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Application of the Bayesian spline method to analyze real-time measurements of ultrafine particle concentration in the Parisian subway

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ABSTRACT

Background: Air pollution in subway environments is a growing concern as it often exceeds WHO recommendations for indoor air quality. Ultrafine particles (UFP), for which there is still no regulation nor a standardized exposure monitoring method, are the strongest contributor to this pollution when the number concentration is used as exposure metric.
Objectives: We aimed to assess the real-time UFP number concentration in the personal breathing zone (PBZ) of three types of underground Parisian subway professionals and analyze it using a novel Bayesian spline approach. Consecutively, we investigated the effect of job, week day, subway station, worker location, and some further events on UFP number concentrations.
Methods: The data collection procedure originated from a longitudinal study and lasted for a total duration of 6 weeks (from October 7 to November 15, 2019, i.e. two weeks per type of subway professionals). Time-series were built from the real-time particle number concentration (PNC) measured in the PBZ of professionals during their work-shifts. Complementarily, contextual information expressed as Station, Environment, and Event variables were extracted from activity logbooks completed for every work-shift. A Bayesian spline approach was applied to model the PNC within a Bayesian framework as a function of the mentioned contextual information.
Results: Overall, the Bayesian spline method suited a real-time personal PNC data modeling approach. The model enabled estimating the differences in UFP exposure between subway professionals, stations, and various locations. Our results suggest a higher PNC closer to the subway tracks, with the highest PNC on subway station platforms. Studied event and week day variables had a lesser influence.
Conclusion: It was shown that the Bayesian spline method is suitable to investigate individual exposure to UFP in underground subway settings. This method is informative for better documenting the magnitude and variability of UFP exposure, and for understanding the determinants in view of further regulation and control of this exposure.

1. Introduction

Outdoor air pollution causes around 4.2 million annual deaths worldwide (Cohen et al. 2017) and transport is an important contributor to this burden (Pagenkopf et al. 2019), particularly through particulate matter (PM) emission. Adoption of clean air policies by public authorities, and interventions such as requested vehicle standards and public transport restructuring, were shown effective with respect to health outcomes related to PM exposure (Burns et al. 2020). Subways are the most commonly used mode of public transportation in large cities (Wen et al. 2020), and are considered as an ecologically friendly transport mode, crucial in meeting climate goals (EEA. 2020) by reducing air pollution above ground (Reche et al. 2017). To limit the effects of air pollution, the World Health Organization (WHO) has set air quality guidelines at 20 μg/m^3 for PM10 and 10 μg/m^3 for PM2.5 annual mean. These are the lowest levels at which total, cardiopulmonary, and lung

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cancer mortality have been shown to increase with more than 95% confidence in response to PM2.5 exposure (WHO 2006). However, PM concentrations measured within subway environments worldwide are systematically higher than PM concentrations in ambient air (Choi et al. 2019; Kim et al. 2008; Loxham and Nieuwenhuijsen 2019; Luglio et al. 2021; Minguillón et al. 2018; Mohsen et al. 2018; Moreno and de Miguel 2018; Pun et al. 2017; Qiu and Cao 2020; Shen and Gao 2019; Smith et al. 2020; Van Ryswyk et al. 2017; Velasco et al. 2019; Vilcassim et al. 2014), presenting a potential risk for regular passengers and employees (Loxham and Nieuwenhuijsen 2019; Wen et al. 2020). Moreover, compared to the outdoor particulate pollution, subway PM has a different physical-chemical composition and size distribution. The latter remains poorly characterized, since most studies focused on the PM10 (Hwang and Park 2018; Kim et al. 2006; Park et al. 2012; Qiu and Cao 2020) or PM2.5 fraction of subway aerosol (Bigert et al. 2011; Byeon et al. 2015; Choi et al. 2019; Kim et al. 2008; Luglio et al. 2021; Posselt et al. 2019; Qiu and Cao 2020; Smith et al. 2020; Vilcassim et al. 2014), using gravimetric measurements. Furthermore, the ultrafine particle(s) (UFP) fraction, with its small contribution to mass concentrations, has been even less studied. Nevertheless, UFP can contribute significantly to the particle number and surface area concentrations, whereby both of these particle exposure metrics are strongly related to adverse health outcomes (Schraufnagel 2020). Recent epidemiological studies, mainly considering the general environment, strengthen the evidence that UFP exposure plays an important role in cardiovascular and respiratory diseases, systemic inflammation, and cancer (Clifford et al. 2018; Corlin et al. 2018; Downward et al. 2018). However, there are currently no practical field recommendations to specifically assess environmental and occupational UFP exposure (Audignon-Durand et al. 2021). At best, UFP are included in the assessment of exposure to total dust or to specific chemical substances. In addition, there are no easily implementable exposure assessment methods for their characterization in epidemiological studies. This may explain the small number of epidemiological data related to environmental and occupational exposure to UFP (Guseva Canu et al. 2020; Guseva Canu et al. 2018) and the absence of such studies related to subway workers.

Given a growing concern regarding the UFP exposure and potential health impairments in subway workers (Loxham and Nieuwenhuijsen 2019; Loxham et al. 2020; Wen et al. 2020), we launched a Franco-Swiss epidemiological research project, called "ROBoCoP" (Respiratory disease Occupational Biomonitoring Collaborative Project). ROBoCoP aimed at assessing the exposure to indoor airborne pollutants among subway workers of the Parisian urban transport company (Guseva Canu et al. 2021). In this study, we present the results of UFP number concentration assessed in the personal breathing zone (PBZ) of three types of Parisian subway professionals, working at different locations. For the first time, we implemented a Bayesian spline method to analyze real-time UFP concentration measurements over a six-week period and to investigate the UFP number variation according to several exposure determinants including job, subway station, worker location, and some particular events occurring during the work-shift.

2. Material and methods

2.1. Data collection

Data were collected in the frame of a longitudinal pilot-study dedicated to a comprehensive exposure assessment as described in the study protocol (Guseva Canu et al. 2021). We focused primarily on subway line 7. This line entered into operation in 1910 and crosses Paris from north-east to south-east following a slightly curved route, and connects the stations "La Courneuve – 8 Mai 1945", in the north-east in Seine-Saint-Denis, to "Mairie d'Ivry" and "Villejuif - Louis Aragon", in the south-east in Val-de-Marne. Line 7 is the fourth busiest in the Parisian subway network with more than 136 million yearly passengers. It is also one of the longest (22 km and 38 stations) entirely underground lines and has two embranchments. The entire one-way route takes between 48 min and 56 min depending on the embranchment.

The data collection lasted for a total duration of 6 weeks (from October 7 to November 2019, i.e. two weeks per type of subway professionals). Measurements were conducted during daily work-shifts. Nine professionals were included from 3 different job types, i.e. station agents (n = 3), locomotive operators (n = 3) and security guards (n = 3). Station agents oversee passenger information and ticket sales. They have a fixed workstation in the ticket counter / information desk located in the subway station "Corentin Cariou". This station is the second after the northern terminal station "Porte de la Villette" and has a standard configuration with two platforms separated by the subway tracks and an elliptical vault. Having been originally constructed in 1910, the station was renovated in 2001. The station has two entrances on either side of Avenue Corentin-Cariou, each consisting of a fixed staircase. In 2019, 2,766,678 passengers entered this station. The depth of the platforms is 7 m but information desks are located at a shallower level, very close to an entrance gate, suggesting a strong influence of the outside air on the particle concentration at this workstation. Station agents also have mobile activity when intervening on automated ticket distributors in the the station concourses and when performing inspection rounds along the subway line. Locomotive operators spent most of their work-shift inside the train cabin travelling along subway line 7. Cabins have no ventilation and air exchange is done primarily through the cabins' windows and doors. Security guards constantly move from station to station on demand, also beyond subway line 7.

