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NSO User Needs Study
Air Quality and Climate

Final Report

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Enschede, The Netherlands, 5 April 2019

Table of content

Tables

Acronyms

AAOD	Absorption aerosol optical depth
AE	Ångström Exponent
AI	Aerosol index
AOD	Aerosol Optical Density
AOT	Aerosol Optical Thickness
APSP	Aerosol Particle Size Parameter (Ångström Exponent)
AVHRR	Advanced Very High-Resolution Radiometer
BC	Black Carbon
CALIPSO	Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations
CH_4	Methane
CO_2	Carbon dioxide
CTM	Chemical transport model
DMSP	Defense Meteorological Satellite Program
ECV	Essential Climate Variables
APAR	Absorbed Photosynthetically Active Radiation
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GCOS	Global Climate Observing System
GOES	Geostationary Operational Environmental Satellite
GOME	Global Ozone Monitoring Experiment
HCHO	Formaldehyde
HMS	Hazard Mapping System
HYSPLIT	Hybrid Single Particle Lagrangian Integrated Trajectory

IPAR	Including Incident Radiation
IPCC	Intergovernmental Panel on Climate Change
LAI	Leaf Area Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MOPITT	Measurements of Pollution In The Troposphere
NAME	Numerical Atmospheric-Dispersion Modelling Environment
NDVI	Normalized Difference Vegetation Index
NERI	National Environmental Research Institute
NO_2	Nitrogen dioxide
NOAA	National Oceanic and Atmospheric Administration
NSO	Netherlands Space Office
O_3	Ozone
OML	Operational Meteorological Air Quality Model
PM	Particulate Matter
RIVM	Rijksinstituut voor Volksgezondheid en Milieu (National Institute for Public Health and the Environment)
SLR	Sea-Level Rise
SMMR	Scanning Multichannel Microwave Radiometer
SO_2	Sulphur dioxide
SODAR	Sound Detection and Ranging
SSM/I	Special Sensor Microwave/Imager
SST	Sea Surface Temperature
STT	Stratosphere-To-Troposphere Transport
SWI	Summer Warmth Index
TOMS	Total Ozone Mapping Spectrometer
UFP	Ultra fine particle
VHRR	Very High-Resolution Radiometer
VOC	Volatile Organic Compounds

1. Introduction

The poor air quality in large parts of the world, in Asian megacities as well as in urban regions in Europe, as well as changing global climate patterns are among the biggest environmental problems nowadays. They are affecting several sectors such as public and environmental health and biodiversity and have major consequences for the changing global climate. While in Europe a slight decrease of air pollution in general can be observed over the last 15 years (Priemus et al. 2009), air pollutant concentrations particular in many urban regions are still too high, i.e. above defined standards, and harm human health and ecosystems (Guerrerio et al. 2014). Also in other parts of the world, e.g. in Asian cities, air quality levels and ambient air quality standards indicate that levels for instance of PM_{10} and SO_2 continue to exceed air quality guidelines. At the same time global climate patterns are increasingly changing, mainly in terms of temperature and precipitation. Though the awareness that air quality and climate need to be improved is increasing among all relevant actors nowadays, there is often not sufficient data to assess and monitor air quality, e.g. $PM_{2.5}$ and ozone pollution levels, of climate characteristics, which hamper the development of effective measures and interventions.

In order to address these challenges, proper and accurate data of various atmospheric constituents contributing to air pollution as well as meteorological parameters is needed for detecting single severe events and sources affecting air quality as well as for monitoring long-term trends in changing air quality patterns and climate change impacts. Data of atmospheric pollutants retrieved from current and future satellite sensors and instruments of high spatiotemporal resolution can be important sources of information for various applications and users dealing with the effects of poor air quality.

1.1 Goals of the study

Goal of this study is to identify and to develop an inventory and overview of potential and future user needs of national and international scientific, governmental and commercial users in terms of information from products and services that may or may not include satellite data within the domain of air quality and atmosphere related climate. In doing so, the added value and usability of satellite data on air quality as well as existing challenges and bottlenecks for the same will be investigated, also in comparison to data and information derived from other sources, such as in situ or airborne measurements. In detail this report investigates the following questions:

- What are the different users and fields of application using air quality and climate data?
- What are the specific user needs of these groups for air quality and climate data?
- What are advantages and disadvantages of air quality and climate data captured from satellite sensors as seen by the different user groups?
- What is the added value of air quality and climate data from satellite based measurements?
- What are new business models and new (commercial) markets for valorising satellite based air quality and climate data?
- What are future needs of different users/fields of application for air quality and climate data?

