually expressed as Air Changes per Hour (ACH) by referring it to the volume of the room:

$$\text{ACH} = \frac{Q}{V}$$

where ACH is conventionally expressed in h$^{-1}$.

ACH is an IAQ indicator, as it is one of the main parameters that regulates the concentration of airborne contaminants. Assuming that the reposition air that enters the room is cleaner than the air inside, higher ventilation rates allow for remotion and dilution of contaminants. Consequently, the ventilation rate is one of the main engineering parameters for the design of both natural and mechanical ventilation systems. For example, the ANSI/ASHRAE 62.1-2019 standard [30] stipulates a minimum ventilation rate for occupied spaces according to their intended use, surface area and number of occupants. For the classroom previously described, the standard yields a minimum ventilation rate of 3.8 h$^{-1}$.

Additionally, in the context of the SARS-CoV-2 pandemic, several recommendations have been made regarding ventilation rates. For example, the World Health Organization (WHO) has recommended a minimum ventilation rate of 10 L/s per person [31]. This implies 6.4 h$^{-1}$ for the selected classroom.

One relatively simple way of estimating the ventilation rate in a certain environment is by using fully-mixed box models. These are based on performing a mass balance to an airborne tracer by assuming that the air in the room is perfectly and instantly mixed. Hence, the tracer concentration is supposed to be uniform.

Several researchers have applied box models for studying IAQ. There seems to be consensus that CO$_2$ is a suitable tracer for studying ventilation, particularly in schools [5]. It has the advantage of being an inert gas that is relatively easy and inexpensive to measure. Furthermore, its generation is guaranteed in any occupied environment, as it is produced by humans when they breathe. Nonetheless, CO$_2$ poses some disadvantages. There is a significant concentration of it in outside air, which can have slight variations. Additionally, determining the human generation rate of CO$_2$ is not straightforward.

The mass balance for CO$_2$ in a certain room can be expressed as

$$V \frac{dC(t)}{dt} = Q(C_{\text{ext}} - C(t)) + nG$$

where $V$ is the room’s volume, $C$ is the volumetric concentration of CO$_2$, $t$ is the time, $Q$ is the volumetric flow of outside air, $C_{\text{ext}}$ is the concentration of CO$_2$ in the air that enters the room, $n$ is the number of persons in the room and $G$ is the volumetric generation rate of CO$_2$ of one individual.

Assuming that $C$ is the only time function, Equation (2) can be solved to obtain

$$C(t) = C_{\text{ext}} + \frac{nG}{Q} - \left( C_{\text{ext}} - C_0 + \frac{nG}{Q} \right) e^{-\frac{Q}{V} t}$$

where $C_0$ is an initial condition for $C$. A concentration time series could be fitted via a non-linear least-squares technique in order to determine the model parameters.

Although box models are a compelling option for determining ventilation rates, they present some difficulties. Firstly, they rely on the perfect mix hypothesis, which could be inappropriate. There is little information regarding this concern. Quantitative criteria is mentioned in the ASTM D6249 and E741 standards [32,33], which establish that the concentration difference between measurement points should be below 10% of the difference between the room’s average concentration and the outdoors concentration.

Secondly, although model parameters can be obtained by fitting concentration measurements, in practice this is quite difficult. Some systems may exhibit rapid dynamics, which permit getting just some measurements before there are changes in the model param-
eters. In particular, naturally ventilated rooms can present rapid changes in the ventilation rate, which is highly dependant of environmental variables (e.g., wind speed). Thus, it might be advisable to independently estimate as many parameters as possible. For the CO$_2$ generation rate this can be difficult. Although there are references for individual generation rates, they depend on the sex, age, weight, height and metabolic activity of the occupants. Furthermore, occupation should be constantly monitored \[5,32\].

Additionally, $C_{\text{ext}}$ is a somewhat cumbersome parameter. If the air entering the space was guaranteed to come from outside, it could be estimated between 350 ppm and 400 ppm. Nonetheless, this is hardly ever the case. Air could be flowing in from other parts of the building, where there could be significant occupation, so part of the air entering the room may have CO$_2$ concentrations well above atmospheric levels. In this case, $C_{\text{ext}}$ should be interpreted as a weighted mean of the concentrations at the different points of entry by the respective airflow. It follows that usually $C_{\text{ext}}$ cannot be measured.

As a consequence of the aforementioned problems, Equation (3) has usually been adjusted for simplified situations. For example, it is common to adjust it to CO$_2$ measurements made just after a room is emptied, when there is no generation, or when equilibrium is achieved \[5,6,8,9\]. These are usually referred to as the decay and the equilibrium methods, respectively. These simplified methods have the disadvantage of only being able to depict ventilation rates during specific situations. Alternatives like the ones in \[5,7\] have been proposed, but they usually require filtering high frequency noise out of measurements, which is not simple, as there could also be high frequency changes in the model’s parameters.