Each day of the exposure measurement campaign started and finished inside the study room located in the subway station "Porte de la Villette" for station agents and subway conductors, and "Gare de Lyon" for security agents. It is worth noting that "Gare de Lyon" station has its platform at only 6 m depth, but it has 12 entrance gates with long corridors between them. Moreover, it has landing doors, installed in 2010 and is the only station served by metro lines that are all automatic and using rubber wheels. It ranks 3rd for its ridership among among 302 subway stations, with 36.5 million passengers entering this station in 2019. The study rooms were closed rooms where technicians who accompanied every study participant were equipped with the exposure measurement devices.

The Particulate Number Concentration (PNC - Particle/cm^3) was recorded every 10 s using the DISCmini (Testo, Mönchaltorf, Switzerland) monitoring the aerosol fraction from 10 to 300 nm. PNC was measured in the PBZ of study participants from their arrival in the study room until the end of their work-shift, in real working conditions. Noteworthy, all PBZ measurements were performed with RATP technicians' assistance, who documented every participant's location and event that occurred during his/her work-shift in a standardized activity logbook.

Complementing PBZ measurements, stationary PNC measurements were obtained using DISCmini devices both outdoors (right above subway stations Corentin Carriou, Porte de la Villette and Gare de Lyon) and indoors (inside the ticket counter within Corentin Carriou station), and served as contextual data, rather than for modeling. It is worth noting that the above-ground environment of the concerned stations differs notably. The Porte de la Villette station is one of the 35 gates of the "Boulevard Périphérique", i.e., the high-traffic road that bypasses Paris, and has a connection with the National Route 2. Porte de la Villette is an important hub for public transport connections, served by 4 bus lines, a tramway line and two night bus lines. In 2019, the annual average PM10 concentration in this area was 27 μg/m^3. Gare de Lyon is a station on lines 1 and 14 (with the tracks built in the open air and having an exotic garden inside), located in the center of Paris. It has several public transport connections around, including the railway station, two regional trains, 9 bus lines and 14 night bus lines. In 2019, the annual average PM10 concentration in this area was 21 μg/m^3. It was 24 μg/m^3 above Contin Carriou station in the same year.

2.2. Data management

PNC records in PBZ and activity logbooks were processed as follows. Firstly, we defined the time-series from the daily collected PNC measurements, i.e. each time-series corresponded to a complete 6-hour work-shift, linked with the corresponding activity logbook. Then, three independent variables were extracted from activity logbooks: *Station*, *Environment* and *Event* along with their corresponding timing and duration. It is worth mentioning that the time recorded in the activity logbooks were accurate on a minute-by-minute basis and were mapped to the first time point in the corresponding minute in the PNC time-series. The variable *Station* corresponds to the participant's location in the subway rail-network. The possible stations are composed of a subset of the Paris subway stations, which are found in line 7 (M7, 2021). Furthermore, when a participant travelled in subway line 7, we imputed intermediate stations that were not present in the activity logbooks. For this, we used the official Paris Subway traveling time (RATP Timetable 2021) assuming that the train waits 30 s in every intermediate stations. When traveling underground between two subway stations, the variable *Station* was set to *Tunnel* for all corresponding time points. In the case where the station was not defined, the variable was set to *Not determined* for the corresponding time points. The *Environment* variable defines the type of local or setting the participant was located in or visited during his/her work-shift, coded *Sampling room*, *Cloakroom*, *Break room*, *Ticket-counter*, *Outside*, *Underground corridor*, *Subway platform*, *Subway train* or *Subway cabin*. The *Event* variable documented the events that occurred during the recording such as *Exposure to tobacco smoke*, *Intervention on ticket distributor*, *Passenger entry into cabin*, *Printing paper*, *Subway cabin door open*, *Subway cabin heater on*, *Subway cabin window open*, *Ticket counter door open*, *Toilet break* or *Train passing*. The event duration was most often greater than 1 min but some events such as *Train passing* or *Printing paper* were sometimes only defined by the starting time. In that particular case, the event duration was set to 90 s in order to capture the full effect of those events. Finally, the variables *Job* and *Day* were defined as a three-classe variable (*Station agent, Locomotive operator, Security guard*) and a descrite quantitative variable corresponding to the date of the daily measuments, respectively.

2.3. Statistical model

We used a spline-based model fitted within a Bayesian framework as described by Houseman and Virji (Houseman and Virji 2017) for the explorative analysis of the association of PNC in PBZ with *Station*, *Environments* and *Events* variables.This model has three major advantages compared with other typically used methods: 1- It makes very few assumptions on the distribution of the data, 2- It accounts for non-stationary autocorrelated time-series, and 3- it allows to jointly estimate all parameters at once from multiple time-series into easily interpretable results (Klein Entink et al. 2015).

We considered the log10-transformed PNC denoted by $Y_i, i \in \{1, \cdots, n\}$ of lengthT_i as the dependent variable. For the sake of clarity, we note $Day_i \in \{1, \cdots, n\}$ the recording day of the time-series$i$. We assumed that each measured value Y_{ir} (where r indexes individual sequential measurements) is a normally distributed random variable with mean μ_{ir} depending upon a series of factors. We first considered that μ_{ir} depends on a random series-specific intercept (δ_i), centered at the mean of the job, and reference *Station*, *Environment* and *Event*. On top of that, we supposed that μ_{ir} also depends on fixed effects (*Station*, *Environment* and *Event*), series-specific measurement errors (σ_e^2) and random series specific effects. The latter is represented as stochastic error process implemented using a B-spline basis. This led us to write the following model:

$$Y_{ir}\ N\left\{\mu_i + XStation_{ir}^T\alpha + XEnvironement_{ir}^T\beta + XEvent_{ir}^T\gamma + \zeta_i^T b(t_{ir}), \sigma^2(Day_i)\right\}\# \quad (1)$$

Where $\mu_i\ N\{\mu_\delta(Job_i), \sigma_\delta^2(Job_i)\}$ denotes the inter-day-specific intercept absorbing the corresponding job random effect. Both μ_i and $\mu_\delta(\cdot)$ coefficients are expressed in terms of geometric mean ($GM = 10^\mu$) of PNC per day and job, respectively. Similarly, $\sigma^2(\cdot)$ and $\sigma_\delta^2(\cdot)$ are expressed as the within- and between-day Geometric Standard Deviation ($GSD = 10^\sigma$). The fixed coefficientsα, β and γ respectively represent the *Station*, *Environment*, and *Event*-specific effects and can be interpreted as a fold change ($10^{coefficient}$) with respect to the reference category. We chose the sampling room in the station Porte de la Villette when no events were recorded as the reference categories.

