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Technical report on environmental burden of disease

Deliverable B5.1

December 2018

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Technical report on environmental burden of disease

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CONTENTS

1. EXECUTIVE SUMMARY

Action B5 aims at estimating the health impacts of particulate matter air pollution using disease burden methods (BoD) in school children.

Methods were drafted using data for Kuopio, Finland, and tested first for Lisbon. This report presents also tentative BoD results for other target cities, based on European Environmental Agency (EEA) data on exposure levels.

Disease burden in school children were quantified using upper respiratory infections and calculating estimates for sick days at school, school absenteeism, and hospitalizations.

BoD methods developed in Action B5 will be combined with exposure estimates from Action B3 in the LIFE Index-Air Tool and will be used in Action B6 to calculate project estimates for all target cities.

Difficulties in learning, school absenteeism and lower academic performance impacts are important consequences of the exposures. Use of sick days makes it possible to relate the impacts to school absenteeism. Further development of the method could allow relating the school absenteeism to school performance.

2. INTRODUCTION

Burden of disease is a comparable metric to measure health losses including both premature mortality and morbidity. A lot of the development was conducted in the 1990's in collaboration between World Health Organization (WHO) and World Bank (e.g. Murray et al., 1996). Burden of disease is measured in disability adjusted life years (DALY), which is calculated as the sum of years of life lost due to premature mortality (YLL) and disability weighted years lived with disabilities (YLD):

(1) DALY = YLL + YLD

As such, burden of disease measures complete losses caused by mortality and illnesses. However, further analysis is warranted for the part of this burden that can be attributed to environmental (or other) risk factors. Such approach was actively developed as part of the World Health Organization Environmental Burden of Disease (EBD) –programme (Pruss-Üstün et al., 2003). Population attributable fraction can be estimated from standard epidemiological data on relative risks (RR) and applied on background burden of disease. Burden of disease can be expressed in YLL, YLD, DALYs, incidence or prevalence rates, or in number of deaths.

In air pollution health impact assessments environmental burden of disease methodology has become a de facto international standard by WHO and more recently Institute of Health Metrics and Evaluation work (e.g. Forounzanfar et al., 2015, Cohen et al. 2017). The global assessments focus on natural cause mortality (e.g. Heroux et al., 2015) or chronic diseases such as ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD) and lung cancer (LC). Similarly, the toxicological risk assessment methods that have preceded burden of disease methods (e.g. EPA 2009) look at cancer risks. All of these endpoints are substantial public health issues also in the developed world, but affecting mostly the ageing population (Lehtomäki et al., 2018).

Health impacts attributable to PM2.5 exposure in Finland were estimated according to WHO HRAPIE working group recommendations (Heroux et al 2018; Lehtomäki et al. 2018). When attributable burden was divided into age groups, the impacts for aging population were clearly the highest (Figure 1). The attributable burden for 5-14 years old children was 32 DALY/a in Finland. As seen in the figure, these mainstream methods are not well suited to characterize disease burden in children due to the dominant role of years of life lost due to premature mortality.

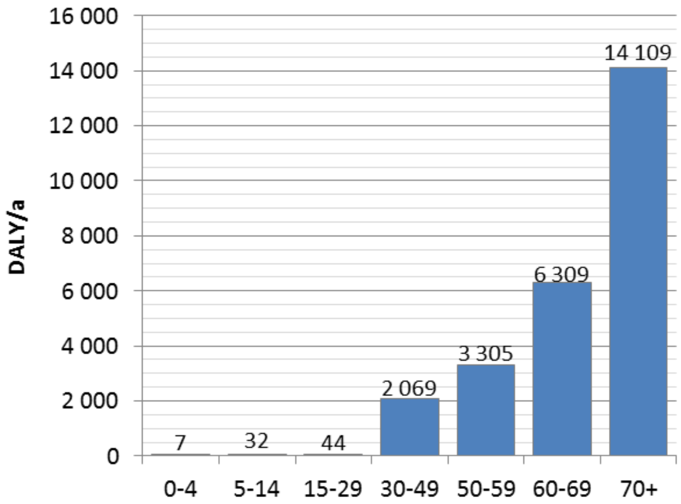


Figure 1 Disability adjusted life years (DALYs) attributable to PM2.5 exposure in Finland in 2015 by age groups (based on Lehtomäki et al. 2018).