As an alternative, we present a novel adjustment methodology for the classical box model, which is remarkably simple. It can easily be shown from Equation (2) that the CO$_2$ equilibrium concentration is

$$C_{\text{eq}} = C_{\text{ext}} + \frac{nG}{Q}$$  \hspace{1cm} (4)

Using Equation (4) as a change of variable in Equation (3), Equation (5) is obtained.

$$C(t) = C_{\text{eq}} - (C_{\text{eq}} - C_o) e^{-\frac{Q}{V}t}$$  \hspace{1cm} (5)

Equation (5) can be directly fitted to data with several advantages over Equation (3). It reduces the number of explicit parameters in the model, which simplifies the application of regression methods. Furthermore, occupation levels, CO$_2$ generation rates and $C_{\text{ext}}$ do not explicitly participate in the model. Instead, they are considered under $C_{\text{eq}}$, which can be estimated from the CO$_2$ concentration time series, as it is its horizontal asymptote. Finally, $C_o$ can easily be obtained by restricting a certain interval around the first point in the adjusted concentration series.

A final remark should be made regarding the selection of adjustment intervals. If a continuous CO$_2$ time series is available, it should be sectioned in several adjustment intervals, which will be referred from now on as adjustment windows. For the present paper, this selection was manually executed via visual inspection of data. Portions of concentration time series with no clear exponential evolution were not fitted. The selection was assessed in terms of the adjustment Root Mean Square Error (RMSE), which was found to be always well below instrumental uncertainty. Future work will pursue automation of the adjustment windows selection process.

### 2.3. Estimation of the Risk of Airborne Infection

The risk of airborne infection for a certain disease in a room can be assessed by using Wells-Riley models. These are all based on the concept of quanta, a term which Wells \[10\] defined as a certain amount of pathogen which could cause an infection. Wells used a fully-mixed box model and proposed that the probability of infection of the individuals within the room could be modelled with a Poisson distribution of parameter $\lambda$, where $\lambda$ is the total amount of quanta inhaled by an individual during a certain period. Assuming
Wells’ hypothesis, it can be shown that the probability $P$ of having at least one infected individual in the room can be expressed as

$$P = 1 - e^{-\lambda}$$  \hspace{1cm} (6)

Therefore, a quantum ($\lambda = 1$) can be interpreted as the infectious dose with a 63% chance of infection within a certain population.

All of the Wells-Riley models stem from Equation (6) and mainly differ on the way in which $\lambda$ is calculated. The Gammaitoni-Nucci approach [26,27], which extends the original steady state model proposed by Riley and his collaborators [11], is based on a mass balance of quanta, which can be expressed as

$$\frac{dN(t)}{dt} = \sigma(t)qI - \frac{Q}{V}N(t)$$  \hspace{1cm} (7)

where $N$ is the number of quanta in the room, $t$ is the time and $Q$ is the volumetric airflow entering and leaving the room, which is supposed to be pathogen-free. $qI$ expresses the generation of quanta within the room as the product of the number of infected individuals $I$ and the quanta generation rate per person $q$, which is supposed to be the same for each infected individual. Additionally, $\sigma$ is a Heaviside operator (unitary step function), which allows to consider time periods where the room is unoccupied.

$$\sigma(t) = \begin{cases} 
1 & \text{if the room is occupied} \\
0 & \text{if the room is unoccupied} 
\end{cases}$$  \hspace{1cm} (8)

It should be noted that the original Gammaitoni-Nucci model did not include a Heaviside operator. We have introduced this modification by emulating what [12,15] did for the Rudnick-Milton method.

Assuming that only $N$ is a function of time, Equation (7) can easily be solved with a certain initial condition for quanta ($N_0$). Furthermore, assuming that the quanta is evenly distributed in the room’s volume, the quanta inhaled by an individual over a certain time period $T$ can be expressed as

$$\lambda = \frac{p}{V} \int_0^T \sigma N(t) \, dt$$  \hspace{1cm} (9)

where $V$ is the room’s volume and $p$ is the breathing rate per person, approximately 8 L/s [25]. The Heaviside operator is introduced in order not to account for breathed quanta while the room is unoccupied.

The Gammaitoni-Nucci model is not the best choice for naturally ventilated rooms, as it requires to know the ventilation rate. Nevertheless, it is useful for simulating different scenarios and associating ventilation rates with risk levels. We present a parametric study by selecting different ventilation rates and calculating $N$ for each time step by solving Equation (7). After that, we numerically compute $\lambda$ with Equation (9).

Another approach for calculating $\lambda$ is presented by Rudnick and Milton [25]. It uses CO$_2$ as a tracer for estimating the fraction of the air in the room that has already been breathed by someone ($f$), which is the air that can cause infection. By performing a mass balance to CO$_2$, it can be shown that said fraction can be calculated at any instant as

$$f = \frac{C - C_{\text{atm}}}{C_a}$$  \hspace{1cm} (10)

where $C$, $C_{\text{atm}}$ and $C_a$ are the CO$_2$ concentrations in the room, outside and in people’s exhaled breath, respectively. We assume 380 ppm for $C_{\text{atm}}$ and 37,500 ppm for $C_a$ [12,34].

A slight modification to the original Rudnick-Milton model is introduced in [12] and in [15] to account for intermittent occupation. Assuming that the room can only be either fully occupied or totally empty and that changes in occupation occur fast, the number of
persons in the room at any time can be obtained by multiplying the nominal occupation by a Heaviside operator. It can then be shown that [12,15]

\[ \lambda = \frac{I}{n} \int_0^T \sigma(t) f q \, dt \]  

(11)

The Rudnick-Milton model is particularly useful for naturally ventilated rooms, as the infection risk can be directly inferred from CO\textsubscript{2} levels. There is no need to calculate Q. For either the Gammaitoni-Nucci or the Rudnick-Milton models, a time period T must be selected. In the case of virus, it is customary to select the incubation period. This is reasonable under the hypothesis that after said period the individual will develop symptoms and will stop attending school. We have selected T to be 5 days, as it has previously been done in [12,17].