Note that*XStation*, *XEnvironments* and *XEvents* are one-hot encoded matrices with time-points as rows and possible categories as columns, such that each matrix X is build as:

$$X[t_1, category_1] = \begin{cases} 1 & if\ \ categor\ y_1\ \ occured\ \ at\ \ t_1 \\ 0 & otherwise \end{cases}\# \quad (2)$$

The rest of the equation is defined as in the original paper (Houseman and Virji 2017). The stochastic error process is constructed with $b(t)$ which is a k-dimensional vector of B-spline values dependent on time t and k previously chosen knots, and ζ_i which is a series-specific k-dimensional vector of spline coefficients. Furthermore, ζ_i is modeled as a k-dimensional multivariate-normal random effect such as $\zeta_i\ MVN\{0_k, \sigma_\zeta^2 I_k\}$with 0_k being the k-dimensional zero vector, I_k the $k \times k$ identity matrix and σ_ζ^2 the variance component. The number of knots is treated as a given hyperparameter, a larger number of knots being able to represent a greater level of curvature than a smaller set of knots. In the context of this study, we placed boundary knots at the limits of the time-series and we varied internal knots placements from 4 to 12 min. We selected a knot interval placement at 6 min (36 time-points) which we found to be a good compromise between computational time and overall accurateness.

To complete the specification of the model in a Bayesian setting, we specified the prior distribution for all estimated parameters as described in Table 1. The μ_δ coefficients were modeled as a weakly informative normal distribution around the global average and the coefficientsα, β and γ were set as weakly informative normal distribution around zero.

Finally, to infer the posterior distribution we used Markov-Chain Monte-Carlo methods as implemented in the JAGS software. Together with the definition of the model and the data, this algorithm returns a Markov-chain representing values sampled form the posterior distribution. This gives rise to the estimation of the posterior distribution of each free parameter of the model. In our simulation, we built three Markov-chains with initial values of parameters sampled from their corresponding prior distribution. The convergence of the three chains was achieved after 1000 iterations. In total, we ran 10,000 iterations and considered only the latter 9000so that 27,000 values were used to estimate the posterior distribution.

The final model was validated according to the "When to worry and how to Avoid the Misuse of Bayesian Statistics" (WAMBS) checklist (van de Schoot et al. 2021). The convergence was checked for all parameters using Gelman and Rubin convergence diagnostic (Brooks and Gelman 1998) and by visualizing the trace and density plots of all coefficients except the many ζ coefficients. The sensitivity analysis was performed on the prior distribution of α, β and γ coefficients by varying the standard deviation from 5 to 3 or 10. In addition, we checked for large degrees of autocorrelation in the Markov-Chain using autocorrelation plots with lags varying from one to 20. Finally, we conducted a posterior predictive checking step by predicting the PNC for complete time-series using the input data and then comparing it with the observed PNCs.

We performed the data management and statistical analysis using the R software (version 3.6.2). The Bayesian inference step was performed with R2Jags library and the JAGS standard software with the model described in Bayesian inference Using Gibbs Sampling (BUGS) format (Supplementary File 1).

Table 1
Summary of priors and their distributions for the Bayesian spline model parameters.

Variable	Reference category	Prior distribution	Prior elicitation source	Informativeness
Job mean	None	$\mu_\delta(j)\ N\left\{\mu = \overline{Y}, \sigma^2 = 5^2\right\}$ forj $\in [1, numJob]$	Expert knowledge	Weakly informative
Job variance	None	$\sigma_\delta^{-2}(j)\ N_+\{\mu = 0, \sigma^2 = 10^6\}$ forj $\in [1, numJob]$	Expert knowledge	Weakly informative
Station effect	Porte de la Villette	$\alpha_i\ N\{\mu = 0, \sigma^2 = 5^2\}$ fori $\in [1, numStation - 1]$	Expert knowledge	Weakly informative
Environment effect	Study Room	$\beta_i\ N\{\mu = 0, \sigma^2 = 5^2\}$ *fori* $\in [1, numEnv - 1]$	Expert knowledge	Weakly informative
Event effect	No Event	$\gamma_i\ N\{\mu = 0, \sigma^2 = 5^2\}$ *fori* $\in [1, numEvent]$	Expert knowledge	Weakly informative
B-spline	None	$\zeta_i\ MVN\left\{\mu = 0_k, \sigma^2 = \sigma_\zeta^2 I_k\right\}$ *fori* $\in [1, numDay]$ $k : numberofBÂ\text{-}splineknots$ $\sigma_\zeta^{-2}\ N_+\{\mu = 0, \sigma^2 = 10^6\}$	(Houseman and Virji 2017)	Informative
Variance	None	$\sigma_e^{-2}(j)\ N_+\{\mu = 0, \sigma^2 = 10^6\}$ *forj* $\in [1, numDay]$	Expert knowledge	Diffuse

$\overline{Y}$ is the average value over all points and numDay, numJob, numStation, numEnv, numEvent are the number of time-series for, *Job*, *Station*, *Environment* and *Event*, respectively. N_+ denotes a truncated normal distribution restricted to positive values.

3. Results and discussion

3.1. Descriptive results

Overall, we obtained 24 time-series of particle number concentrations (PNC) measured in the PBZ. The 1st and 11th of November 2019 were bank holidays with no PNC measurements. The 9th and 23rd of October and 8th of November 2019 DISCmini failed or was misused, while the 6th of November 2019 PNC measurement only lasted 40 min and this day was thus discarded from further analysis. Besides, we obtained 7 stationary time-series measured inside the underground ticket counter of station “Corentin Cariou” (only for station agents) and 19 and 9 stationary time-series measured above the “Porte de la Villette” and “Gare de Lyon” stations, respectively.

The daily PNC distributions assessed in station agents’ PBZ were stable over two weeks (Fig. 1), contrasting with stationary PNC measurements inside the ticket counter, which varied significantly. Interestingly, the latter were generally above the interquartile range (IQR = Q1-Q3) of PBZ PNC values but also of the stationary outdoor records. The outdoor measured daily median PNC were lower than median PBZ PNC except once (on the 8/10/2019), and fluctuated over the two-week study period. Similarly, daily locomotive operator’s median PBZ PNC tended to be higher than the PNC recorded outdoor above the station “Porte de la Villette”. The depth of the platforms is 10 m at this station, and it was entirely renovated in 2002. However, due to its status as a former terminus, it has a particular configuration with four tracks, divided into two identical half-stations (one per direction) with two tracks framing an island platform under an elliptical vault. Moreover, it has five accesses divided into six entrance gates. These characteristics might explain the difference between locomotive operators’ BBZ and otdoor PNC levels, (i.e. the outdoor PNC was significantly higher lower than PNC in locomotive operator’s PBZ (IQR = 1365–9391 $\#/cm^3$), except on the 30th of October 2019). As expected, PNC measured in PBZ of security guards presented a large variability, given their larger intervention perimeter compared to other professionals. The highest PNC IQR registered in security guards’ PBZ was 5327–26,880 $\#/cm^3$ on the 29th of October. Generally, the PNC measured outdoor above “Gare de Lyon” station were within the upper interquartile boundary of the PBZ PNC (largest IQR = 13,991–26,269 $\#/cm^3$ the 12th of November 2019).

These descriptive results challenge the hypothesis that subway indoor UFP concentration is determined by outdoor UFP concentration (Chen et al. 2020). The highest PNC concentrations measured in PBZ of station agents, together with the PNC measured outdoor above their fixed workstation being lower than in two other outdoor locations and more than twice lower compared to indoor PNC, suggest that the latter is also determined by internal sources of UFP within subway that should be identified.