The evidence for these impacts is growing (e.g. MacNaughton et al., 2017; Aucejo and Romano, 2016; Grineski et al., 2015). Therefore, a method to estimate disease burden in sick days was developed.

The aim of Action B5 is to apply disease burden methods for quantifying the health impacts of school children attributable to air pollution. Specific objectives were to

(i) collect WHO Global Health Estimates on upper respiratory infections and other air pollution related diseases for the target countries and calculate corresponding age-adjusted estimates for the target cities.

(ii) calculate estimates of sick days in three categories (mild: sick at school or other daily activities; medium: sick at home; and hospitalizations) for all target cities.

(iii) create population attributable fraction estimates based on a review of scientific literature and the tentative exposure estimates, and

(iv) calculate sick days attributable to air pollution.

In addition, we discuss the impacts of school absenteeism and sick at school days on academic performance of the children.

3. MATERIAL AND METHODS

3.1. ENVIRONMENTAL BURDEN OF DISEASE -METHOD

In the B5 Burden of Disease module the health impacts of particulate matter are quantified using population attributable fraction and disease burden methods (Hänninen & Knol, 2011, method 1A). The environmental burden of disease (EBOD) is calculated using equation (1):

$$EBOD = PAF\ x\ BBoD \tag{1}$$

Population attributable fraction (PAF) (2) can be estimated using relative risks at prevailing exposure levels (RR_E) and fraction of the population exposed (f).

$$\text{PAF} = \frac{\text{f} \times (RR_E - 1)}{\text{f} \times (RR_E - 1) + 1} \tag{2}$$

in which f is the percentage of the exposed population in the whole target population. RR_E is the relative risk of the population at the prevailing exposure level, calculated as

$$RR_E = RR_1^E \tag{3}$$

in which RR_1 is the relative risk estimate per unit of exposure and E is the exposure in the population level

3.2. POPULATION HEALTH CHARACTERISTICS

There is evidence of air pollution exposure causing several health effects on children. Those effects include adverse birth outcomes, infant mortality, neurodevelopmental disorders, childhood obesity, lung function, acute respiratory infections, asthma, otitis media and childhood cancers (WHO, 2018).

Basic health endpoints were based on the recommendations by WHO HRAPIE working group (table 1) (Heroux et al. 2015). The recommendations included classification of the concentrations-response functions into A and B classes, A being more reliable than B. In addition, the pollutant-outcome pairs which are possible to sum up together were marked with an asterisk (*).

Table 1. Relative risk (RR) estimates with confidence intervals for $PM_{2.5}$ and PM_{10} (based on Heroux et al., 2015).

Pollutant	Health Endpoint	Ages	RR Per 10 μg/m³ (95% CI)	a
$PM_{2.5}$	Natural mortality	>30 year	1.062 (1.040–1.083)	A*
	CVDs (hospital admissions)	all	1.0091 (1.0017–1.0166)	A*
	Respiratory (hospital admissions)	all	1.0190 (0.9982–1.0402)	A*
PM_{10}	Infant mortality	1–12 month	1.04 (1.02–1.07)	B*
	Chronic bronchitis (children)	6–12 year	1.08 (0.98–1.19)	B*
	Chronic bronchitis (adults)	>18 year	1.117 (1.040–1.189)	B*
	Asthma symptoms (children)	5–19 year	1.028 (1.006–1.051)	B*

[a] Additivity category, see Heroux et al. (2015) for definition.

We did literature searches for additional relative risks. Even though several pollutant related health outcomes are reported, many studies lack estimates of relative risk which would enable the use in health impact calculations. Additional set of relative risk functions derived from literature is presented in the Annex 1.

