A Stochastic Approach to Estimate Uncertainty in Pollutant Concentrations in an Archetypal Chilean House

Constanza Molina[1], Benjamin Jones[*1], Michael Kent[1] and Ian P Hall[2]

*1 Department of Architecture and Built Environment, University of Nottingham Nottingham, NG7 2UH, UK. *Corresponding author: benjamin.jones@nottingham.ac.uk*

2 Division of Respiratory Medicine, School of Medicine, University of Nottingham Nottingham, NG7 2UH, UK.

ABSTRACT

As policy makers strive to reduce the energy demands of houses by reducing infiltration rates, an unintended consequence could be a fall in the quality of indoor air with corresponding negative health effects at a population scale. Measuring pollutant concentrations *in-situ* is difficult, expensive, invasive, and time consuming and so the simulation of indoor conditions, using representative models of a housing stock, is a more common method of investigation.
The AIVC asserts that fine particulate matter ($PM_{2.5}$) from indoor sources poses the greatest risk to the health of occupants of dwellings. Accordingly, this paper uses a stochastic modelling approach to assess the relative influence of several sources of $PM_{2.5}$ in the housing stock of Santiago, Chile. A single multi-zone archetype is modelled in CONTAM where model inputs are randomly varied between known limits to produce a distribution of mean $PM_{2.5}$ concentrations over the heating season weighted by the time spent in the kitchen, living rooms, and bedrooms ($\overline{\mathrm{PM}}_{2.5}$). Ambient air is only exchanged by infiltration. Three sources of $PM_{2.5}$ are investigated: a heater commonly found in Chile that burns wood or paraffin, the cooking of meals, and the toasting of bread. A range of data sources are used to inform environmental, geometric, physical, and pollutant data inputs, and a sensitivity analysis is used to rank them by their influence on the model output.
The median $\overline{\mathrm{PM}}_{2.5}$ in Santiago houses over the heating season is predicted to be 107μg/m^3: 90% credible intervals [5, 883μg/m^3]. The WHO annual mean average threshold is exceeded in 77% of houses and so they could require remediation measures to protect occupant health. Cooking is shown to be the most important model input and so at-source interventions, such as a range hood, may be the most appropriate.
The modelling approach can now be expanded to consider a more archetypes and pollutant sources, to give a better indication of the uncertainty in pollutant concentrations found in Chilean houses. The outputs can be used to inform future standards and guidelines for Chilean houses that simultaneously focus on energy demand reduction and occupant health.

KEYWORDS

Indoor air quality, Indoor sources, Modelling, Sensitivity analysis, Fine particulate matter

1 INTRODUCTION

The disability-adjusted life year (DALY) is a measure the disease burden in a population, expressed as the sum of the number of years lost due to morbidity and mortality. In 2016, 7% of global DALYs where attributed to air pollution exposure (Gakidou *et al.,* 2017). In Chile,

air pollution exposure was ranked as the 10th greatest risk to morbidity and mortality in 2016, with 4% of DALYs attributed (IHME, 2017).
The Commission of Social Determinants of Health states that home and work conditions are two of many social determinants of health (WHO, 2009). People spend around 70% of their time in their homes where they are exposed to a range of pollutants amongst which $PM_{2.5}$ is considered the most important (AIVC, 2016). Cooking is a predominant source, but in Chile, it is common to heat houses using stoves (Narváez *et al.*, 2016) and so these are a parochial source of $PM_{2.5}$ worthy of investigation. The most effective mitigation strategy against occupant exposure to indoor pollutants is *source control*, but this is not always possible. Therefore, it is essential to quantify the contribution of known emitters to indoor pollutant concentrations and to test remediation measures, such as trickle vents and cooker hoods. This is particularly important in the heating season when windows tend to be closed to save energy. Then, in the absence of mechanical systems, infiltration is the primary source of ambient air required for pollutant dilution.
Measuring pollutant concentrations *in-situ* is difficult, expensive, invasive, and time consuming and so the simulation of changes in concentrations of indoor pollutants over time using representative models is a common method of investigation. However, there is significant uncertainty in the inputs to – and the outputs from – any model, and so it must be quantified using appropriate methods, such as a probabilistic sampling framework and sensitivity analyses (see Das *et al.*, 2014 and Jones *et al.*, 2015). These methods produce distributions of predictions that show their likelihoods and can be used to inform stakeholders and guide housing policies.
The Chilean housing stock comprises >6m houses, with 37% concentrated in the Santiago Metropolitan region. There are neither previous analyses of the Chilean housing stock nor any significant modelling programs. Accordingly, this paper seeks to start this process by applying a stochastic approach to model the pollutant concentrations in the Santiago housing stock during the heating season. Here, a single pollutant type and dwelling archetype are used to demonstrate the approach, which will be used in the future to model any number of species and sources in any stock of Chilean dwellings. A framework is applied so that the results show uncertainty in pollutant concentrations, and parameters that have the greatest influence on those results are identified to inform future data gathering. Section 2 identifies the dwelling archetype, the stochastic modelling and sensitivity analysis methods, and sources of data. Section 3 presents the results of the simulations and discussed preliminary findings. And, in Section 4 a sensitivity analysis is used to show those parameters that most influence model output.