Furthermore, the quanta generation rate must be estimated. This is probably the most difficult point in the application of Wells-Riley models. Traditionally quanta emission rates have been backwards calculated by studying previous outbreaks [35]. Nonetheless, there is still not enough data to do so in the case of SARS-CoV-2. Consequently, Buonanno and collaborators [13,14] have proposed a method based on viral load analysis of the saliva of infected individuals and have inferred a quanta emission rate probability distribution for different vocal activities. We have chosen to perform a parametrical analysis with different mean values associated with some special scenarios. Quanta emission rates of 1 quanta/h and 5 quanta/h have been selected to represent quiet and noisy classrooms, respectively [12]. Additionally, emission rates of 10 quanta/h and 20 quanta/h have been selected to represent super-emission cases or more contagious strands.

It should be noted that both T and q are dependant on the virus strand. The values used were inferred for the original SARS-CoV-2. Newer and more aggressive strands could have higher quanta emission rates. Nonetheless, they have been observed to have shorter incubation periods [36], so the effects may partially compensate each other.

Probability of infection is usually expressed in terms of the basic reproduction number $R_0$. This is defined as the expected number of infections if only one primary infected individual is introduced in a population ($I = 1$), and can be calculated as shown in Equation (12) [25]. A certain scenario is considered to be safe if $R_0 < 1$.

\[ R_0 = P(n - 1) \]  

(12)

3. Results

3.1. Ventilation Rate

3.1.1. Controlled Tests

Several controlled tests were performed, two on the 10th of September and three on the 15th of October 2021. The monitors were positioned along a diagonal of the room, 0.7 m above the ground. The selected measurement points are described in Figure 2. Monitors AQ1, AQ2, AC1 and AC2 were set in positions P1, P2, P3 and P4 respectively, except for tests 1 and 2, in which monitors AQ1 and AQ2 swapped positions. Table 1 shows the ventilation configuration for each test.

| Test | Open to Exterior | Open to Corridor |
|------|-----------------|-----------------|
| 1    | V2              | —               |
| 2    | V2              | V5              |
| 3    | V1 + V4         | V5              |
| 4    | V1              | V5 + door       |
| 5    | V2              | V5              |

Table 1. Controlled tests configurations. Windows are labelled as described in Figure 2.
Figure 2. Floor plan of the classroom. The sensors positions P1 to P4 are identified and windows are labelled. Windows V1 to V4 connect to the outdoor playground and window V5 connects to an interior corridor.

The CO$_2$ decay series registered at each point were adjusted to the model given in Equation (5). A non-linear least squares method was used, with the following restrictions

$$
\begin{align*}
0 \text{ h}^{-1} & \leq \text{ACH} \leq 30 \text{ h}^{-1} \\
350 \text{ ppm} & \leq C_{eq} \leq 500 \text{ ppm} \\
C_1 - 20 \text{ ppm} & \leq C_0 \leq C_1 + 20 \text{ ppm}
\end{align*}
$$

(13)

where $C_1$ is the first data point in the adjustment window. The restrictions imposed to ACH were observed not to constrain the results. The restrictions imposed to $C_{eq}$ are reasonable as there were no occupants during the decay tests. Finally, the restriction imposed to $C_0$ was selected to relax the initial condition value, which otherwise could have been just selected to be $C_1$.

The parameters adjusted are shown in Table 2, as well as the RMSE of the adjustment. Furthermore, the mean ($\bar{\text{ACH}}$) and standard deviation ($s_{\text{ACH}}$) of ACH for each test are included.

Additionally, Table 3 provides the mean values for indoor air temperature ($T_{in}$) and relative humidity ($R_{in}$) measured by the AC1 and AC2 sensors during the controlled tests. We also provide the mean values for outdoor air temperature ($T_{out}$), relative humidity ($R_{out}$), wind speed ($U$) and wind direction ($\phi$) registered by a nearby (approximately 800 m) environmental station (Aeroqual AQM10 Environmental Monitor). These values are provided in order to further characterise the analysed scenarios, but evaluating their impact on the ventilation rate is beyond the scope of the research.

The results show that the classroom can attain very high ventilation rates, well above ASHRAE's requirement and WHO's recommendation. Furthermore, there is a significant difference between the ventilation rates attained with unilateral (test 1) and crossed ventilation (tests 2–5). Ventilation rates in a crossed scheme are an order of magnitude higher and comply with the ASHRAE requirements and WHO’s recommendation. It should be noted that during the controlled tests a relatively small portion of the total window area was actually open. Opening only half of an exterior window and the awning window attained more than 10 ACH (tests 2 and 5).
Table 2. Adjustment results for the box model parameters for each test and monitor.