MacNaughton et al. (2017) found that 1 $\mu g/m^3$ increase in $PM_{2.5}$ during the academic year increased chronic absenteeism by 1.58 % (p value < 0.0001). School absenteeism is related to lower academic performance (Aucejo and Romano, 2016). Grineski et al. (2015) found that increase in hazardous air pollutants was associated with decrease in students' grade point averages. There is also emerging evidence for associations between air pollution exposure and infants born small for gestational age (SGA) (WHO, 2018). SGA has been linked to poorer school performance (Lindström et al., 2017). Further development of the method could include looking taking into account school absenteeism impacts on school performance.

Liu et al. (2017) conducted a meta-analysis of cohort studies looking at the exposure to ambient PM2.5 and the risk of respiratory tract diseases. They identified 1,126 articles from which 35 were included in the meta-analysis. The pooled relative risk estimates presented significant increases for children in wheezing, cough and lower respiratory illness.

Li et al. (2018) studied the association between air pollution exposure and upper respiratory tract infection in (URTI) in hospital outpatients aged 0-14 in Hefei, China. In this time series study data was collected between 1 January 2014 and 31 December 2015. They found that short-term exposure to PM10, PM2.5, SO_2, NO_2 and CO were associated with increased risk of URTI. Relative risk estimates were reported for several lags.

Anenberg et al. (2018) estimated the number of asthma emergency room visits and new asthma cases attributable to fine particulate matter (PM2.5), ozone, and nitrogen dioxide concentrations worldwide. They searched for meta-analysis of epidemiological studies looking at the relation between air pollution exposure and asthma, finding 10 meta-analysis on short-term exposure and six meta-analysis on long-term exposure to $PM_{2.5}$ and NO_2.

We used background disease burden data for 2015 by World Health Organization (WHO, 2018). This data is reported in country level. Disease burden data is shared in seven age groups: 0-4, 5-14, 15-29, 30-49, 50-59, 60-69 and 70+ years old. In this work we focus on 5-14 years old children.

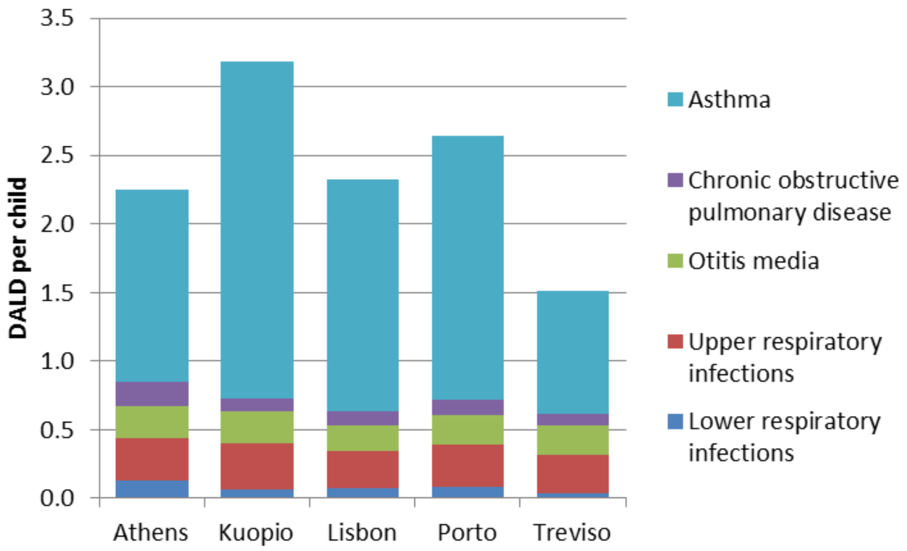


Figure 2 Background health in the target cities for 5-14 years old children described in disability adjusted life days (DALD) per child.

Population data were collected for the target cities and countries for 2015 except for Greece for which the data were for 2011. The studied cities varied clearly in the number of population, smallest city being Kuopio with 116,900 inhabitants, while Athens metropolitan area being the largest with 3,754,000 inhabitants (Table 2).

Table 2 Population in the studied cities by age groups. Share of the country's population in the studied city shown in the brackets.

