Comparing the aggregated health risk from air pollution calculated from different earth observation resources

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ABSTRACT

Ambient air quality (AQ) is a recurrent issue in cities, exacerbated in low- and middle-income countries. Global AQ impacts on health can be assessed using an aggregated health risk indicator (ΣRIs), derived from in-situ stations, chemical transport models (CTMs) or satellite data.

AQ monitoring is well covered in the city of Munich (Germany): in-situ stations, POLYPHEMUS CTM with three domains, CAMS-Reanalysis of the regional model ensemble and satellite data from MODIS. From these data sets, the ΣRIs was calculated considering four major air pollutants (NO_2, PM_{10}, $PM_{2.5}$, O_3), using their respective relative risk for the mortality-all causes health end-point. Then, the ΣRIs from the models and the satellite data were compared to the $\Sigma RIs_{\text{in-situ}}$ by means of basic statistics, time series and violin plots and the mean relative difference (MRD).

Using the ΣRIs allows to further observe the contribution of individual pollutants to the index. For the mortality all causes health end point between 2017 and 2018, ground observations and CTMs show an increase of ca. 12-13% when exposed to ambient air pollution. The difference between traffic and background stations can be observed: $\Sigma RIs_{\text{in situ}}$ mean is higher at the traffic station than at the background stations. This order is however reversed when considering ΣRIs mean from the models. The four CTMs simulate the ΣRIs well and its seasonality is also represented. Most of the data are spread around the mean and the median for all data sets and stations with an overall distribution skewed towards high values. With $0.5<r^2<0.6$, POLYPHEMUS/DLR yields medium correlation, regardless the domain, while CAMS-Reanalysis returns high correlation ($r^2 \approx 0.8$) for all the studied stations. The MRD indicates an underestimation of the ΣRIs by CAMS-Reanalysis, while POLYPHEMUS tends to overestimate it for the larger domains (positive MRD).

The difference in the r^2 between the two CTMs is due to their singularities: POLYPHEMUS/DLR uses free runs while CAMS-Reg uses a data assimilation process with station measurements (among them the two studied background stations). The overestimation of Johanneskirchen by POLYPHEMUS/DLR comes from its location nearby a power plant and the wind direction. Finally, the very high values in early 2017 can be explained by fireworks, which are not reproduced by models.

It is show in this study that estimating a global health risk from air pollution is possible using in-situ measurements, models and satellite. Finally, satellite data can be helpful to assess the ΣRIs worldwide.

Keyword list: Air pollution – remote sensing – earth observation – health – data set comparison

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1. INTRODUCTION

With the galloping urbanisation, more city dwellers are exposed to air pollution. Besides, in 2016 the World Health Organisation (WHO) reported that more than 80% of city dwellers live in cities not complying with the WHO air quality (AQ) criteria [1]. In Europe air pollution is also considered to be the largest environmental health risk, with around 400 000 premature deaths attributed to it in 2018 [2]. Low- and middle-income countries (LMCIs) often have a lesser ground station coverage for monitoring AQ than high-income countries. Satellites and models can support the assessment of AQ in cities where ground measurements are lacking [3, 4].

Air pollution impacts on health have mainly been studied considering pollutants separately because of their different health endpoints [5]. Only few attempts have been made to consider globally the health risk increase from short-term exposure to a mixture of air pollutants, using relative risks values from epidemiological studies and aggregated air pollution indices [5, 6].

The objectives of this study were to assess the health risk from short term exposure to a combination of air pollutants, using an aggregated risk index, and to assess how this index differs when calculated from different Earth Observations (EO) resources. The study is carried out within the frame if the H2020 project e-shape and the pilot on "Health risks profiling in the urban environment" [7].

2. DATA AND METHODS

2.1 Area of Interest

The city of Munich (Germany) was chosen for the variety of available data. Indeed, not only monitoring stations and the CAMS regional re-analysis data set are openly accessible, but three domains of POLYPHEMUS/DLR and the MODIS data also cover the city. The data from monitoring stations, available on by EEA channels, are used as reference data while data from CTMs and satellite are being compared to the previous one.