3.1.1. Activity logbooks context integration

Fig. 2 shows a time-series of PNC measurements along with the contextual information from the corresponding activity logbook. We chose the 21st of October as an example of a work-shift of a locomotive operator. This professional’s work-shift starts in the study room at “Porte de la Villette” (sampling room), and has two back and forth drives between the “Porte de la Villette” and “Villejuif-Louis Aragon” terminals. If not otherwise specified, the variable Environment was set to PBZ PNC inside the cabin during drives. The PNC variation is obvious whenever the environment changes, particularly during the drive along the line with its sequence of stations and between-station tunnels, and visible even at log10 scale. The shape of PNC in this illustrative time-series clearly requests a model supporting the non-stationarity autocorrelation while taking into account different fixed effect variables (*Station*, *Environment* and *Event*) and confirms the relevance of the Bayesian spline model (Equation (1)).

We observed that the first peak in PNC registered around 8:30 (98,459 $\#/cm^3$) when locomotive operator was walking to the train along the underground corridor. Similarly, another peak, at 11:41 (46,172 $\#/cm^3$) corresponds to the measurement outside of the cabin, at the “Villejuif-Louis Aragon” station platform. Finally, we observed that the locomotive operator opened his cabin window mostly when travelling towards Villejuif-Louis Aragon and less on the way back, thereby influencing the PNC level.

A descriptive summary of the PNC distribution per Station, Environment, Event, and their combination can be consulted at the Unisanté Research Data Repository (https://doi.org/10.16909/DATASET/26).

3.2. Bayesian modelling results

The fitting of the Bayesian spline model (Equation (1)) to the PBZ PNC time-series resulted in a good mixing behavior in Markov-chains. The model validity was supported by low Gelman and Rubin convergence diagnostic and autocorrelation. Furthermore, we found that modifying the prior distribution for different parameters did not impact

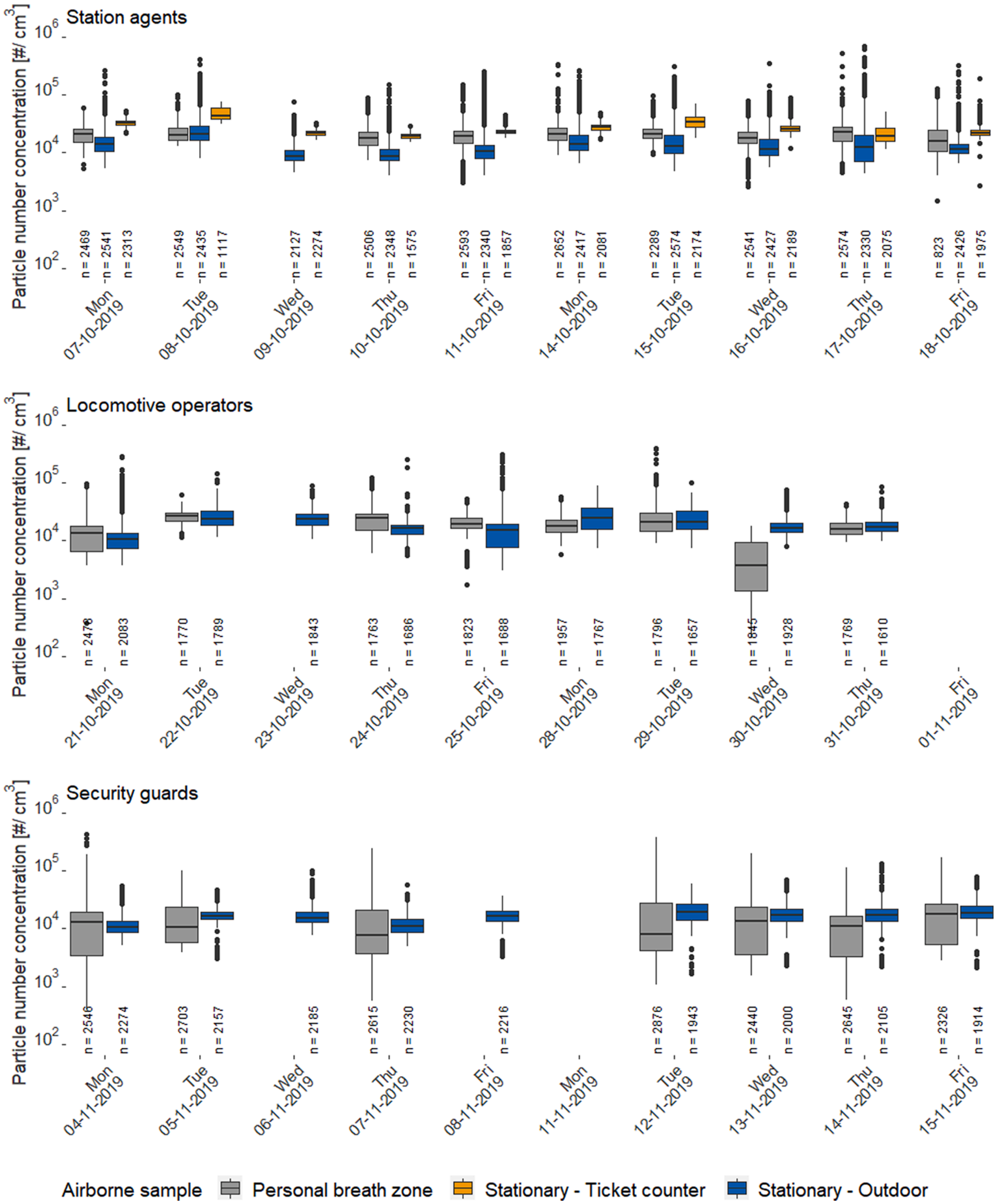

Fig. 1. Particulate Number Concentration (PNC) boxplots for different airborne samples. The airborne samples are the Personal breathing zone (PBZ), the one measured in the ticket counter in Corentin Cariou station and the outdoor samples measured above the station Porte de la Villette and Gare de Lyon for security guards only.

the estimation of the posterior distribution, thus demonstrating the robustness of the model. Fig. 3 shows that the prediction of the PNC by the Bayesian spline model overlaps the observed PNC, using the same working example (21st of October 2019 time-series). All estimated parameters of this model, including the posterior distributions of the coefficients for each examined effect are available at the Unisanté Research Data Repository (https://doi.org/10.16909/DATASET/26).

3.2.1. *Daily PNC background per job*

Station agents had the highest estimated PNC (GM = 17284.34 $\#/cm^3$), but the lowest between-day variation (GSD = 1.07). This latter was expected due to their fixed underground workstation and small between-day variation in their mobile activities. Similarly, for security guards the estimated PNC was stable over the working week (GSD = 1.11), but with a lower GM (10723.91 $\#/cm^3$). In contrast, we observed a surprisingly high between-day PNC variation in locomotive