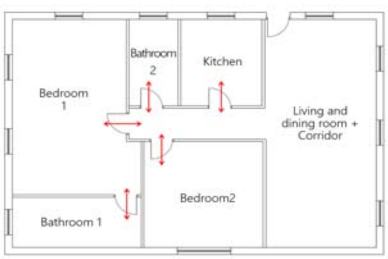
2 METHODS

The Chilean housing stock is currently being documented and a database containing the information required to model representative houses, known as *archetypes*, defined in our previous work (Molina *et al.*, 2017). The archetypes were defined by geometry, building size, dwelling type and construction period, values for the floor area, and the number of storeys and number of occupants assigned to each of them. In this database, sets of 7, 19 and 46 archetypes were found to represent 32%, 58% and 83% of the national stock, respectively. Nevertheless, data is still limited for some parameters and so their uncertainty and relationships must to be considered. In this section the archetype chosen for analysis is described, suitable sources of input data are identified, and a method of obtaining distributions is given. Finally, a methodology to test the dependence of the model's outputs on its inputs is identified.

2.1 Modelling the archetype in CONTAM program

We previously identified the most common archetype in the Chilean housing stock (Molina *et al.*, 2017), which represents 9% of both the national and Santiago housing stocks; see Figure 1 (left). It is a detached single storey house with 6 rooms, with two bedrooms and two bathrooms, a self-contained kitchen, and a living-dining room. All rooms are connected to a common family room so that the living room, dining room and corridor can be consider a single volume, to which all other rooms are connected via doors.

A generic model is developed accounting for the rooms and their characteristics using CONTAM; see Figure 1 (right). CONTAM (Dols & Polidoro, 2015) is a multizone indoor air quality and ventilation analysis tool that models airflows between multiple indoor zones, and between them and the external environment. It has been extensively validated by comparing its performance against other models, measurements in a controlled environments, and measurements in field studies (Das *et al.*, 2014). The volumes, floor areas, and number of the rooms are constant, but the airflow path parameters are all variables and are amended using bespoke software to manipulate the CONTAM project file before a model is simulated, following (Das *et al.*, 2014); see Section 2.1.1. By systematically varying each CONTAM input and running multiple simulations, the models are used to quantify uncertainty; see Section 2.3. In order to generate a single concentration value for each house, the concentrations in the kitchen, bedroom, and living room are weighted by time spent in each zone using a 10:45:45 ratio, following Hamilton *et al.* (2015), to give a room weighted indoor $PM_{2.5}$ concentration averaged over the heating season, $\overline{\mathrm{PM}}_{2.5}$ (µg/m^3).



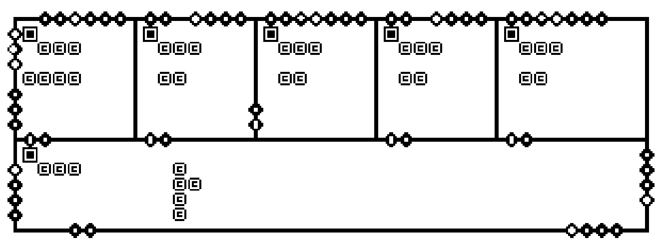


Figure 1: House layout (left) and CONTAM model (right).