2.2 Data sets

2.2.1 In-situ observations

Table 1 Description of the selected EEA stations used of the heath risk increase calculation

European ID	Name	Coordinates (LAT-LON)	Station type
DEBY037	Munich - Stachus	48.137 32 - 11.564 81	traffic
DEBY039	Munich - Lothstraße	48.154 534 - 11.554 669	background
DEBY089	Munich - Johanneskirchen	48.173 194 - 11.648 036	background

In-situ data are gathered by the EEA from Member States and EEA cooperating countries [8]. Since 2014 and the implementation of the Decision 97/101/EC, they are centrally collected. Before this date, data were assembled through bilateral agreements with the collaborating countries. The change of data collection process allowed to have more data available than before [9]. However, the completeness of the data may still vary a lot from a day to another and from a station to another [9, 10]. This database is comprised of multi-annual time series of AQ measurements and calculated statistics for certain air pollutants, as historical data and data from the current year [8].

Hourly data from 2017 and 2018 are used as reference data set in the present study. These two years are in common with the following models and satellite data. The stations were selected considering whether the pollutants required (NO_2, Ozone, PM_{10}, $PM_{2.5}$) for the risk increase index calculation (The Aggregated Risk Index section) were monitored or not. Thus, out of the five stations in Munich city gathered by the EEA, only three were kept for this study. They are described in Table 1. Ground measurements were downloaded from the European Environment Agency (EEA) webpage "Download of air quality data" (https://discomap.eea.europa.eu/map/fme/AirQualityExport.htm) for the years 2017 and 2018.

2.2.2 Polyphemus/DLR

POLYPHEMUS is a system of chemical transport models, bringing together different dispersion models, methods for data assimilation and tools for data processing. In this study, the POLYPHEMUS air quality modelling system of the German Aerospace Centre (POLYPHEMUS/DLR) was applied. It uses a nesting approach, going from the European scale to the Augsburg-Munich metropolitan area, by way of Bavaria (the two latter being in Germany). The domain extends and their resolutions are given in Table 2. The Weather Research Forecast model was applied as input for the weather conditions and parameters, while, for the European domain, initial and boundary conditions were obtained from a ten years run of MOZART (Model for Ozone and Related chemical Tracers). To model the biogenic emissions, the land cover data set from CORINE Land Cover inventory was used. Finally, anthropogenic emissions, principal input implemented in CTMs, come from the TNO emission inventory for Europe and from the Bavarian emission cadastre for Bavaria State [10].

In the frame of this study, model data were extracted for the three POLYPHEMUS/DLR domains (Europe, Bavaria, Augsburg Munich) using a nearest neighbour approach. We used grid cells having the best fit with the station locations.

Table 2. Names, domains and resolution of the three POLYPHEMUS models used in the present study.

Domain Name	Domain	Resolution
POLYPHEMUS-Europe	-12.0°E – 40.2°E, 34.0°N – 60.4°N	0.3°x0.2° (ca. 22x22 km)
POLYPHEMUS-Bavaria	-1.0°E – 17°E, 44°N – 52°N	0.125°x0.0625° (ca. 6x6 km)
POLYPHEMUS-Augsburg-Munich	10.5°E – 11.84°E, 48.0°N – 48.68°N	0.014°x0.009° (ca. 1x1 km)

2.2.3 CAMS-Reanalysis regional model ensemble

CAMS Regional products are a set of data issued from an ENSEMBLE approach. Among others, core air pollutant species (O_3, NO_2, SO_2, CO, PM_{10} and $PM_{2.5}$) are daily forecast by seven European models (CHIMERE, EMEP, EURAD-IM, LOTOS-EUROS, MATCH, MOCAGE, SILAM). In 2019 DEHM and GEM-AQ models were also added [11]. These regional CTMs run locally on common input for meteorology, boundary conditions and emissions. Then hourly output from the distinct model is re-gridded in order to match the 0.1° latitude by 0.1° longitude European domain. The median value from all the models is extracted to give the ENSEMBLE value for each grid coordinate. This way of proceeding allows the data to be less sensitive to outliers or to occasional lacking forecasts [8, 11].

CAMS Reg. stretches from 30°N to 72°N in latitude and from -25°E to 45°E in longitude and has a resolution of 0.1°x0.1°. Similarly as for the Polyphemus data set, data were extracted from CAMS re-analysis data set for the station locations using a nearest neighbour method. Contrary to the POLYPHEMUS data, where a free run is used, the CAMS re-analysis is subject to data assimilation using in-situ observations. Out of the three previously selected stations, the two background stations (Table 1) are applied in this data assimilation process [“personal communication Lorenza Gilardi”].