Age group	Athens metropolitan	Kuopio	Lisbon metropolitan	Porto	Treviso
0-4	184 700 (34%)	6 026 (2.1%)	145 600 (33%)	8 910 (2.0%)	41 500 (1.6%)
5-14	337 900 (33%)	11 605 (1.9%)	300 800 (29%)	17 620 (1.7%)	90 570 (1.6%)
15-29	672 200 (35%)	25 020 (2.6%)	428 000 (26%)	28 900 (1.7%)	129 500 (1.4%)
30-49	1 198 000 (37%)	27 720 (2.0%)	820 200 (27%)	54 160 (1.8%)	263 400 (1.5%)
50-59	496 300 (36%)	15 820 (2.1%)	362 000 (25%)	32 140 (2.2%)	127 600 (1.5%)
60-69	382 600 (34%)	15 770 (2.1%)	345 100 (28%)	32 520 (2.6%)	100 800 (1.4%)
70+	482 400 (30%)	14 960 (2.0%)	409 200 (27%)	42 160 (2.8%)	134 000 (1.4%)
Total	3 754 000 (35%)	116 900 (2.1%)	2 811 000 (27%)	216 400 (2.9%)	887 300 (1.5%)

3.3. SICK DAYS AND SCHOOL ABSENTEEISM

Sick days are calculated for a whole year. Year is divided into school days, weekends and holidays (Figure 3). When looking at the school absenteeism, it is necessary to take into account the number of school days in a year.

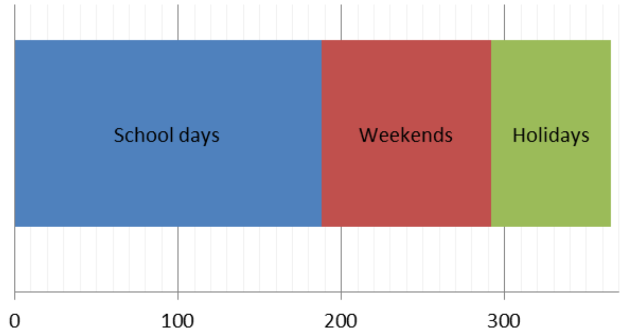


Figure 3 Division of a year into school days, weekends and holidays. Number of school days varies somewhat between countries.

Number of school days per year in primary school varied between the studied countries from 177 (Greece) to 200 (Italy) days in primary school (Table 3).

Table 3 Duration of primary and lower secondary school in the studied countries (based on OECD, 2018).

Country	Primary school			Lower secondary school		
	Starting age	Number of grades	School days per year	Starting age	Number of grades	School days per year
Finland	7	6	188	13	3	188
Greece	6	6	177	12	3	166
Italy	6	5	200	11	3	200
Portugal	6	6	180	12	3	178

Data related to school absenteeism are scarce. However, for Finland TEAviisari (2015) reported total and illness related absenteeism in primary school in academic year 2014-2015. Average absenteeism was on average 33.0 h/pupil from which the illness related absenteeism was 23.7 h/pupil.

Global health estimates (GHE) background disease burden data for 2015 was scaled into city level by doing an age adjustment. City level adjustment was done by multiplying the country level data with the share of the population in city (4):

$$BBoD_{city} = BBoD_{country} \times \frac{Pop_{city}}{Pop_{country}} \tag{4}$$

where BBoD is background disease burden data and Pop is population. This adjustment was done for all seven age groups. This is a coarse way to estimate the population in different age groups in cities while there might not be such data available in city level. This method though is not capable of taking into account differences in morbidity/mortality between regions.

Special focus of this work was on school children (5-14 years old). Their background disease burden was scaled into units which are easier to interpret. WHO reported disability weights for several health conditions (WHO, 2017). Disability weights are given based on the severity of the condition. It can vary from 0 (complete health) to 1 (death). Several health conditions are given three severity levels which we utilized in DALY scaling.

Upper respiratory infections were used as an endpoint for the sick day calculations. The relative risk function (RR: 1.0038 per 10 µg/m^3) was from Li et al. (2018). Upper respiratory infections (URI) were divided into three categories given by WHO (Table 4). We used expert judgement in defining the average length of the condition. This judgement is adjusted for Finland and for other countries the parameters could be readjusted.

Table 4 Disability weights (DW) for infectious diseases (WHO, 2017) and an average duration of the condition in days (expert judgement).