2.1.1 Airflow Paths

The rooms are represented by a multi-zone model connected by airflow paths, such as windows and doors and air leakage paths. The indoor spaces are predominantly naturally ventilated and so the dominant drivers are the wind and temperature differences between zones and the ambient environment. Extractor fans are located in the kitchen and bathrooms and operate when cooking or showering, respectively. Windows and doors are modelled by one-way power laws; see Das *et al.* (2014). All facades are assumed to be uniformly porous, following Jones *et al.* (2013), and so air leakage paths are placed at the floor, ceiling, and the centre height of each wall. To simulate a "worse-case" scenario, windows are considered to be closed during the winter season. Internal doors are modelled using a rectangular section with a discharge coefficient of 0.78 when closed and using a two-way two-opening flow model when open. Bedroom doors are open except at night, and kitchen door is closed except when cooking. Party walls are assumed to be impermeable.

The only vent in the models is in the kitchen, an opening for combustion gases. The section of the opening is 100cm^2, which complies with the current standard, DS Nº 66 (SEC, 2007), for rooms with a cooker range hood.

2.2 Inputs and Sources of Data

Data inputs to CONTAM describe the local environmental and physical properties of the house, and the contaminant sources and sinks. A range of data sources are used to inform these inputs, such as Chilean national surveys (INE, 2003; CASEN, 2015), Chilean building permit database (INE, 2016), and local weather data (Meteotest, 2017). Other sources from the literature describe cooking and common Chilean heaters (CENMA, 2011). A summary of input values and sources of information are shown in Table 2.

2.2.1 Environmental Inputs

Census data (INE, 2003) describes the national housing stock and gives a location. The nearest weather station to each archetype is selected from the Meteonorm meteorological database using Meteonorm 7 software (Meteotest, 2017). A weather file containing the data for a statistically representative typical year at Santiago is created and converted into the CONTAM format using bespoke software.

The wind speed is scaled according to the local terrain and dwelling height (see Section 2.2.2) using a standard power law formula (BSI, 1991). The four BSI terrain types and the local wind pressure shielding coefficients (see Section 2.2.2) of Deru and Burns (2002) are mapped to the six BSI terrain types with format BSI{Deru & Burns}: city{very heavy}; urban{heavy}; suburban{heavy}; rural{moderate}; country with scattered wind breaks{light}.

CONTAM is not a thermal model and so the internal air temperature must be specified. There are no reported measurements of indoor air temperature for Chilean houses in the literature. In the absence of knowledge, we follow a distribution of temperatures based on UK houses (Jones *et al.*, 2015) and test the influence of this parameter on predictions in Section 4.

The heating season is between June 21st and September 21st.

2.2.2 Geometric and Physical Inputs

Building geometry parameters are given in Table 2. Air leakage paths are modelled using a power law whose coefficient is informed by measurements of air leakage reported as an Air Permeability, Q_{50} (m^3/h/m^2). There are only a limited number of Q_{50} measurements in Chilean houses. A national research project (Citec UBB & Decon UC, 2013) measured Q_{50} in 187 houses using the blower door test; see Table 1 and Figure 2. The data does not conform to any known distribution and so inverse cumulative distribution functions are developed using Piecewise Cubic Hermite Interpolating Polynomials, following Jones *et al.* (2015). The dimensionless flow exponent, n, is not reported by Citec UBB & Decon UC (2013) and so is assumed to be a Gaussian random variable with a mean μ =0.65 and standard deviation σ =0.08, following Sherman & Dickerhoff (1998) and Jones *et al.* (2015).

Wind pressure coefficients are defined for the vertical surfaces. The algorithm of Swami & Chandra (1987) gives a normalized average wind pressure coefficient for long-walled low-rise dwellings and is a function of the angle of incidence of the wind (for wind direction see Section 2.2.1), local sheltering, and the block aspect ratio (Table 2). The coefficient is then scaled to account for local shielding (Section 2.2.1).

2.2.3 Pollutant Inputs

In this study, changes to indoor $PM_{2.5}$ concentrations are attributed to cooking and the use of a heater commonly found in Chilean houses. They are generally fuelled by kerosene, paraffin, LPG, propane, and butane gases, and wood, although data is only available for wood and paraffin. CONTAM requires an emission rate and a deposition rate, and because the sources are not used constantly, an emission rate schedule is also required.