2.2.4 $PM_{2.5}$ from MODIS

With the later goal of calculating the ΣRIs for locations worldwide where monitoring stations are unavailable, satellite data were used for the city of Munich in an experimental phase. More specifically, $PM_{2.5}$ concentrations were derived from MODIS (Moderate Resolution Imaging Spectroradiometer) measurements of the aerosol optical depth (AOD) [9].

MODIS sensor operates on board of NASA satellite AQUA, globally retrieving aerosols products since 2002. MODIS has a swath width of 2330km and takes the measurements of spectral reflectance of 36 spectral bands, from solar to thermal wave length. More details on the method used to retrieve ground level $PM_{2.5}$ concentrations from MODIS-AOD can be found in [9]. A nearest neighbour method was applied to extract $PM_{2.5}$ concentrations at the station locations, from a grid with a 0.01°x0.01° resolution.

As mentioned, only $PM_{2.5}$ was derived from satellite for year 2018. To cope with the absence of satellite data for the other pollutants needed in the ΣRIs calculations, CAMS Reg. data were used. Furthermore, the ΣRIs was computed only when

$PM_{2.5}$ concentrations from MODIS was available for the three stations presented above. The ΣRIs was then calculated for the year 2018 only. To differentiate this hybrid data set from the model data sets, it is later called “satellite”.

2.3 Methodology

2.3.1 The Aggregated Risk Index

The Aggregated Risk Index is a method developed by Sicard et al. [5, 12] to consider the additive effect on health from short-term exposure to major air pollutants. This method comes out of the API methodology (Air Pollution Index, [6]).

The ARI has been developed for being an index understandable by the public. It is calculated from the exposure-response relationship and the Relative Risk (RR) for different health endpoints. The final index is the sum of the normalised RR of the considered air pollutants. Detailed explanation can be found in [5, 12]. In the frame of this study, only the part of the ARI relationship concerning the RR was considered, called here ΣRIs (sum of the Risk Increases). The air pollutants used in the aggregation are NO_2, PM_{10}, $PM_{2.5}$ and O_3. The ΣRIs is obtained as follows:

$$\sum RIs = \left(\sum P_i \times \frac{(RR_i)}{10}\right) \times 100 \tag{1}$$

where P_i is the average pollutant (24 hours for NO_2, PM_{10} and $PM_{2.5}$ and 8 h maximum for O_3), RR_i is the Relative Risk per 10 µg/m3 for the health end point mortality all causes [5].

2.3.2 Evaluation methods

The ΣRIs calculated from different data sets was evaluated using basic statistics. The mean, median of the models and satellite data sets were compared to the same statistics for the in-situ data set. Similar analysing was done using the mean relative difference (MRD). The latter is the average of the normalised differences between the ΣRIs from models (or satellite) and the ΣRIs from in-situ data (Eq. 2)

$$MDR = 100\% \times \frac{1}{n}\sum \frac{\Sigma\text{RIs}_{\,models,i} - \Sigma\text{RIs}_{\,in-situ,i}}{\Sigma\text{RIs}_{\,in-situ,i}} \tag{2}$$

where $models_i$ is one of the model or satellite data sets. When MDR returns positive values, it indicates an overestimation by models (satellite), while when returning negative values, it indicates an underestimation [13].

The difference in time series variation was assessed plotting the model (satellite) time series against the in-situ time series. Finally, the distribution and the density of ΣRIs from the different data sets was appraised using violin plots.

3. RESULTS

During the years 2017 and 2018, the ΣRIs calculated at the station Lothstaße (Figure 1) indicates that the risk of dying from the exposure to pollutant mixture increased by almost 14% on average. Figure 1 also shows where the interest of the aggregated risk lies. Under the line of the ΣRIs, one can observe the importance of the considered pollutants: for instance, during the warm period ozone predominates in the ΣRIs while NO_2 is more important in winter. It can also be observed that for some period of the year the particulate matters portion of the ΣRIs gains some weight, like at the beginning of year 2017 or of year 2018.