Health state	DW (%)	Duration (d)	Symptom descriptions
mild	0.60	5	Wheezing and cough once a month, no difficulty with daily activities.
moderate	5.1	6	Wheezing and cough once a week, some difficulties with daily activities.
severe	13	0.05	Wheezing, cough and shortness of breath more than twice a week, difficulty in daily activities and sleep

For the scaling we calculated the burden of disease using equation (5):

$$\text{Sick days per person per year} = \text{PAF} \times (L_1 + L_2 + L_3) \qquad (5)$$

Where PAF is the population attributable fraction and L is the length of the condition L_1 being mild, L_2 moderate and L_3 severe sick days.

It was assumed that during the mild symptom days children can still go to school. Moderate and severe symptoms days were assumed to lead to school absenteeism. Those were calculated for the school children in Kuopio using equation (5):

$$\text{Absenteeism (d/a)} = L_2 \times n + L_3 \times n \times \frac{\text{School days}}{365} \qquad (6)$$

N is the number of pupils in Kuopio (11,000). In primary schools in Finland there are 188 and in Portugal 180 school days per year (OECD 2018).

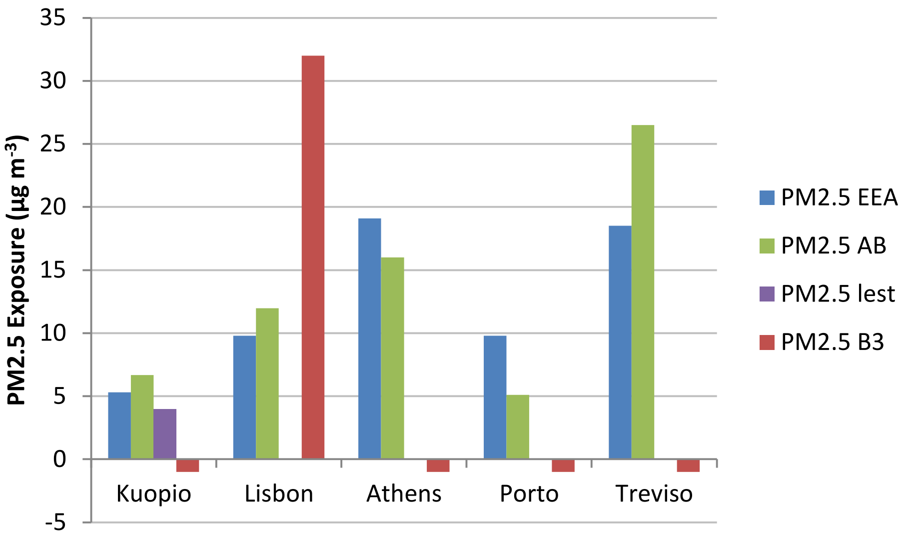
4. RESULTS

4.1. EXPOSURE ESTIMATES

Exposures are estimated in Action B3 and will be provided by respective module in the LIFE Index-Air Tool. While the exposure modelling in B3 is currently ongoing and only tentative value for Lisbon in 2015 was available (Figure 4), we used the air quality database from Action B2 values collected from Air Base ("$PM_{2.5}$ AB" in the Figure) and European Environmental Agency population weighted national values for each country for comparison and demonstration of the burden of disease methodology.

Especially the B3 estimate for Lisbon was substantially higher than the Air Base and Portuguese national exposures. The Air Base estimates are slightly higher than national values in Kuopio, Lisbon and Treviso and lower in Athens and Oporto. In Kuopio we have also a national estimate (4 µg m^{-3}) which is actually slightly lower than the national population weighted average (5 µg m^{-3}).

These exposure values will be cross-evaluated and updated accordingly as part of the Tool implementation process in 2019.



Negative values (-1) indicate currently missing data.
EEA: National population weighted outdoor concentrations
AB: Airbase monitoring stations in the target city; annual average
Iest: local estimate; in Kuopio: BATMAN estimate from SILAM model
B3: tentative estimate from INDEX AIR Action B3

Figure 4. Currently available tentative $PM_{2.5}$ exposure levels for target cities in 2015.