External sources of $PM_{2.5}$ are not considered. Indoor $PM_{2.5}$ emissions from cooking activities are modelled using three studies that report μ and σ for the emission rates of several different cooking methods and meal types (Dacunto *et al.*, 2013; He *et al.*, 2004; O'Leary & Jones, 2017). A cumulative distribution was generated by sampling values of emission rates following those distributions with equal probability. A bootstrapping technique was used to increase the sample size until its μ and σ differed less than 0.01%, giving $\mu = 2.66$ mg/min and $\sigma = 4.94$mg/min. A second cooking source was taken from O'Leary & Jones (2017) who present a distibution of emission rate from the cooking of toast with $\mu = 0.22$ mg/min and $\sigma = 0.06$mg/min. Although it is a specific cooking method, the data is robust and specifically developed for stochastic analysis, making it worthy of investigation. The cooking is sampled from an inverse cumulative distribution functions and toasting emission sources is a Gaussian random variable. All cooking occurs in the kitchen.

The $PM_{2.5}$ deposition rates onto surfaces can also be considered a Gaussian random variable with $\mu = 0.39h^{-1}$ and $\sigma = 0.16h^{-1}$, which have been widely used; see Hamilton *et al.* (2015), Das *et al.* (2014), and Milner *et al.* (2014).

The CASEN (National Socio-Economic Characterisation) survey (CASEN, 2015) data gives information on the type of heating system, and fuel used (where a system is present) by region. There are six common types of heaters that burn gas (no emissions), paraffin and wood whose $PM_{2.5}$ emission rates have been measured by CENMA (2011). Therefore, the probability of presence of a heater can be estimated, and the emission rate is a constant determined from the fuel type and measurements. The heating time follows the same schedule every day, with a constant start time of 7am. The heater is located in the living room.

Table 1: Air Permeability at 50Pa, Q_{50}($m^3/h/m^2$), and air change rate at 50Pa, N_{50} (h^{-1}).
(Citec UBB & Decon UC, 2013) n=187.

	Min	**Max**	**Median**	**Mean**	**SD**
Q_{50} [$m^3/s/m^2$]	1.3	37	**5.7**	7.6	6.38
N_{50} [h^{-1}]	1.6	44.6	5.0	7.81	7.81

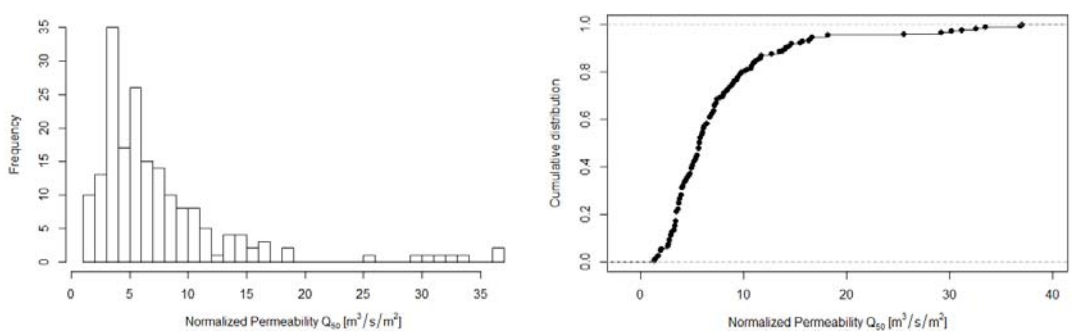


Figure 2: Left: Air leakage @50Pa.
Right: empirical CDF of Q_{50} data. (Data source: Citec UBB & Decon UC, 2013)

Table 2: Environmental, geometric, physical and source-related inputs, and their variability in these simulations.