| Test  | Monitor | ACH [h⁻¹] | C₀ [ppm] | C_{eq} [ppm] | RMSE [ppm] | ACH [h⁻¹] | s_{ACH} [h⁻¹] |
|-------|---------|-----------|---------|-------------|-----------|-----------|-------------|
| 1     | AQ1     | 3.44      | 1744    | 500         | 56.87     | 3.03      | 0.77        |
|       | AQ2     | 1.88      | 1816    | 350         | 12.16     |           |             |
|       | AC1     | 3.32      | 1690    | 500         | 53.12     |           |             |
|       | AC2     | 3.49      | 1625    | 500         | 51.73     |           |             |
| 2     | AQ1     | 12.12     | 2313    | 433         | 74.82     | 13.16     | 1.48        |
|       | AQ2     | 11.90     | 2189    | 497         | 18.71     |           |             |
|       | AC1     | 13.52     | 2063    | 500         | 28.64     |           |             |
|       | AC2     | 15.11     | 1898    | 488         | 36.34     |           |             |
| 3     | AQ1     | 16.70     | 1758    | 500         | 7.83      | 16.63     | 1.99        |
|       | AQ2     | 15.08     | 1842    | 500         | 23.96     |           |             |
|       | AC1     | 15.32     | 1795    | 500         | 39.87     |           |             |
|       | AC2     | 19.42     | 1915    | 500         | 41.78     |           |             |
| 4     | AQ1     | 14.70     | 1507    | 500         | 25.83     | 14.95     | 1.68        |
|       | AQ2     | 13.38     | 1383    | 500         | 31.17     |           |             |
|       | AC1     | 14.39     | 1496    | 500         | 25.67     |           |             |
|       | AC2     | 17.33     | 1465    | 500         | 43.49     |           |             |
| 5     | AQ1     | 9.32      | 1826    | 477         | 35.86     | 10.09     | 1.72        |
|       | AQ2     | 8.06      | 1645    | 415         | 40.67     |           |             |
|       | AC1     | 11.85     | 1836    | 449         | 77.67     |           |             |
|       | AC2     | 11.13     | 1786    | 500         | 73.92     |           |             |

Table 3. Environmental conditions during controlled tests. Mean values were computed from the time series provided by AC1 and AC2 monitors (indoors) and by a nearby environmental station.

| Test  | T_{in} [°C] | RH_{in} [%] | T_{out} [°C] | RH_{out} [%] | U [m/s] | ϕ [°] † |
|-------|--------------|-------------|--------------|-------------|---------|---------|
| 1     | 18.6         | 67.7        | 14.8         | 96.3        | 1.6     | 141     |
| 2     | 18.4         | 67.6        | 14.7         | 96.3        | 1.5     | 149     |
| 3     | 21.1         | 35.9        | 17.9         | 47.9        | 2.3     | 130     |
| 4     | 20.7         | 35.6        | 16.3         | 51.4        | 2.4     | 131     |
| 5     | 20.1         | 37.6        | 15.1         | 56.6        | 2.0     | 80      |

† The usual meteorological convention is used here, with wind coming from the north at 0° and clockwise increasing directions.

Figure 3 illustrates the difference found between unilateral and crossed ventilation. It shows the measured CO₂ concentration series and the adjusted box models curves for tests 1 (unilateral) and 2 (crossed ventilation). The concentration decay speed with crossed ventilation is approximately four times larger than with unilateral ventilation.

Finally, it is interesting to notice that the ACH results obtained at different measurement points are fairly consistent, with differences between the maximum and minimum estimated ACH of less than 30% of the mean value, except for test 1.
With this method, around 50% of the measurements performed during classroom occupation periods for the classroom.

Fig. 3. Example of results for controlled tests. (a) depicts test 1, with unilateral ventilation. (b) depicts test 2, with crossed ventilation. Each colour identifies a monitor at a specific measurement position. The jagged curves correspond to experimental data and the smooth curves represent the adjusted box model.

3.1.2. Daily Measurements

Daily measurements during normal operation were fitted in the same way as controlled test data, but the upper restriction to $C_{eq}$ was set at 3000 ppm, which is well above the maximum concentration registered. It should be noticed that this restriction will be mainly relevant when $Q$ is very small and the solution for Equation (2) degenerates into a linear function. In these cases, allowing $C_{eq}$ to reach higher values reduces the adjusted ACH value. It was observed that setting a restriction for $C_{eq}$ above 3000 ppm produced insignificant changes in ACH (e.g., the cases bounded by this upper restriction changed their adjusted ACH from 0.1 $h^{-1}$ to 0.05 $h^{-1}$).

All measurement series at the front of the classroom were sectioned in adjustment windows according to what was described in Section 2.2. An example is shown in Figure 4. With this method, around 50% of the measurements performed during classroom occupation were adjusted with a box model.

Fig. 4. Example of the sectioning into adjustment windows for a particular day. The grey curve corresponds to the CO₂ concentrations at the front of the classroom with monitor AQ1. Orange and blue areas identify adjustment windows with build-up and decay of CO₂, respectively. Orange and blue curves depict the adjusted box model for each window. The grey shaded background identifies occupation periods for the classroom.