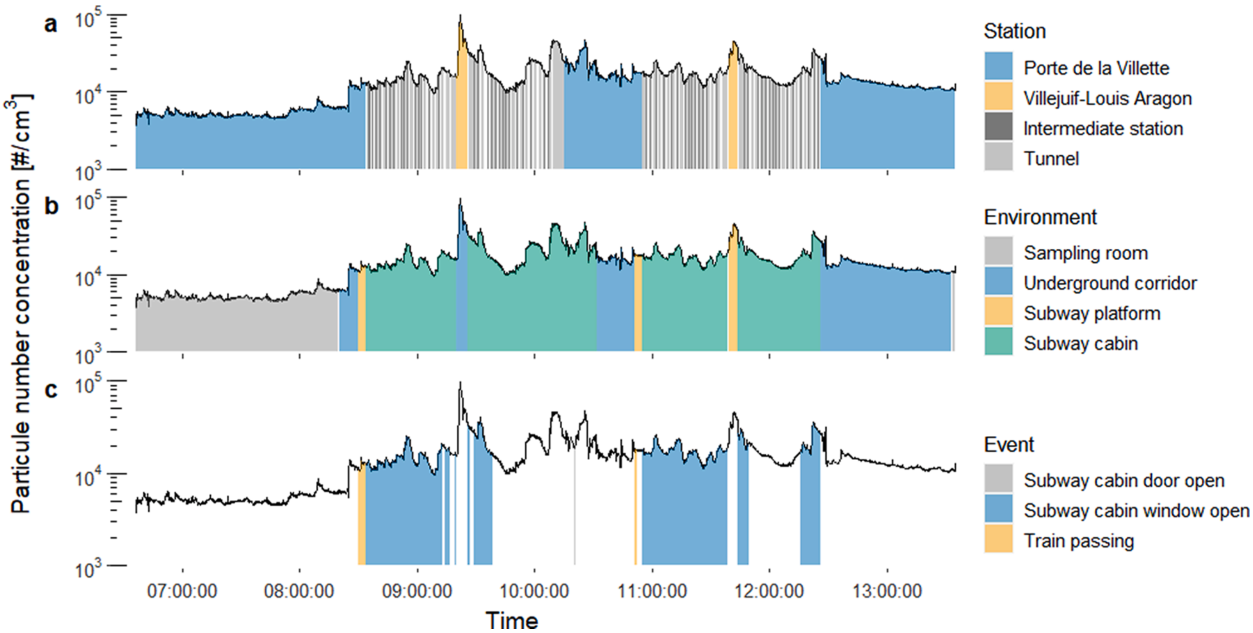

Fig. 2. Locomotive operator work-shift of the 21st of October 2019 and the corresponding personal breath zone particle number concentration. The PNC ribbon is coloured according to *Station* (a), *Environment* (b) and *Event* (c). In the first panel, the *Intermediate station* corresponds to stations in subway line 7 that were not displayed for the sake of clarity.

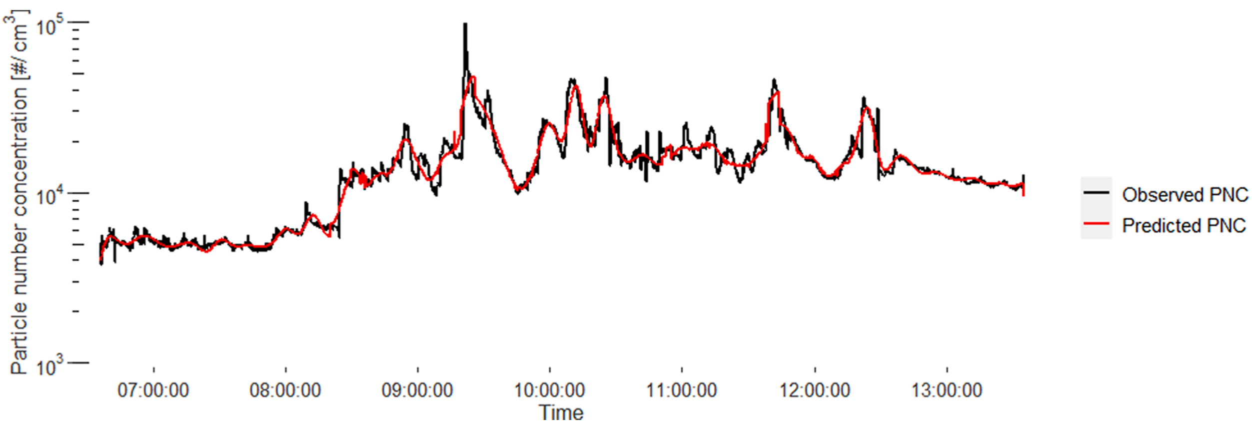

Fig. 3. Prediction of the Bayesian spline model. Visualization of the Bayesian spline model prediction (red) for the personal breath zone Particle number concentration (PNC) of the locomotive operator's work-shift of 21 October 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

operators (GSD = 1.71), and an intermediate average PNC 13197.38 #/cm^3, though its credible interval at 95% was much larger than in two other professionals (CI95% = 8603.72–20152.17). The outlying distribution of PNC from the 30th of October 2019 explains this result, as removing it from the dataset reduces the between-day PNC variation in locomotive operator. Nevertheless, removing this time-series did not affect the estimation of other parameters, thus, further demonstrating the robustness of the model.

3.2.2. *Effect of the station on the PNC*

Fig. 4a represents the posterior distribution of the *Station* coefficients in terms of fold change (10$^{\text{coefficient}}$) with respect to the reference (Porte de la Villette, observed PNC = 13933.09 #/cm^3) along the subway line 7.

Most coefficients credible intervals are above 1, indicating increase in PNC at most stations compared to reference. However, the magnitude of change is similar between stations and rarely greater than 10%. This is consistent with a weak between-station PNC variation documented in Viennese subway lines (Posselt et al. 2019). Conversely, Rech et al. reported that UFP number concentration varied widely among Barcelonese subway lines and stations (Reche et al. 2017). They found that lower train frequency and advanced ventilation setup correspond to the lowest PNC observed in the newest stations, while the highest PNC were measured in the oldest subway stations and was moderately correlated with the depth of each station. They also documented the influence of the station design on the outdoor particle emissions and concluded that for narrow platforms served by single-track tunnels, or by two rail tracks separated by a middle wall, it seems to strongly depend on the mechanical ventilation in the tunnel as the motion of the train is insufficient to maintain similar air quality (Reche et al. 2017). At four stations out of the 38 stations of line 7, we observed greater PNC in locomotive operators' PBZ compared with concentration measured at the reference station: at Villejuif-Louis Aragon (32.8%, CI95% = 1.254–1.407, observed PNC = 17368.75 #/cm^3), Villejuif-Léo Lagrange (8.7%, CI95% = 1.030–1.146, observed PNC = 14827.70 #/cm^3), Mairie d'Ivry (9.6%, CI95% = 1.056–1.137, observed PNC = 20350.44 #/cm^3), and