4.2. SICK DAYS AND SCHOOL ABSENTEEISM

The WHO-method (Heroux et al., 2015) was used to calculate overall burden of disease in school children (5-14 year) in Kuopio by age-standardizing national estimates (Lehtomäki et al., 2018), resulting circa 2 % of the national estimate (0.6 DALY/a). As the national exposure values for Kuopio are only 80% of the national population weighted average, we assume that the true value would be slightly lower.

To create a more relevant and realistic picture of the burden affecting these children we developed a novel approach to estimate sick days at school and school absenteeism days (Figure 5).

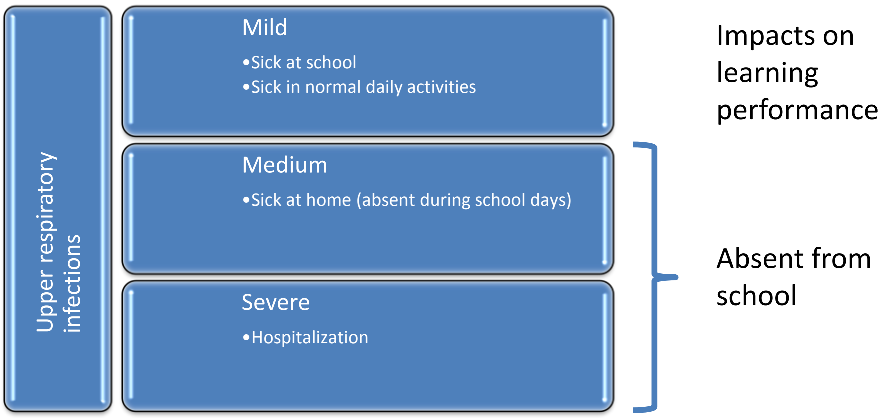


Figure 5.Conceptual model for school absenteeism and academic performance developed in Action B5.

The model is based on World Health Organization Global Health Estimates for upper respiratory infections and respective disability weights for three severity categories defined here. Model accounts for the number of national school days during the calendar year and assumes that the sick days are evenly distributed across school year, weekends and holidays. Hospitalization days and sick at home days are both accounted in estimation of absenteeism. The top-down three category model was evaluated against the expert judgment.

The model was used to calculate first sick days in the three categories in each city, compared WHO GHE disability weighted against the age-adjusted overall WHO estimate (results ranging from 92% in Kuopio to 116% in Lisbon, other target cities residing in between). Then the air pollution attributable burden was calculated using PAF-approach. The number of attributable sick days range from 20 days per 1000 children in 2015 in Kuopio to ca. 95 sick days in Athens and 90 days in Treviso. Mild sick days are dominant in all cities, followed by sick days at home and very small fraction of hospitalization days.