On average, between 2017 and 2018, the mortality all causes health end point increases by ca.14% when exposed to air pollutant mixture (Figure 2). A maximum increase is reached in summer 2018 (ca. 25%) and a minimum in winter 2017-2018 (ca. 10%). The four presented models simulate well the ΣRIs variations observed by the in-situ data. Furthermore, a seasonality can be noted: ΣRIs is higher during summer while it is lower in winter. Models also keep this seasonality. However, the four models are unable to simulate the very high peak in early 2017 from $\Sigma\text{RIs}_{\text{in-situ}}$. The drop in POLYPHEMUS/DLR models beginning 2017 is explained by unavailable data. The similar drop in early 2018 has the same explanation but it is smoothened by the use of the weekly mean.

The distribution of ΣRIs seems independent from the station type and the data source. Indeed, for all data sets and stations, most of the data is distributed around the mean and the median (Figure 3). Like in Figure 2, the very high values of

ΣRIs $_{in\text{-}situ}$ are not represented by the models. Also, for all data sets and stations, ΣRIs is skewed towards high values (median below the mean). Moreover, the difference between traffic and background stations can be observed: the traffic station has the highest ΣRIs $_{in\text{-}situ}$ mean. However, when considering POLYPHEMUS-Augsburg-Munich, POLYPHEMUS-Europe and CAMS regional models it has the lowest mean.

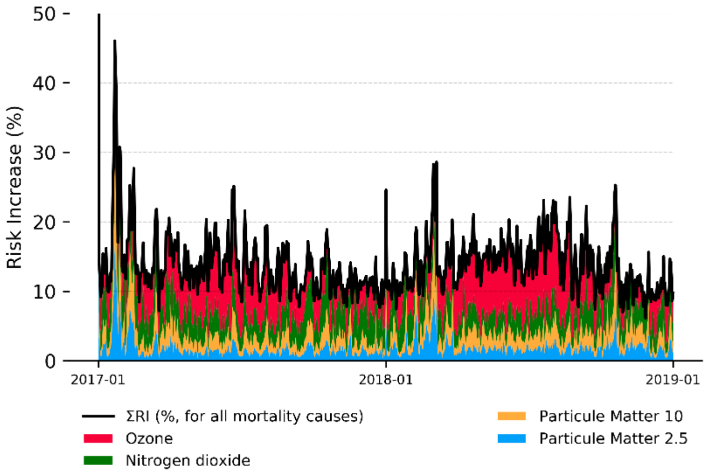

Figure 1 ΣRIs at Lothstraße in-situ station, from 2017 to 2018, represented with the considered pollutant weights.

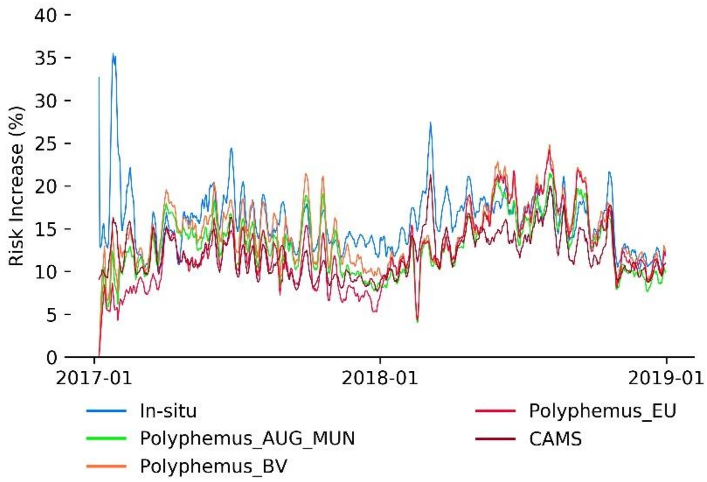

Figure 2 Weekly mean of the ΣRIs calculated from the in-situ data set, the three Polyphemus domains and CAMS-regional at Lothstraße station.

Considering year 2018 and satellite data set only, the data set is smaller due to MODIS data availability only on certain days and times of the year (e.g.: cloudiness). Despite this, ΣRIs from satellite follows the variation of ΣRIs $_{in\text{-}situ}$. Furthermore, during 2018, the risk of dying from short-term exposure to air pollutant mixture increases by ca. 12% (Figure 4; ΣRIs $_{in\text{-}situ}$ figure 5-c). The maximum is reached in spring 2018 (ca.27%) and the minimum in winter with a risk increase of ca. 7%.