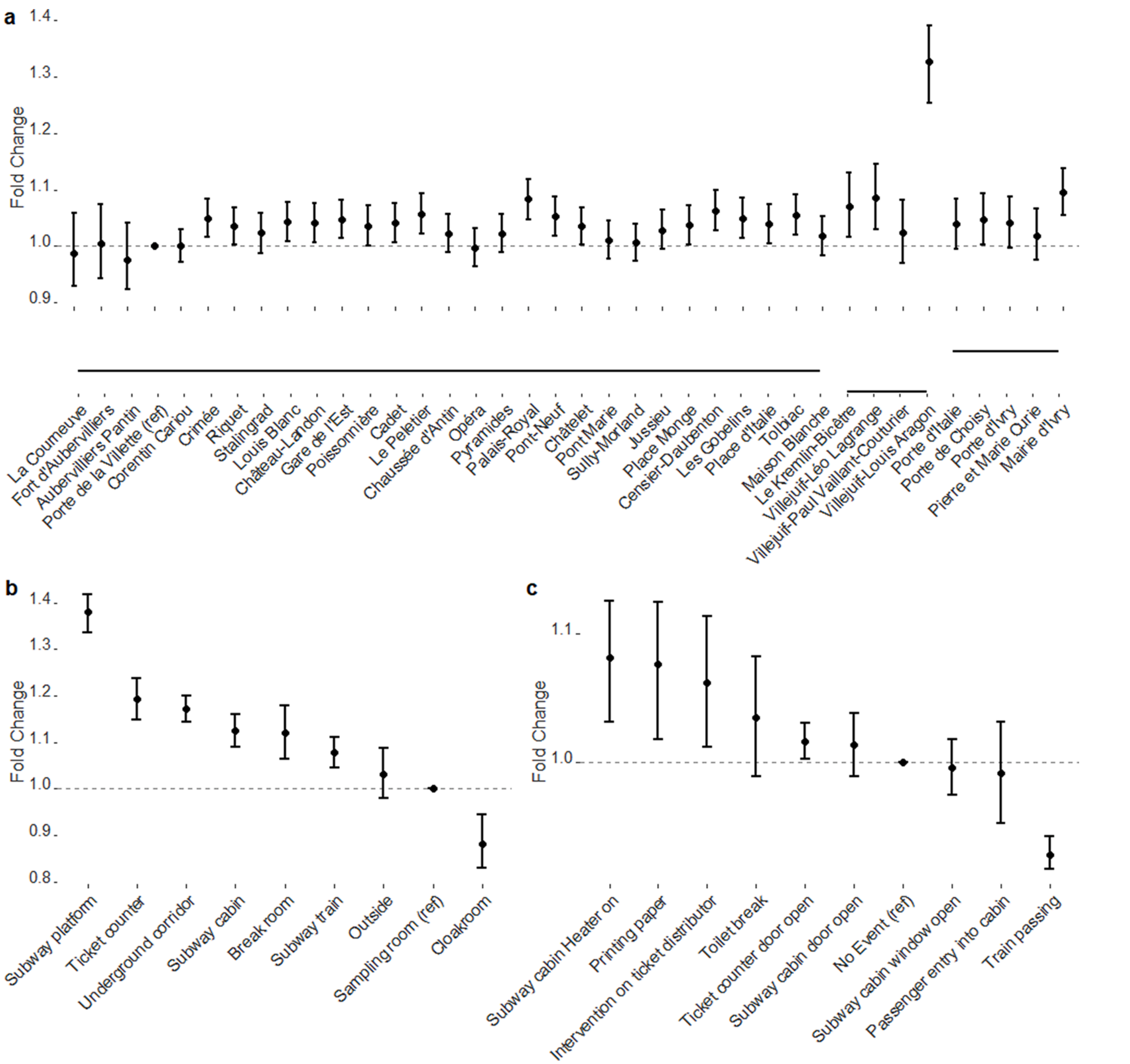

Fig. 4. Particle number concentration variation per stations in subway line 7 (a), environments (b) or events (c). The three panels represent the posterior distribution of the coefficient transformed as fold change ($10^{\text{coefficient}}$) for every categories of stations in subway line 7 (a), environments (b), and events (c). The bar is the 95% credible interval, and the point is the median of that distribution. The bottom sub-panel in panel (a) represent the subway line 7. The discontinuity shown at the "*Maison Blanche*"station corresponds to two embranchements, one towards "*Villejuif-Louis Aragon*" and the second one towards "*Mairie d'Ivry*". The reference category is noted with (ref).

Palais-Royal (8.3%, CI95% = 1.047–1.119, observed PNC = 15520.40 #/cm^3). To better understand these findings, we assessed the correlation between *Station's* coefficients and the station minimum altitude. We found a Pearson's correlation coefficient of 0.47, suggesting a positive and fair correlation, while the correlation between station median PNC and station minimum altitude was only 0.03. Regarding the ventilation, RATP reported an identical setup at these stations: the air enters through the gates, circulates along the corridors, then along the platforms and is evacuated by inter-tunnel extraction fans located closest to the concerned station. This ventilation system operates only if the fans are operational, but no data on the latter during the study period was available. Moreover RATP has not assessed the air flow within subway stations, which would enable investigation of ventilation's effect on PNC. A thorough description of station's characteristics is thus given here to circumvent this drawback.

The Villejuif-Louis Aragon station was opened in 1985. It is an important terminus of the line 7 although its configuration is standard with two platforms separated by the subway tracks and four entrance gates, unlike the other terminal stations. It is a very frequently used station, with 7,198,931 passenger entries registered in 2019. In fact, *Villejuif-Louis Aragon* is located near the intersection of the old national road 7 and two transverse roads. The annual average PM10 concentration in 2019 was 23 µg/m^3. The station is currently served by 7 bus lines, one tramway line and two night bus lines. However, by 2025, it should also house an underground station for line 15 of the Grand Paris Express, whose construction started in 2017. The molded walls and the cover slab of the future station were completed in 2018 and in 2019, the cover slab and the mole digging were made.

The station Villejuif-Léo Lagrange is located in the suburbs of Paris, in the commune of Villejuif and is served served by two bus lines. Its configuration is similar to *Villejuif-Louis Aragon* although it drains only 2,830,893 passengers. The annual average PM10 concentration registered above the station in 2019 was 19 μg/m^3.

The station Mairie d'Ivry is located in the commune of Ivry-sur-Seine and became operational in 1946. As a terminal station, it has three platforms with a side platform for arrival and a central platform for departure and two entrance gates. However it is less used by passengers than the *Villejuif-Louis Aragon* terminal; 3,074,561 passengers entered there in 2019. It is served by 4 bus lines and a regional train line. The annual average PM10 concentration registered above the station in 2019 was 21 μg/m^3.

The Palais-Royal station of the line 7 is curved and has platforms separated by the metro tracks located in the center and an elliptical arch. However, it is distinguished by the lower part of the pedestals being vertical rather than curved, and its platforms are slightly offset from each other. It has five entrance gates connected by corridors. One of them links the station to the Louvre museum and is 40 m long and 6 m wide and consists of twelve 1.6 m deep alcoves hosting a shopping gallery and public toilets. The station ranks 18th among metro stations for its ridership, with 9,592,920 passengers registered in 2019 and is served by 8 bus lines and two nigh bus lines. The annual average PM10 registered in 2019 was 22 μg/m^3.

Based on these data, we assume that outdoor air pollution (PM10) above stations tends to parallel the coefficients of these stations on PNC in PBZ of subway workers, essentially the locomotive operators. However, it does not explain the 30%-difference corresponding to the *Villejuif-Louis Aragon* station. In fact, the outdoor air above the Porte de la Villette station in 2019 was more polluted compared with the air pollution above the former, although this comparison is based on PM10 annual average concentrations. Therefore, it seems that construction works conducted at *Villejuif-Louis Aragon* station influences the level of particle concentration within the station, including UFP. The traditional configuration of the station despite its terminal location and the large number of passengers are likely additional determinants of the PNC results. For the other stations, the particularities identified in station design might explain the PNC levels observed.