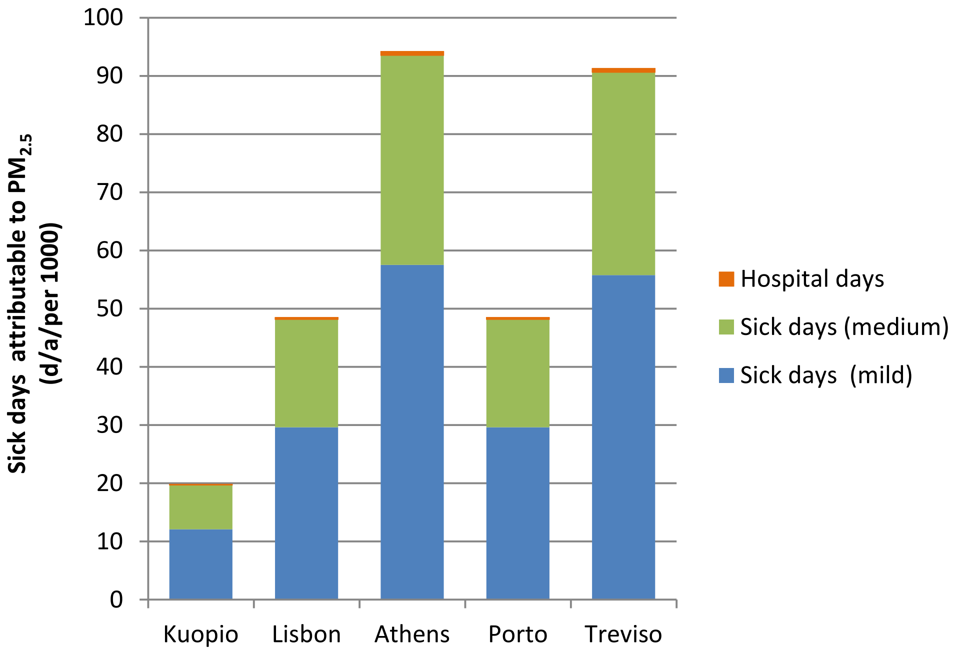


Figure 6.Estimated number of sick days, by severity, attributed to $PM_{2.5}$ in the target cities per thousand children in 5-14 year olds.

Numerical results are summarized in Table 5.

Table 5 School days related to upper respiratory infections attributable to $PM_{2.5}$ exposure in Kuopio per year and per person per year. Mild symptom days were assumed to not lead to absenteeism like moderate and severe days.

	Kuopio	Lisbon	Athens	Porto	Treviso
Persons (5-14 years)	11 605	300 804	337 886	17 619	90 570
Exposure (µg m^{-3})	5.3	9.8	19.1	9.8	18.5
Attributable fraction (%)	0.15 %	0.37 %	0.72 %	0.37 %	0.70 %
Attributable sick days	230	14 595	31 841	855	8 269
Attributable absenteeism days	46	2 802	6 011	164	1 764
Attributable hospitalization days	2	111	243	7	63

4.3. MODEL EVALUATION

The three-category upper respiratory infections model was evaluated by comparing the resulting disability weighted burden, calculated using expert judgment episode durations and WHO disability weights against the WHO GHE source data. Comparison showed that using the duration parameters estimated based on Finnish situation fits relatively well also the other cities (Figure 7).ytt7ne

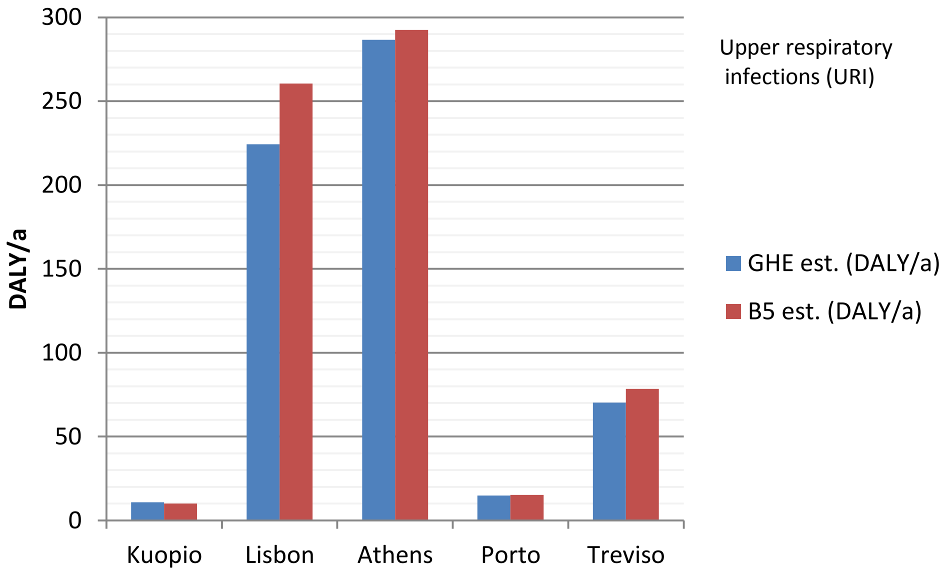


Figure 7.Evaluation of the duration parameters (8/5/0.1 days per person per year) against WHO source data for upper respiratory infections.

5. DISCUSSION

This is the final draft of the Deliverable D5.1 circulated for internal feedback and updates related to inputs from the subsequent actions.