Input	Unit	Range Value or PDF assumed	Data or source of information
Geometric and physical inputs			
Ceiling Height	m	2.4	Chilean building code.
Floor area ; Volume	m^2 ; m^3	86.6 ; 207.8	*f(archetype).* Aggregated data from INE (2016).
Permeable surface area	m^2	205.1	*f(archetype).* Floor is considered as solid.
Relative North	º	*U*[0,359]	
Wind Speed at dwelling, $\boldsymbol{u}$	m/s		*f(Dwelling location, wind speed at weather station)*
Internal Temperature, $\boldsymbol{T_{int}}$	ºC	*N*(21.5,2.5)	Jones *et al.* (2015)
Block Aspect ratio (Width:Depth)	-	*U*(0.1,0.99)	
Air Permeability, $\boldsymbol{Q_{50}}$	$m^3/h/m^2$	eCDF* shown above	Citec UBB & Decon UC (2013).
Airflow exponent, $\boldsymbol{n}$	-	*N*(0.651,0.77)	Sherman & Dickerhoff (1998).
Environmental inputs			
Geographic Region	-	Metropolitan region	-
Dwelling location	-		*f(Urban : rural*) ratio. Obtained from location data in CENSUS 2002 (INE, 2003), Variable 5.1.
Weather file	-	Santiago	*f(coordinates of the capital region, coordinates of the monitoring station).* Data obtained from Meteonorm software.
Heater type	-	Wood, paraffin, gas, no fuel.	*f(Region, fuel type)* Fuel type used for heating. The proportion of the stock using each heater type is assumed from a national survey. CASEN 2015 question v35b (CASEN, 2015).
Heating hours	h	15.25	*f(Weather file, internal temperature)*
Source- related inputs			
Emission rate from Heaters	mg/min	Type 1 = 0mg/min (gas); Type 2 = 0mg/min (gas); Type 3 = 0.29mg/min (Paraffin); Type 4 = 0.14mg/min (Paraffin); Type 5 = 0.15mg/min (Paraffin); Type 6 = 0.05mg/min (Wood); Type 7 = None.	*f*(Heater type). CENMA (2011). According to the type of heater.
Emission rate from cooking meals	mg/min	eCDF*	He *et al.* (2004), Dacunto *et al.* (2013) and O'Leary & Jones (2017a)
Toasting bread	mg/min	*N*(0.22,0.06)	Unpublished data (O'Leary, 2018)
$PM_{2.5}$ Deposition Rate	h^{-1}	*N*(0.39±0.16)	Ozkaynak *et al.* (1996)

*Empirical cumulative distribution CDF.

2.3 Stochastic Sampling Method

The sampling method follows that described in Das *et al.* (2014) and Jones *et al.* (2015). There are eight direct inputs to the CONTAM model: 10 sets of these are chosen at a time using a Latin Hypercube. Each set is applied to CONTAM to predict $\overline{PM}_{2.5}$ (see Section 2.1) during the heating season. The total sample size increases incrementally according to the number of sets, which is chosen to minimize calculation time. After each set of predictions are made, the mean (μ) and standard deviation (σ) of the whole sample is calculated and used to decide if a stopping criterion has been met. The total number of samples is deemed adequate if the change in μ and σ from one set of 10 samples to the next is less than 0.1%. The stopping criterion is chosen to reflect the lower limit of accuracy of a good Indoor Air Quality (IAQ) sensor.

2.4 Sensitivity Analysis Methods

A sensitivity analysis is used to test the dependence of $\overline{\mathrm{PM}}_{2.5}$ on the inputs to the CONTAM model. Here we follow the method of Jones *et al.* (2015) and a full description is found in the reference. The method tests for linearity (Kendall's τ, Pearson's r product moment, linear regression), monotonic (Spearman's ρ rank correlation coefficient, rank-transformed standardized variables), and non-monotonic (Kolmogorov-Smirnov) relationships between the inputs and outputs. The Kruskal-Wallis quantile tests are not included here for brevity. All inputs are ranked according to the magnitude of the resultant correlation or regression coefficient. A fundamental assumption is that all tested inputs are independent of each other, and so any that are themselves correlated are combined.

3 RESULTS AND DISCUSSION

Table 3: Summary of $\overline{\mathrm{PM}}_{2.5}$.

Statistical measure	$\overline{\mathbf{PM}}_{2.5}$ **[µg/m³]**
Mean, $\boldsymbol{\mu}$	223
Stand. Dev., $\boldsymbol{\sigma}$	324
Minimum	1
5th centile	5
25th	29
Median	107
75th	253
95th	883
Maximum	2,837

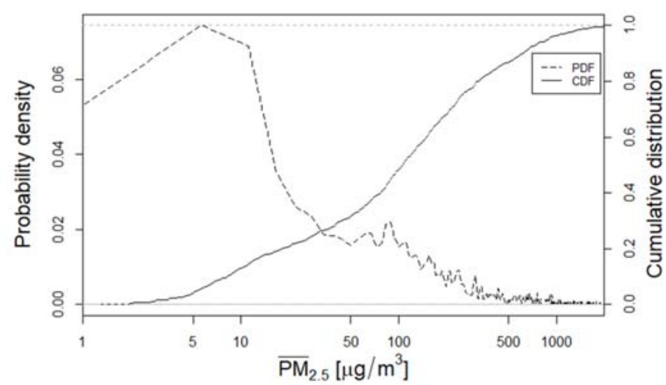


Figure 3: Predicted probability density and cumulative distribution for weighted concentrations averaged over the heating season, $\overline{\mathrm{PM}}_{2.5}$.