A first analysis of the adjusted box models showed that a significant proportion of the adjustment windows during occupation hours had high ventilation rates, with median values of 6.6 $h^{-1}$ and 6.4 $h^{-1}$ for the morning and afternoon shifts, respectively. These values comply with both the ASHRAE 62.1 standard and WHO’s recommendation. Nonetheless,
they can be misleading if not carefully interpreted. In particular, it is important to notice that adjustment windows are of variable duration. Consequently, these results could not be quite representative of what usually happens in the classroom. For example, adjustment windows of short duration with high ACH results could inflate results. This is, in fact, what was observed: there is a correlation between ACH and the adjustment windows’ duration, with longer duration corresponding to lower ventilation rates and vice versa. Figure 5 illustrates these results for the afternoon shift. Similar results were obtained for the morning shift.

![Figure 5](image.png)

**Figure 5.** Distribution of adjusted ACH values for the afternoon shift during occupation hours (above) and duration of adjustment windows stratified by ACH ranges (below). N indicates the total data points for each histogram.

In order to compensate for the variable duration of adjustment windows, a daily temporally weighted ACH average was computed. This average is defined for each shift of each measurement day as follows:

\[
ACH_p = \frac{\sum_{i=1}^{v} ACH_i \Delta t_i}{\sum_{i=1}^{v} \Delta t_i}
\]

where \(v\) is the number of adjusted windows and \(ACH_i\) and \(\Delta t_i\) are the adjusted ventilation rate and the duration of the \(i\)-th window.

Figure 6 shows the monthly weighted average results and compares them with the distribution directly computed from the adjustment results. The contrast is striking and clearly illustrates that while the classroom is capable of reaching very high ventilation rates, as it was also shown by the controlled tests, during normal operation this happens only for reduced periods. This is probably related to thermal comfort restrictions. With such high ventilation rates and air coming from outside, it would be almost impossible to maintain a comfortable temperature inside the classroom. Consequently, occupants only ventilate the classroom for short periods.

Even though the daily mean ventilation rates do not comply with the ASHRAE standard and WHO’s recommendations, the question arises weather short but intense ventilation events help reduce the airborne transmission risk. This will be analysed via the Wells-Riley models in Section 3.2.

Finally, Figure 7 presents the temperature and relative humidity results obtained from the Davis Instruments weather station that was installed on the roof of the school on August, September, November and December.
**3.1.3. Assessment of the Perfect Mix Hypothesis**

The perfect mix hypothesis was evaluated by comparing daily CO$_2$ measurements at the front (main measurement point) and at the back (potential stagnation zone) of the classroom. A typical day is shown in Figure 8, with a slower CO$_2$ concentration dynamic at the back of the classroom.

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**Figure 6.** Monthly ACH results. (a) shows mean ACH results computed from all the box model adjustments. (b) shows results computed from daily time-weighted ACH averages. Results for both occupation shifts are included, as well as the minimum ventilation rate indicated by the ASHRAE 62.1 standard and WHO’s pandemic recommendation.

**Figure 7.** Results obtained from the weather station on the roof of the school. (a) shows monthly temperature boxplots. (b) shows monthly relative humidity boxplots.
Figure 8. Example of CO₂ measurements at the front and at the back of the classroom. The grey shaded background identifies occupation periods.

The CO₂ concentration difference between the front and the back of the classroom was computed for all available simultaneous measurements. For about two thirds of the measurements the concentration at the back of the classroom was higher than at the front. The absolute differences third quartile was of 81 ppm, with a median of 39 ppm. These differences were deemed acceptable given the monitor’s accuracy [37]. Nevertheless, when expressing the results in the percentage form indicated by the ASTM D6249 and E741 standards, it is evident that the classroom does not comply with the perfect mix hypothesis in terms of these standards (less than 10%). These results are summarised in Figure 9.

Figure 9. CO₂ concentration difference between the front and the back of the classroom. (a) shows the distribution of the differences. (b) shows monthly differences. (c) shows monthly results as a percentage of the difference between mean concentration and external concentration, which is assumed to be 380 ppm.

Taking into account the monitors’ accuracy (±(20 ppm + 5%)), the perfect mix hypothesis is considered acceptable. This is also supported by the ventilation rate results of the controlled tests, which were relatively insensible to monitor position. Nonetheless, the classroom does not comply with ASTM standards’ requirement for perfect mix. These could be too exigent for the application at hand, particularly considering the relatively low concentrations measured in the classroom, which rarely surpass 1500 ppm. Further evaluation of the perfect mix hypothesis might be needed. Its applicability should not only be analysed in terms of CO₂ concentrations, but also considering its impact on ventilation rate and risk results.

3.2. Risk of Infection
3.2.1. Rudnick-Milton Model

The Rudnick-Milton model was run for the daily CO₂ concentration measurements. For each week and for each occupation shift the basic reproduction number was computed. Figure 10 shows an example and Table 4 the results for the analysed weeks.
**Figure 10.** Risk results from a weekly measurement in August, for the afternoon shift. CO₂ measurements and the evolution of the probability of infection for different quanta generation rates are shown. The grey shaded background identifies occupation time for the afternoon shift. The coloured boxes detail the probability of infection and the basic reproduction number by the end of the week.