Current tentative numerical estimates presented are based on national population weighted exposure values for each target city provided by European Environmental Agency. These exposure values will be replaced by correct values for each target city, school, district etc. as applicable in the LIFE Index-Air Tool. The national values are used here to demonstrate the burden of disease methodology and to give an indication of type and magnitude of the impacts expected.

The model is partly based on expert judgment parameters tentatively defined for the Finnish and Kuopio conditions, including national statistics on school absenteeism hours, school day duration etc. The coordinating institute provided some national statistics for Portugal, applied here for Lisbon and Porto. Corresponding national and local values can be inserted for the other target cities as soon as becoming available. Especially the characteristics for upper respiratory infection episodes per patient (pupil) were defined using top-down modelling approach. The model allows to adjust these parameters, too.

6. CONCLUSIONS

The present Deliverable describes the methodology and needed input data for disease burden modelling. Calculations are demonstrated for Kuopio and Lisbon. In addition to basic burden of disease modelling, this report includes methodology for calculating sick days as well. Sick days are divided into three categories according to severity of the symptoms. This division enables estimating attributable school absenteeism days. Further development could enable considering school absenteeism related changes in school performance.

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ANNEX 1 – EPIDEMIOLOGICAL DATA

We conducted a narrative review of scientific studies to create an overview of health risks in children that are related to fine particle exposures. Some identified studies are summarized in Table A1.1.

Table A1.1. Narrative review of $PM_{2.5}$ related risks in children.

Health outcome	Age	Relative risk			per unit (µg/m^3)	Other information	Source
		central	lower	upper			
Chronic absenteeism		1.0158			1		MacNaughton et al. 2017
Acute LRI	3-17	1.32	1.2	1.44	10	0-27 days	Horne et al. 2018
Childhood asthma		1.03	1.01	1.05	1		Khreis et al. 2017
Pneumonia	< 18	1.018	1.005	1.031	10	Daily mean	Nhung et al. 2017
URTI	0-14	1.0038	1.0017	1.006	10		Li et al. 2018
Asthma	all	1.07	0.99	1.16		Pooled estimate 15 studies	Liu et al. 2017
Wheezing	all	1.07	1.02	1.13		Pooled estimate 14 studies	Liu et al. 2017
Cough	all	1.05	1.002	1.1		Pooled estimate 14 studies	Liu et al. 2017
Bronchitis	all	1.12	0.96	1.29		Pooled estimate 6 studies	Liu et al. 2017
Respiratory infections	all	1.05	0.93	1.18		Pooled estimate 2 studies	Liu et al. 2017
LRI	all	1.15	1.03	1.29		Pooled estimate 4 studies	Liu et al. 2017
Pneumonia	all	2.58	0.91	7.29			Liu et al. 2017
Lung cancer	all	1.06	0.99	1.14		Pooled estimate 5 studies	Liu et al. 2017
Wheezing	children	1.082	1.011	1.158		Pooled estimate 10 studies	Liu et al. 2017
Bronchitis	children	1.145	0.957	1.37		Pooled estimate 5 studies	Liu et al. 2017
Cough	children	1.075	1.019	1.134		Pooled estimate 10 studies	Liu et al. 2017
Asthma	children	1.119	0.989	1.266		Pooled estimate 8 studies	Liu et al. 2017
LRI	children	1.153	1.033	1.287		Pooled estimate 4 studies	Liu et al. 2017
Respiratory infections	children	1.05	0.93	1.184		Pooled estimte 2 studies	Liu et al. 2017
Asthma exacerbation	< 18	1.03	1.01	1.04	10	Short term exposure	Zheng et al. 2015 (Anenberg et al.2018)
Asthma exacerbation	< 18	1.02	1.02	1.03	10	Short term exposure	Zheng et al. 2016 (Anenberg et al.2018)
Asthma incidence	< 18	1.34	0.96	1.86	10	Long term exposure	Anderson et al. 2013 (Anenberg et al.2018)
Asthma incidence	< 18	1.34	1.11	1.63	10	Long term exposure	Khreis et al. 2017 (Anenberg et al.2018)

LRI: Lower respiratory infection URTI: Upper respiratory tract infection

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