We finally reexamined the raw activity logbook data and interviewed study technicians, to reveal that notification of the Locomotive operator's location inside his cabin was rarely reported and clearly mentioned only at 21 out of 38 stations within the line 7. However, as we had PBZ PNC measurements at many stations and in different station locations, including subway platforms and corridors visited by security guards, we assumed that these increases in PNC in PBZ of locomotive operators corresponded to PNC measured outside of subway cabin or when the cabin's doors were opened. This is particularly likely for PBZ PNC corresponding to *Villejuif-Louis Aragon* station, with the largest regression coefficient obtained. Indeed, besides its above-mentioned characteristics, this station is a terminus of line 7, where locomotive operator had to change the train and wait on the platform during the break before the next train departure. This is not the case for other line 7s terminals where locomotive operators remaine inside the cabin. Therefore, the PNC concentration is measured in the subway cabin and when walking across the platform before entering the cabin of another train, although this activity was notified neither as *Environment* nor as *Event*. Fig. 2 confirms this assumption. Moreover, this coefficient is in line with those estimated in security guards' PBZ when they intervened on the subway station platforms, even beyond line 7 (Unisanté Research Data Repository (https://doi.org/10.16909/DATASET/26). For intermediate stations, which which locomotive operators simply cross, the uncertainty on the *Environment* (inside the cabin) is much lower since the time table must be respected.

3.2.3. Effect of the Environment on the PNC

In a similar fashion, Fig. 4b displays the *Environment* coefficients in terms of fold-change with respect to the reference (Sampling room, observed PNC = 8940.86#/cm^3).

The distribution of the observed PNC within the studied environments varies to some extent but are within the distribution of PNC observed in the sampling room. Interestingly, when simultaneously considering other explicative variables (*Day*, *Station* and *Event*), the Bayesian spline model gave rise to *Environment* coefficients being associated with a large degree of PNC change when compared to the sampling room. Although this variable has some missing values and imprecision, the model still discriminates its effect on PNC.

The subway platform is the *Environment* associated with the largest PNC increase compared to the reference *Environment* (sampling room) (38.1%, CI95% = 1.335–1.428, observed PNC = 19247.38) followed by Ticket counter (19.2%, CI95% = 1.149–1.236, observed PNC = 21852.39 #/cm^3), Underground corridor (17.2%, CI95% = 1.149–1.236, observed PNC = 18284.59 #/cm^3), Subway cabin (12.5%, CI95% = 1.090–1.161, observed PNC = 16659.93 #/cm^3), Break room (12.1%, CI95% = 1.065–1.179, observed PNC = 9443.05 #/cm^3) and subway train (7.7%, CI95% = 1.044–1.111, observed PNC = 22464.28 #/cm^3). The Cloakroom is the only environment associated with a decrease in PNC (c12.2%, CI95% = 0.818–0.945, observed PNC = 3310.49 #/cm^3). Moreover, the credible interval of the outside *Environment* coefficient is predominantly positive (CI95% = 0.979–1.087) but passes through zero which conveys non-significance.

Interestingly, the *Environment* coefficient results suggest that the PNC tends to increase when getting closer to the underground subway tracks. Moreover, closed subway cabin and train environments exhibit lower PNC than subway tracks for instance. It is worth noting that this supports our interpretation of the Villejuif-Louis Aragon *Station* coefficient, not as indicating the most polluted station, but as an *Environment* misclassification in raw data, corroborated by the effects of all measurements taken together. Despite its inaccuracy for some Locomotive operators, the *Environment* variable could also explain why station agents are the most exposed to PNC. They occasionally perform inspection rounds at subway platforms or corridors, but mostly remain in the ticket counter at station concourse. The latter was reported as being the most polluted environment in some subways, though this finding is still debatable as other have found no significant differences in Viennese subway (Posselt et al. 2019) or even found the opposite in Seoul, Korea or Barcelona, Spain (Kim et al. 2017; Moreno et al. 2020). The suggested reason is the so-called "piston effect", created by the moving subway train, which removes the UFP from platforms towards station concourses (Wen et al. 2020). To further verify this, we need to consider also the events that might significantly change the PNC in different environments.

3.2.4. Effect of events on the PNC

Fig. 4c presents the *Event* coefficient in the same way by displaying the coefficient in terms of fold-change with respect to the reference (No event, observed PNC = 13910.58#/cm^3).

Here again, the PNC distribution for *Events* is largely within the distribution of PNC when no event was logged. Contrarily to the *Environment* coefficients, the *Event* coefficients have a relatively small magnitude of change. Turning on the subway cabin heater (8.2%, CI95% = 1.031–1.137, observed PNC = 23660.58 #/cm^3), printing paper (7.8%, CI95% = 1.018–1.139, observed PNC = 17215.85 #/cm^3) and intervening on the ticket distribution (6.2%, CI95% = 1.012–1.116, observed PNC = 18207.35 #/cm^3) are the three events associated with the largest increase in PNC. Furthermore, opening the ticket counter door is also associated with a small increase in PNC (1.6%, CI95% = 1.002–1.030, observed PNC = 22732.99 #/cm^3). The only event associated with a decrease in PNC was the train passage (−7.3%, CI95% = 0.914–0.941, observed PNC = 22186.39 #/cm^3). The other events were not associated with any significant PNC magnitude change as conveyed by their credible interval passing through zero.

The negative coefficient of the train passing event suggests that the train displaces some portion of the platform air with its particulate content, thus leaving place for a less polluted air. This event was registered when the participants were located on the subway platform, i.

e. the environment with the highest PNC. The literature reports that train frequency does not affect the concentration of particle smaller than 540 nm (Loxham et al. 2020), but the data are scarce. The non-significant finding that the PNC inside the subway cabin varies depending on whether the door or window is opened is likely to be due to the low statistical power with very few measurements corresponding to both conditions and to the large uncertainty, as theses events reporting appears less systematic. In light of the published data, which are again very limited (Posselt et al. 2019), and concentrations measured at different locations (*Environment* variable), opening the cabin door or window should increase the PNC in the cabin.

Other events such as *Toilet break* or *Passenger entry into the cabin* were not associated with any change in PNC. This was expected as the latter was linked with the subway cabin door opening, while the former incorporated into the change of environment (mostly underground corridors). Finally, we did not analyze the effect of a smoking passenger on the PNC on the subway platform, as this sporadic event happened to only one participant.

3.3. Methodological considerations

There are currently no practical field recommendations to specifically assess environmental and occupational UFP exposure (Audignon-Durand et al. 2021) but real-time measurements, though still exploratory, seem to advantageously capture some UFP-relevant exposure metrics. However, the question of how to analyze and interpret real-time exposure measurement results is important to raise, as data become more and more available, with no consensus on the most appropriate statistics. Simpler methods rely on graphical representation (Bekker et al. 2014; Brouwer et al. 2004; Demou et al. 2008; Evans et al. 2010) or time-weighted average approach (Dodson et al. 2007) and others have used regression models (Deffner et al. 2016; Persoons et al. 2011). While enabling result interpretation, these approaches often disregard non-stationarity behaviors in the studied time-series which lead to inappropriate or incomplete analysis. One class of models which explicitly tackles this problem is the autocorrelated integrated moving average (ARIMA) time-series modeling approach (Klein Entink et al. 2011; Pfefferkorn et al. 2010). However, it lacks the flexibility in specifying independent variables and does not allow for the combination of several independent time series. Bayesian spline methods have appeared more recently and have shown great potential to model real-time exposure data within a Bayesian framework while controlling for autocorrelation.

In the context of this study, the Bayesian spline method was well suited to model real-time PNC for three reasons. First, the B-spline term successfully represented the non-stationarity of the time-series that we could adjust by adapting the knot placement interval (see methods); Second, the model was able to simultaneously consider multiple fixed and random variables and highlight their independent effect on PNC; and finally, parameter estimation in terms of posterior distribution enabled estimating the fixed effect coefficients and their uncertainty in an easily interpretable manner.