Convergence was reached with n =1,070 samples (107 sets of 10 samples), giving a sample μ =223µg/m^3 and σ =324µg/m^3; see Table 4. This is double the number of samples required by Das *et al.* (2014), but their convergence criterion was a less rigorous 0.2% change in μ and σ. Following their criteria would have led to a similar number of samples.

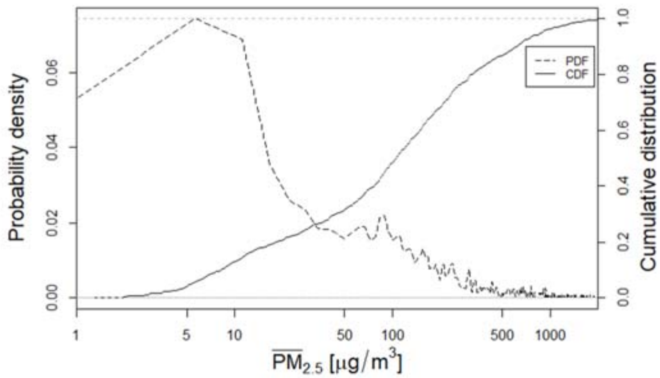


Figure 3: Predicted probability density and cumulative distribution for weighted concentrations averaged over the heating season, $\overline{\mathrm{PM}}_{2.5}$.

shows the predicted Probability Density function (PDF) and Cumulative Distribution Function (CDF) of $\overline{\mathrm{PM}}_{2.5}$ in the Santiago archetype during the heating season. It shows that the WHO annual and 24-hour mean limits of 10µg/m^3 and 25µg/m^3 for $PM_{2.5}$ concentrations are exceeded in 87% and 77% of the houses, respectively. However, the WHO thresholds and $\overline{\mathrm{PM}}_{2.5}$ are not identical statistics and so a direct comparison is not possible. Nevertheless, Figure 3 suggests that a majority of this archetype are insufficiently ventilated to adequately dilute the $PM_{2.5}$. Therefore, additional purpose provided ventilation is required to mitigate the health risks associated with acute and chronic exposures to indoor $PM_{2.5}$. Although the values of $\overline{\mathrm{PM}}_{2.5}$ are weighted by the mean concentrations in 3 rooms, they give an indication of the concentrations that people are exposed to in the house during the heating season. However, occupants who spend more time in a room where a source is located will have a greater risk of exposure. Furthermore, these concentrations are most likely to affect those who spend the most time at home, particularly the elderly and children, and their carers. Finally, we assume prescriptive occupancy habits, and so if they differ, such as by leaving the kitchen door open during cooking, the distribution of $\overline{\mathrm{PM}}_{2.5}$ may also change. The ratios used to weight $\overline{\mathrm{PM}}_{2.5}$ are based on expected occupancy of different rooms, but other ratios would give different $\overline{\mathrm{PM}}_{2.5}$. They could be improved by understanding occupant behaviour in Chilean houses.

There is a need to compare the predictions against measurements made *in-situ*. There is a program that aims to monitor IAQ parameters (including $PM_{2.5}$) in around 300 houses, sponsored by the Chilean government. This data has not yet been processed, but could be used to corroborate the assertions made here in the future.

Figure 3 is a useful tool that Chilean policy makers could use to make informed decisions about appropriate ventilation rates in dwellings, although it would be better to have modelled more archetypes in a wide range of locations to give greater confidence in the predictions; this archetype only represents 9% of the Santiago stock. It may also be important to consider other pollutant types. Therefore, this method will be scaled up to consider these variables in the near future.

Distributions of air change rates are not presented here for brevity, although they are required for comparison against known rules-of-thumb and can be used to estimate heating loads, house and stock energy demands, running costs, and carbon emissions. These outputs will be added to the post processing framework in the near future.