At the traffic station, the satellite data set does not manage to capture in-situ high values whereas, it captures well the data range of in-situ measurements at Johanneskirchen background station (Figure 5). At the latter, both data sets follow a similar distribution. Yet, at the traffic station, in-situ data are skewed towards low values (mean below the median) with still a tail in the direction of high values. On the other hand, $\Sigma RIs_{satellite}$ almost follows the normal distribution.

Regardless the station type and the domain, POLYPHEMUS/DLR yields a medium correlation coefficient ($r^2 \approx 0.5$). On the other hand, CAMS-Reg. returns high correlation coefficient values for all stations ($r^2>0.75$). Similar to the latter, in year 2018 satellite data also generated high correlation coefficients ($r^2>0.8$, Table 3).

Table 4 continues the comparison results between in-situ measurements on one side and models and satellite data sets on the other side gathering the MRDs. Background station Johanneskirchen tends to be overestimated (MRD > 0) by all POLYPHEMUS data sets while the traffic station is underestimated (MRD < 0). On the other hand, CAMS-Reg. is inclined to underestimate the ΣRIs index for all stations (MRD < 0). In year 2018, satellite data set gives a negative MRD, indicating that ΣRIs is underestimated.

Table 3 Correlation coefficient (r^2) table for the comparison between CTMs and satellite (2018) data sets, for the three Munich stations.

	POLY. – Aug. – Mun.	**POLY. – Bavaria**	**POLY – Europe**	**CAMS-Reg.**	**Satellite (2018)**
DEBY037 – Stachus	0.49	0.51	0.41	0.76	0.82
DEBY039 – Lothstraße	0.55	0.57	0.57	0.84	0.94
DEBY089 – Johanneskirchen	0.49	0.52	0.52	0.87	0.94

Table 4 Bias table (MRD) table for the comparison between CTMs and satellite (2018) data sets, for the three Munich stations.

	POLY. – Aug. – Mun.	**POLY. – Bavaria**	**POLY – Europe**	**CAMS-Reg.**	**Satellite (2018)**
DEBY037 – Stachus	-14.61	-4.75	-19.04	-22.99	-24.79
DEBY039 – Lothstraße	-1.44	9.25	7.11	-11.73	-10.99
DEBY089 – Johanneskirchen	12.21	20.61	18.20	-2.45	-21.78