**Table 4.** Weekly estimation of the basic reproduction number for different quanta emission rates.

| Weekly Estimation of $R_0$ |
|----------------------------|
| Morning shift              |
| $q$ [quanta/h]             |
| Week                      | 1  | 5  | 10 | 20 |
|----------------------------|----|----|----|----|
| 09/08–13/08                | 0.26| 1.26| 2.46| 4.71|
| 30/08–03/09                | 0.14| 0.68| 1.35| 2.63|
| 27/09–01/10                | 0.11| 0.55| 1.08| 2.12|
| 25/10–29/10                | 0.06| 0.30| 0.60| 1.14|
| 22/11–26/11                | 0.09| 0.43| 0.86| 1.70|
| 29/11–03/12                | 0.04| 0.19| 0.37| 0.74|
| 06/12–10/12                | 0.05| 0.27| 0.54| 1.07|
| 13/12–17/12                | 0.03| 0.16| 0.32| 0.63|

| Afternoon shift            |
| $q$ [quanta/h]             |
| Week                      | 1  | 5  | 10 | 20 |
|----------------------------|----|----|----|----|
| 09/08–13/08                | 0.16| 0.80| 1.57| 3.06|
| 06/09–10/09                | 0.15| 0.74| 1.47| 2.87|
| 27/09–01/10                | 0.11| 0.55| 1.08| 2.12|
| 04/10–08/10                | 0.09| 0.43| 0.86| 1.69|
| 29/11–03/12                | 0.06| 0.29| 0.57| 1.12|
| 06/12–10/12                | 0.06| 0.31| 0.62| 1.24|

Several weeks could not be analysed due to gaps in the measurements. In order to maximise data usage, monthly risk means ($\bar{P}$) were computed as

$$\bar{P} = 1 - e^{-\frac{1}{\sigma f} \int_0^T \sigma(t) dt}$$

where $f$ is the monthly $f$ average, computed from all the available measurements during occupation time. The previous expression is an approximation which stands valid while the exponent is small, due to the exponential’s non-linearity. For the concentrations registered and the values of the other parameters involved, it was estimated that this introduces
relative errors below 10%, which was considered acceptable. Said error is by excess, that is, the predicted risk will be higher, so a conservative approximation is made. The monthly averages obtained are presented in Table 5.

Table 5. Mean monthly estimation of the basic reproduction number for different quanta emission rates.

| Month       | 1  | 5  | 10 | 20 |
|-------------|----|----|----|----|
| Morning shift |    |    |    |    |
| August      | 0.18 | 0.88 | 1.74 | 3.38 |
| September   | 0.10 | 0.47 | 0.94 | 1.85 |
| October     | 0.11 | 0.52 | 1.03 | 2.03 |
| November    | 0.07 | 0.37 | 0.73 | 1.45 |
| December    | 0.04 | 0.21 | 0.43 | 0.85 |

| Afternoon shift |    |    |    |    |
|----------------|----|----|----|----|
| August         | 0.12 | 0.57 | 1.13 | 2.22 |
| September      | 0.10 | 0.48 | 0.96 | 1.88 |
| October        | 0.07 | 0.35 | 0.70 | 1.37 |
| November       | 0.07 | 0.33 | 0.65 | 1.29 |
| December       | 0.05 | 0.27 | 0.53 | 1.05 |

The results in Tables 4 and 5 show that the risk of airborne infection steadily decreases towards the end of the year. This could be associated with a warmer climate, which would allow for higher ventilation rates while maintaining thermal comfort. Furthermore, it is shown that in general quanta emission rates of up to 5 quanta/h are safe. Depending on the month, quanta emission rates of up to 10 quanta/h could be safe. These results are encouraging, given the fact that an emission rate of 5 quanta/h is associated with a noisy classroom. Nevertheless, care should be taken, as newer SARS-CoV-2 strands could imply higher emission rates.

3.2.2. Gammaitoni-Nucci Model

In order to explore the relationship between ventilation rates and risk of airborne transmission, the Gammaitoni-Nucci model was used. For this section a quanta emission rate of 5 quanta/h was assumed.

First, artificial quanta curves were computed for five consecutive days of occupation based on the solution of Equation (7). Ventilation rates of 0.5 h\(^{-1}\), 1 h\(^{-1}\), 3.80 h\(^{-1}\) and 6.43 h\(^{-1}\) were chosen, the last of which correspond to the minimum requirement of the ASHRAE 62.1 standard and WHO’s recommendation for the pandemic, respectively. Then, the Gammaitoni-Nucci model was used to evaluate the risk of airborne transmission.

Figure 11 shows the results obtained. It is surprising that even WHO’s recommended ventilation rate implies a critical transmission situation. Furthermore, it is remarkable that even though the estimated ventilation rates for the classroom were (as a weighted daily average) below 3 h\(^{-1}\), the transmission risk estimated via the Rudnick-Milton model was significantly lower than what is predicted by the Gammaitoni-Nucci model. This observation raises the question of whether the intense but short ventilation periods observed during normal operation of the classroom might be responsible for significantly lowering the transmission risk.
The results clearly show the tremendous impact that periodic ventilation has on the long occupation periods. The coloured boxes detail the probability of infection and the basic reproduction number by the end of the week.

To evaluate the previous observation, new artificial quanta curves with dynamic ventilation rates were generated. A basal low ventilation rate was selected and after a certain period a high ventilation rate was imposed for a short time. Then the risk was once again evaluated via the Gammaitoni-Nucci model. Figure 12 shows an example.