3.1 Sensitivity Analysis

Table 4: Sensitivity of outputs to inputs, rank of key model inputs. 1 is the highest rank.
Bold indicates a statistical significance correlation or coefficient at 5% level of confidence ($p\leq 0.05$).

Input	Kendall's τ rank	Pearson's r Rank	Spearman's ρ rank	Linear regression rank	Kolmogorov-Smirnov rank
Block Aspect ratio	9	6	9	6	7
Orientation [º]	10	9	10	9	10
Permeability Q_{50} [$m^3/h/m^2$]	**4**	**4**	**4**	**4**	**4**
Flow exponent *n*	**5**	**5**	**5**	5	6
Deposition rate PM [h^{-1}]	**3**	**2**	**3**	**2**	**3**
Emission rate, toast [$\mu g/m^3$]	8	8	8	8	9
Emission rate, cooking [$\mu g/m^3$]	**1**	**1**	**1**	**1**	**1**
Emission rate, heater [$\mu g/m^3$]	**2**	**3**	**2**	**3**	**2**
Wind Speed at dwelling [m/s]	7	7	7	7	8
$T_{int} - T_{ext}$ [ºC]	6	10	6	10	5

The assertions made here are based on the assumptions made in Section 2. Accordingly, the sensitivity analysis described in Section 2.4 is used to determine the relative importance of inputs to CONTAM. All of the inputs are perturbed simultaneously by the Latin Hypercube sampling method and so any interactions between them are accounted for. The ranks of each model input are given in Table 5 where a value of 1 is considered to be the most important because it is the analysis with the highest observed correlation or regression coefficient.

Table 5 shows that the cooking emission rate is ranked the most influential input by all tests, and that the heater emission and deposition rates, and the air permeability are also important. The relationships identified between these inputs and outputs were statistically significant ($p \leq 0.05$). Therefore, efforts should be made to improve the quality of these inputs, particularly the air permeability for which there is little empirical data; see Section 2.2.2. It also indicates the relative importance of each emission source, suggesting that the most important is cooking, and that the heater is more important than toasting. Accordingly, source control and additional ventilation, such as high efficiency range hoods, should be applied to cooking first.

Section 2.2.1 showed that there is no knowledge of T_{int} in Chilean houses and so it is, perhaps, reassuring that no statistically significant ($p > 0.05$) relationships were found for any of the tests. We note that this disagrees with the findings of Das *et al.* (2014) who rank T_{int} as an important variable. The reason for the discrepancy is not clear, but may be related to the use of a window in their CONTAM models.

4 CONCLUSIONS

This paper presents a stochastic method for predicting distributions of weighted indoor $PM_{2.5}$ concentrations, $\overline{\mathrm{PM}}_{2.5}$ ($\mu g/m^3$), during heating hours. It is applied to a single archetype that represents 9% of the Santiago housing stock where fresh air is supplied solely by infiltration. It is predicted that $\overline{\mathrm{PM}}_{2.5}$ is greater than the WHO annual average 77% of the time and so this type of house could require remediation measures to protect occupant health.

Three sources of $PM_{2.5}$ are investigated: a heater commonly found in Chile that burns wood or paraffin, the cooking of meals, and the toasting of bread. A sensitivity analysis shows that $\overline{\mathrm{PM}}_{2.5}$ is most influenced by the cooking of meals, followed by the heater, and then the toast. Because it is unreasonable to expect people to cook outside in winter, additional purpose-provided ventilation, such as a range hood, is required to remove particles at their source or to dilute them once well mixed. To mitigate against heater emissions, ventilation is required in the short term, but safer methods of heating, such as those that use hot water or electricity, may be needed in the long term.

The sensitivity analysis also highlighted data shortages in key areas, such as air permeability and internal air temperatures. Future data gathering should be focussed in these areas.
The framework developed here can be applied to model other archetypes and represent a greater proportion of the Chilean housing stock. It can also incorporate other pollutant sources so that their relative importance can be compared, and future weather data can be applied to investigate the effects of climate change on dwelling energy demand and occupant health. The post processing framework will be improved to include air change rates used to estimate energy demands, running costs, and carbon emissions at stock level. Together, these outputs can be used by stakeholders and policy makers to inform future standards and guidelines for Chilean houses that simultaneously focus on energy demand reduction and occupant health.

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