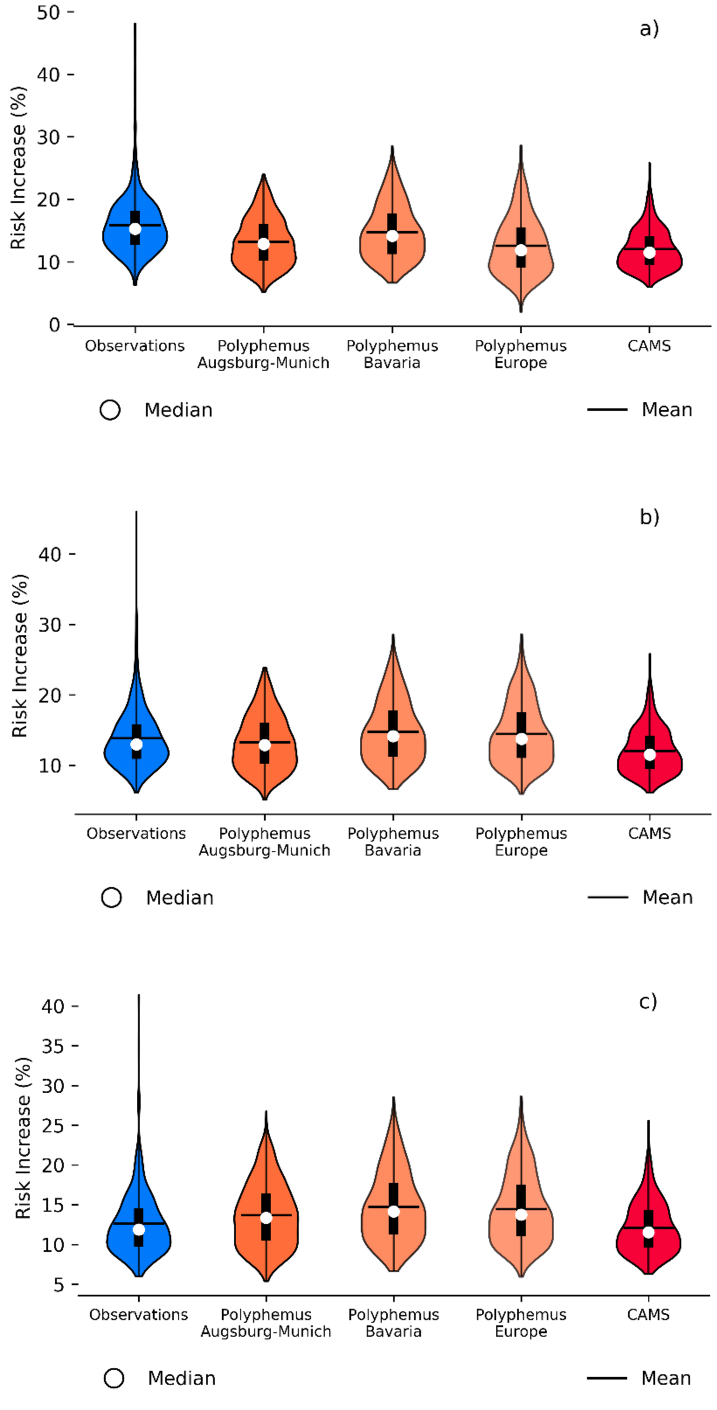

Figure 3 Violin plots of the ΣRIs calculated from in-situ and CTMs data sets, at the station a) Stachus, b) Lothstraße and c) Johanneskirchen.

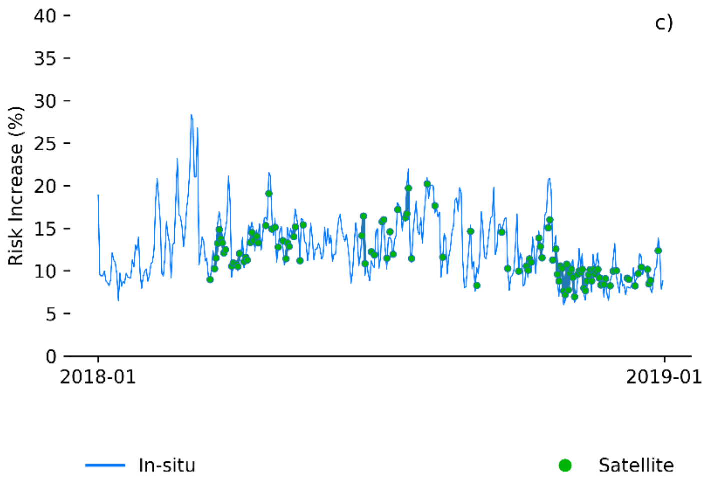

Figure 4 Weekly means of the ΣRIs calculated from in-situ and satellite data sets, at the station Johanneskirchen.