Several scenarios were tested and are summarised in Table 6, in which the percentage decrease in the basic reproductive number with respect to the corresponding static basal ventilation rate is presented, as well as the absolute basic reproduction number achieved. The results clearly show the tremendous impact that periodic ventilation has on the long distance airborne risk of infection. Despite the absolute values of the basic reproductive number might still deem the situation unsafe, their relative reduction is almost always...
above 50%. Even ventilating for just five minutes every half an hour has an enormous impact on reducing risk. This implies that in naturally ventilated buildings where high ventilation rates can be achieved but cannot be maintained (e.g. due to thermal discomfort), periodical ventilation might be a useful compromise solution for reducing airborne transmission of diseases.

Table 6. Reduction of the basic reproduction number with periodical ventilation regimes. ACH_{low} and ACH_{high} are the basal and the high ventilation rates. \( t_{low} \) and \( t_{high} \) are the duration of each ventilation stage (alternating times with ACH_{low} and ACH_{high}, respectively). The percentages of reduction are referred to the basal situation, with a constant ACH_{low} ventilation rate. The basic reproduction number for the basal situation is indicated between parenthesis next to the basal ventilation rate value. The basic reproduction number for each situation is detailed below each percentage result.

| Reduction in \( R_0 \) with Dynamic Ventilation Rates |
|-----------------------------------------------|
| ACH_{low} [h^{-1}] | 0.3 (7.63) | 1 (4.32) |
| ACH_{high} [h^{-1}] | 6 | 10 | 5 | 10 | 5 | 10 |
| \( t_{low} \) [min] | 5 | 10 | 5 | 10 | 5 | 10 |
| \( t_{high} \) [min] | 10 | 15 | 20 | 25 | 30 |
|  | 68.5% | 75.6% | 77.5% | 83.2% | 51.6% | 60.6% | 64.2% | 72.3% |
|  | (2.40) | (1.86) | (1.72) | (1.28) | (2.09) | (1.70) | (1.55) | (1.20) |
|  | 63.2% | 71.5% | 72.5% | 79.6% | 45.6% | 55.3% | 57.8% | 67.1% |
|  | (2.80) | (2.18) | (2.10) | (1.56) | (2.35) | (1.93) | (1.82) | (1.42) |
|  | 59.1% | 67.6% | 68.3% | 76.0% | 41.0% | 50.7% | 52.5% | 62.3% |
|  | (3.12) | (2.47) | (2.42) | (1.83) | (2.55) | (2.13) | (2.05) | (1.63) |
|  | 55.9% | 64.2% | 64.8% | 72.5% | 37.6% | 46.6% | 48.4% | 57.6% |
|  | (3.36) | (2.73) | (2.69) | (2.10) | (2.70) | (2.31) | (2.23) | (1.83) |
|  | 52.7% | 61.3% | 60.9% | 69.6% | 34.1% | 43.3% | 43.7% | 54.0% |
|  | (3.61) | (2.95) | (2.98) | (2.32) | (2.85) | (2.44) | (2.43) | (1.99) |

It should be noted that the risk reduction percentages presented in Table 6 are essentially independent from the quanta emission rate selected, as previously observed for the Rudnick-Milton model in [12]. This can be explained as follows. For any occupation period (\( \sigma = 1 \)), Equation (7) can be solved and plugged into Equation (9) to obtain Equation (16) [26,27,35]

\[
P = 1 - e^{-\frac{\text{ACH}_{low}}{V} \left[ 1 + \left( \frac{\text{ACH}_{low}}{V} \cdot \frac{\sigma}{\sigma} \left( 1 - e^{-\frac{\text{ACH}_{high}}{V}} \right) \right) \right]}
\]  

(16)

If the exponent in Equation (16) is small enough, the expression can be approximated by a first-order Taylor expansion around zero and the probability of infection becomes approximately proportional to \( q \), which then cancels out when computing relative risk reduction. In the Gammaitoni-Nucci model, \( q \) also divides the initial quanta condition, which does not directly cancel out when comparing dynamic ventilation situations. Nonetheless, this term was found to have little impact on the relative risk reduction results. The percentages in Table 6 varied less than 2% for quanta emission rates between 1 quanta/h and 15 quanta/h. Consequently, the percentage results stand valid not only for different SARS-CoV-2 strands, but also for different diseases.

3.3. Discussion

In general, the results presented are consistent with the main observations other studies have made. In particular, the relevance of ventilation as a fundamental risk control strategy [38] is further highlighted. Considering that the airborne infection risk is larger indoors, particularly in poorly ventilated rooms, naturally ventilated buildings are a
major concern. Given that schools are commonly naturally ventilated [39], they entail an interesting and complex case of study.

There are two main aspects that need to be considered when analysing IAQ in a school classroom. On the one hand, the ventilation rates that the room can attain should be determined. These can be influenced by the ventilation configuration (i.e. which windows and doors are open) and by the environmental conditions. On the other hand, it is important to assess the impact that the ventilation rates can have on the airborne risk of infection and on thermal comfort.

We have assessed the potential ventilation rates that the studied room can attain via the tracer gas method using CO\(_2\), a popular strategy in the context of the COVID-19 pandemic. A large increase in the ventilation rate was observed when comparing unilateral and crossed ventilation schemes. This is consistent with the results presented in [40,41], where a similar procedure was used.