3.4. Study limitations and strenghts

This study contains a number of limitations. First, although electrical mobility analysers (e.g., Scanning mobility particle sizer (SMPS), or low-pressure cascade impactors (e.g., Electrical low-pressure impactor (ELPI) are reference instruments for real-time measurement of PNC and average particle size, this is not yet the case for DiSCmini devices - the Handheld Nanoparticle Counter that was that used in this study. However, the assessment of the DiSCmini performance showed that despite a slight tendency to underestimate particle sizes, all particle diameters and number concentrations measured were in the same order of magnitude as reference data (Bau and Witschger 2015). The DISCmini producer declared that its accuracy is $\pm$ 30% in size and $\pm$ 5 #/cm^2 in number concentration, therefore we did not analyse size distribution, but only PNC for all particles smaller than 300 nm. As we applied a mixed model, the measurement errors were comprised in the residual error of the model. The latter being less than 20%, we can conclude that the measurement error was negligible.

Second, we might not have fully characterized the PNC variation in every combination of *Stations*, *Environment* and *Events* because of a lack of measurements. For example, the majority of subway stations in line 7 were only visited within the subway cabin and even if the window was open, we might not have been have been able to grasp the complexity of PNC variations in those stations. Equally important, some environments were predominantly measured in a single subway station and might not reflect the PNC observed in the same environment at other subway stations. Interestingly, this could be true for the subway platform *Environment,* which was mostly measured in stations “Porte de la Villette” and “Gare de Lyon” because every morning, after preparation, professionals waited for their subway on these station platforms. Moreover, it is worth questioning whether these results are generalizable to other subway stations that have different topologies and designs, are maintained differently, or are equipped with ventilation or glass walls separating the tracks from the platform, which were found to affect air composition (Grana et al. 2017; Posselt et al. 2019; Strasser et al. 2018). Furthermore, some studies have found that PNC significantly varies seasonally (Deffner et al. 2016; Reche et al. 2017), which we do not take into account here, as all data were collected during the Fall of 2019.

In the course of this analysis, we observed that the real-time PNC measurement expressed more than what was captured by the activity logbooks. Some variation in PNC did not seem to be explained by any recorded contextual information. More importantly, we also observed that variation in PNC measurements were not always aligned with the information extracted from the activity logbooks. This was particularly true for locomotive operators, as they mostly remained in the subway cabin and the few environment changes seemed inaccurate timewise or even missing. Though the degree of these inaccuracies is difficult to assess, this could impact the estimation of some factors such as *Environment* or *Station.* Considering an additional interaction term between these variables in the model could also be interesting to explore in a further study, though requiring longer computing time and more data. In particular, the measurement of air-flow rate and of train frequency type series, along with the cleaning schedule recording, the daily passenger flow and the subway features would be important to assess as determinants of PNC within subway stations. Though all subways circulating on the Line 7 are identical by conception, their interior and exterior renovation may interfere with UFP infiltration especially through the doors (Chen et al. 2020). The state of renovation of the subways was not assessed in this study, neither the UFP elemental composition nor size, which would allow differentiating the sources of UFP emission.

Finally, there might be some level of imprecision between the time recorded in the activity logbooks and the time it affected the PNC in the corresponding time-series. This might significantly impact the estimation of shorter events which could lead to an underestimation of their effect. As it was the first study in the Parisian subway using a longitudinal design for feasibility assessment purpose, the drawbacks notified here can be mitigated in the next studies. For instance, they allow a revision of the activity logbook and a formalization of the guidelines for their completeness. Our results inform the company occupational physicians and hygienists about the PNC distribution along line 7 and beyond, thus providing comparative exposure estimates between jobs, week days, stations, locations, and some events commonly occurring during the work-shifts. These data will be further used along with other exposure measurements (PM2.5 and PM10) to document the exposure of workers and passengers and perform a health risks assessment.

3.5. Generalization to subway users

Despite the above-mentioned limitations, the results presented here offer an overview of ultrafine PNC in several stations and environments of the Parisian subway, the most popularly used transport of the French capital. The PNC were measured in PBZ of subway professionals, but are also relevant for passengers, if integrated within appropriate exposure duration. The UFP number concentration values measured in PBZ were within the range of values reported within subway stations in Barcelona, Boston, London, Prague, Stockholm, Vienna, and Taipei (Cheng et al. 2009; Cusack et al. 2015; Gustafsson et al. 2012; Levy et al. 2002; Midander et al. 2012; Moreno et al. 2015; Posselt et al. 2019), but lower than in Helsinki (Aarnio et al. 2005). However the stationary indoor PNC measured in our study within the information desk were at the upper limit of these values. From this perspective, the fact that the highest PNC were measured on the subway platform should not be worrisome, as the subway waiting time for the commuters is usually short (a few minutes). However, it underlines the interest of ventilation or walls separating the tracks from the platform, whose effects on PNC deserve further assessment. In contrast, subway users might wait for a long time in the station concourses, by the ticket or information counters, or walking through the underground corridors, which were found to have UFP exposure concerns. This exposure can be even longer during rush hours, in times of annual or monthly subscription renewal, and for users with less mobility. As for station agents primarily staying in those environments, it might be useful to equip the ticket counter with air conditioners or filters. Fortunately, PNC was found to be lower inside the subway train where commuters spend most of their commuting time. These statements are particularly true for stations that were found to have the highest ultrafine PNC.

4. Conclusion

We directly measured ultrafine particle number concentration (PNC) during work-shifts on a daily basis over two weeks for each of three types of subway professionals. The results showed that PNC measured in the personal breath zone (PBZ) of Parisian subway workers are in the range of values reported previously within subway stations in most European cities. To analyze these time-series we applied an innovative Bayesian spline method. The application of this method to investigate the individual exposure to UFP in the underground subway setting, while accounting for contextual information, was shown feasible. This approach was shown informative for documenting the magnitude and variability of UFP exposure according to the week day, job, subway station, environment, and events, and for understanding the UFP exposure determinants in view of its further monitoring and risk assessment. We observed that PBZ PNC levels mostly varied according to the occupation but also according to subway stations and events that occurred during their work-shift. Station agents, which had their work station primarily in the ticket counter were the most UFP-exposed professionals when compared to locomotive operators and security guards. However, the most exposed environments were subway station platforms, underground corridors, and ticket counters. From the interpretation of available data on stations' configuration and topology, age, air pollution above station, and rank of passenger traffic, it seems that particle infiltration/emission from outdoor into the subway station is not the only source of UFP within the subway environment. Due to the shortage of information on the air-flow rate within stations, ventilation setups, and subway characteristics on one side, and the elemental and size analysis of ultrafine particles on the other side, our model was not adjusted for these parameters. However with additional data available, this precise time-series analysis method should provide robust results on UFP exposure determinants and sources and help to reduce them.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

Supplementary File 1: link to the BUGS model file: *Suppl_file_1_BUGS_model.R.* Additional results and data are available at the **Unisanté Research Data Repository (DOI: 10.16909/DATASET/26.)**, including *Suppl_file_2_Summary_airborne_sample.xlsx, Suppl_file_3_Summary_PNC_for_Day_Station_Environment_Event.xlsx, and Suppl_file_4_Bayesian_Spline_coefficient.xlsx*. Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2021.106773.

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