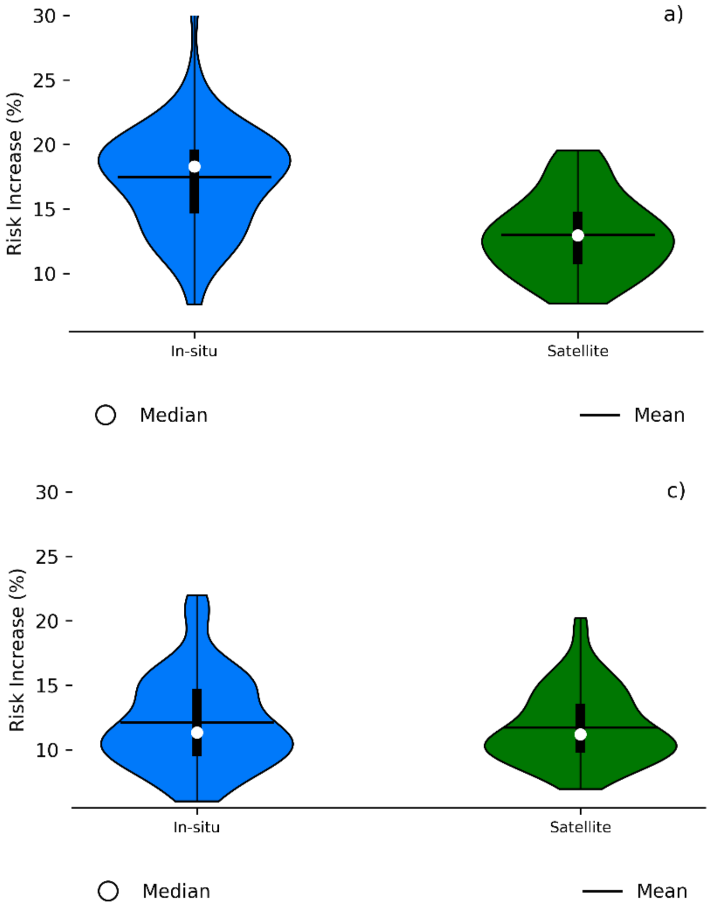

Figure 5 Violin plots of the ΣRIs calculated from in-situ and satellite data sets, at the station a) Stachus and c) Johanneskirchen.

4. SUMMARY AND CONCLUSION

In the city of Munich, on average the exposure to pollutant mixture leads to an increase of the health end point "mortality-all causes" by 12-13%, with a minimum in winter and a maximum during warm periods. One can also observed the difference between traffic and background stations.

Instead of considering the impact on health of individual pollutants, the ΣRIs gathers several pollutants under a common indicator and estimates the health impact of the pollutant mixture. Also, when the weight of one pollutant decreases, the ΣRIs is not automatically reduced as another pollutant can dominate in the aggregation.

ΣRIs was calculated using in-situ measurements (pollutant concentrations from stations) and proxy means (CTMs and satellite). It has been found that ΣRIs from model and satellite data sets (mix between satellite and CAMS-Reg. data) closely follows the variations of station measurements. Moreover, data from models and satellite has the same distribution as the in-situ measurements. The exception is in 2018 from the satellite data set which has a very different distribution than the in-situ data set at the traffic station. Also, the high peak from ΣRIs_{EEA} in the beginning of the year 2017 could be explained by the firework tradition on New Year's Eve in Munich City and is not reproduced by any of the data sets except for the in-situ measurements.

No matter the domains, POLYPHEMUS yields medium r^2 while CAMS-Reg. yields higher ones. This first difference finds its source in the use of background stations (Lothstraße and Johanneskirchen stations) for the data assimilation process implemented in CAMS Ensemble, while a free model run is used from POLYPHEMUS. This also explains the difference in r^2 between the traffic and the background stations [12]. A second reason could come from the extraction process from the models: the data at the station locations were extracted from the original model grids. No re-gridding was involved. Hence as well, for example, the same mean and median which can be observed for POLYPHEMUS-Bavaria at the three stations.

Generally, CAMS-Reg. underestimates ΣRIs for all the stations while POLYPHEMUS tends to overestimate ΣRIs for background stations, especially at Johanneskirchen station and to underestimate it for the traffic station. The overestimation at the Johanneskirchen station comes from the fact that it is located near a power plant. The effect of the latter is probably overestimated by POLYPHEMUS. Furthermore, uncertainties remain regarding the time and vertical distributions of the pollutants emitted by the power plant. The overestimation of the ΣRIs at Johanneskirchen station could be also explained by a wind effect taken into consideration by POLYPHEMUS model; a dominant wind coming from the west crosses the domains over Munich city [11].

Satellite data set has less ΣRIs values because $PM_{2.5}$ could not be retrieved everyday (e.g.: cloud conditions). The contrast between lower data availability at Stachus and Lothstraße stations and Johanneskirchen on the other side, could be explained by the two first stations being located inside the city where surface reflectance is higher [15]. This is fully consistent with what is expected from the MODIS retrievals, as they represent urban conditions and are unable to catch the variability of a traffic station.

This study shows that globally quantifying the health risk regarding air pollution exposure is possible using station measurements. It also shows that in the case of missing ground measurements (missing data or low ground station coverage), models and satellite are helpful for quantifying the health risk increase, especially in urban background conditions. Finally, the use of satellite data can be worthwhile for assessing the health risk increase from air pollution exposure worldwide.

5. OUTLOOK

The use of an Ensemble data set would allow to increase data availability of satellite based PM2.5 concentrations [10]. Besides, implementing satellite data also for other pollutants would expand the satellite data set. Furthermore, the Bland-Altman method would be implemented to enhance the evaluation of the agreement between ΣRIs from in-situ observations on one hand and ΣRIs from proxy methods on the other hand. Within this method, the biases would be further used along with an analysis of the variability of the differences and the use of limits of agreements [16].

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