The tracer gas method was also used to estimate the ventilation rates during normal operation of the selected classroom for five months. This method has been recently used by several authors, see for instance [40–43]. From the computed ventilation rates, it is concluded that the classroom can be well ventilated, which is consistent with the results of the control tests. Nonetheless, it was observed that sufficient ventilation mostly occurs during short time windows. Consequently, the weighted averaged ventilation rate is below the reference values specified in ASHRAE’s standard [30] and by WHO [31].

Furthermore, the risk of airborne infection for the CO\(_2\) measurement months was computed in a similar way than the one presented in [12,15]. The results are lower than the ones obtained by using the Gammaitoni-Nucci model for a ventilation rate close to the weighted averaged previously mentioned. This could be related to the effect of intermittent ventilation. To assess this hypothesis, artificial quanta curves were obtained for different dynamic (intermittent) ventilation strategies and the infection risk was computed via the Gammaitoni-Nucci model. The results show that a ventilation scheme comprising intervals of low and high ventilation rates can drastically reduce the airborne transmission risk and is therefore encouraged. This is in line with the manual airing of naturally ventilated classrooms proposed in [44]. Another dynamic procedure for risk reduction is presented in [45], although this study focuses on controlling the pathogen source in buildings with mechanical ventilation rather than the ventilation rate.

The intermittent ventilation of naturally ventilated classrooms is probably mostly needed during the cold season, when high ventilation rates can preclude thermal comfort and contagion risk is therefore higher. This is supported by the results of the measurement campaign that were presented, which exhibit seasonal trends similar to the ones observed in [12,17].

A limitation of the present study is that the methods used for both computing the ventilation rate and the airborne transmission risk rely on the perfect mix hypothesis. This is a common approach in the research community, as it has been previously mentioned. In this work, a first assessment of the hypothesis has been done. The results show, particularly regarding the airborne transmission risk, that it is a reasonable assumption. Furthermore, the family of Wells-Riley models has been shown to provide reasonable and informative results when compared with methods that do not rely on the perfect mix hypothesis, like the ones based on computational fluid dynamics simulations [46,47].

Furthermore, the Rudnick-Milton approach poses an additional limitation to the results. As it has been mentioned, said model relies on using CO\(_2\) as a proxy for the studied pathogen. Nonetheless, in reality, the SARS-CoV-2 virus is transmitted via small droplets of fluid. The movement and dispersion of these droplets is more complex than that of gaseous CO\(_2\) and is highly dependent on the droplet size, which in turn depends on environmental conditions, such as temperature and humidity [48]. This limitation is inherent to the Rudnick-Milton model. Nonetheless, the authors wish to highlight that it remains useful model for risk estimation, particularly for naturally-ventilated environments, as it avoids the problem of explicitly estimating the ventilation rate.
In light of the above-mentioned aspects, it can be concluded that, despite some limitations, the Wells-Riley models are useful tools to quickly estimate the advantages and disadvantages of different ventilation and risk reduction strategies.

4. Conclusions

The natural ventilation scheme of an Uruguayan primary school classroom was quantitatively assessed by both estimating ventilation rates and airborne transmission risk.

Ventilation rates were studied in controlled situations without occupants and during normal use by fitting a box model by measuring CO\textsubscript{2} concentrations. It was found that the classroom has the potential of reaching very high ventilation rates when cross-ventilated. Nonetheless, during normal occupation this only happens during short periods. Consequently, daily mean ACH values remain low. This may happen due to thermal discomfort of the occupants, which prevents them from operating the windows.

Transmission risk for SARS-CoV-2 was assessed via a Wells-Riley approach. Mean monthly risk was estimated through CO\textsubscript{2} measurements by using a modified Rudnick-Milton model. Risk was shown to steadily decline towards spring. This is compatible with the thermal discomfort hypothesis, as warmer outside air would allow for more frequent high ventilation rate events.

The relationship between ventilation rates and airborne transmission risk was explored by using a modified Gammaitoni-Nucci model. It was shown that for constant ventilation rates similar to the daily mean values determined for the classroom, transmission risk was predicted to be much higher than what was estimated via the Rudnick-Milton model. By studying periodic ventilation schemes with the Gammaitoni-Nucci model, it was shown that this could be explained by the short but intense ventilation events observed. It is therefore concluded that periodic ventilation is an extremely valuable strategy for reducing transmission risk, which allows for a compromise with thermal comfort in naturally ventilated spaces during wintertime. Nonetheless, periodic ventilation might need complementary risk reduction strategies to further reduce risk values.

Additional ongoing work is aimed at extending the measurement campaign, including more classrooms of the same school building and other variables such as temperature and relative humidity. In the near future, we intend to include more schools. Furthermore, data analysis could be complemented with other models. For example, the performance of box models could be evaluated via Computational Fluid Dynamics (CFD). CFD would also allow to assess the influence of the airflow pattern in the airborne infection risk. In addition to this, taking into account the relevance of the thermal comfort and its influence in the ventilation, Building Energy Management (BEM) models will be used

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Abbreviations

The following abbreviations are used in this manuscript:

IAQ Indoor Air Quality
CO₂ Carbon dioxide
ACH Air Changes per Hour
WHO World Health Organisation
RMSE Root Mean Square Error
CFD Computational Fluid Dynamics
BEM Building Energy Management

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