1.2 Scope of the study

The focus of the study is on the needs of governmental, academic and commercial users for air quality and climate data from various sectors and fields of application. Therefore, at first an inventory of potential user groups and field of applications was developed, particular focussing also on future needs and potential users, including those who do not work with satellite data of air quality yet. In addition, a comprehensive literature review was conducted exploiting scientific literature as well as reports and documents from practice, as far as available. Thereafter, interviews with selected experts from governments, academia and industry were conducted. The expert interviews were selected and conducted in order to include:

- Experts form academia and science, practice, governmental, and commercial institutions
- Experts working on different scales from global to sub-local
- Experts from Europe as well as other parts of the world
- Experts working in different disciplines resp. fields of application
- Experts producing air quality and climate data resp. relevant applications based on these, and experts using data, e.g. for air quality planning or health impacts assessment.

1.3 Methodology of the study

Main methods applied in the study are literature review and expert interviews. The literature review includes mainly journal articles and conferences proceedings. Based on an initial reading of relevant review papers (Duncan et al. 2014, Streets et al. 2014, Martin 2008) we first identified the main fields of application of air quality and climate data and then searched on Scopus the amount of relevant publication per field. The following domains were distinguished.

1. "Urban planning" or "spatial planning"
2. "Epidemiology" or "health"
3. Climate modelling
4. Air quality modelling
5. Environmental monitoring

Single search strings and results of the literature search are shown in table 1. Given the huge amount of scientific publications found per field of application, we decided to focus only on peer reviewed review papers, which provide a very good overview of the state of art in a certain field and typically include more or less specific future research and data needs. For the literature review we focused solely on publications that include aspects of satellite based/remote sensed data (search string "satellite OR remote sensing"), because otherwise the number of potential review papers would have even been larger and consequently not to be read within the scope of the assignment.

Table 1 Literature search results

Field of application	Search string	Scientific publications	Review papers
health	TITLE-ABS-KEY ((satellite OR "remote sensing") AND ("air pollut*" OR "air quality") AND (epidemiology OR health)) AND PUBYEAR > 2009	694	37
Urban planning	(TITLE-ABS-KEY (satellite OR "remote sensing") AND TITLE-ABS-KEY ("air pollut*" OR "air quality") AND TITLE-ABS-KEY ("urban plan*" OR "spatial plan*")) AND PUBYEAR > 2009	64	3
Environment and monitoring	(TITLE-ABS-KEY (satellite OR "remote sensing") AND TITLE-ABS-KEY ("air pollut*" OR "air quality") AND TITLE-ABS-KEY (environment AND monitoring)) AND PUBYEAR > 2009	225	8
Climate studies	(TITLE-ABS-KEY (satellite OR "remote sensing") AND TITLE-ABS-KEY ("air pollut*" OR "air quality") AND TITLE-ABS-KEY (climate)) AND PUBYEAR > 2009	738	35
Air dispersion modelling	(TITLE-ABS-KEY (satellite OR "remote sensing") AND TITLE-ABS-KEY ("air pollut*" OR "air quality") AND TITLE-ABS-KEY (air AND dispersion AND modelling)) AND PUBYEAR > 2009	92	4

For selecting interview partners, we started also from the given domains and identified key actors that we have access to already from earlier and ongoing studies. Other interview partners were suggested by NSO. Furthermore, relevant further interview partners mentioned by the interviewees were contacted as well. Interviews took usually between 30 and 45 minutes and were conducted using guiding questions (Annex 7.1).

2. Air quality, climate and satellite based data collection and use

2.1 Current situation with respect to air quality and climate

Over the past 15 to 20 years the air quality in Europe has improved significantly, also due to the approval and enforcement of the EU air quality directive in year 2008. However, large parts of the European population is still breathing air with pollution levels exceeding EU and WHO standards (Guerreiro et al. 2014). In other parts of the world, particular in large Asian cities the situation is much worse. Ninety-eight percent of cities in low and middle-income countries with populations of more than 100,000 are suffering from heavily polluted air. Moreover, ongoing trends towards urbanisation and expansion of road traffic in these cities are anticipated to further increase population exposure to bad air quality (Kumar et al. 2014). Due to global warming, i.e. the gradual increase in the overall temperature of the earth's atmosphere generally attributed to the greenhouse effect, also essential climate variables have been changing substantially over the last decades and are supposed to change further. Particular temperature and precipitation patterns are likely to change significantly further on.

2.2 State of the art of air quality and climate data collection from satellite **sensors**

Industrialization induced by population growth and increased human capacity has increased anthropogenic activities, which influences chemical composition of the troposphere, the lower part of the atmosphere. The resulting common pollutants are aerosols (particulate matter), ozone (O_3), nitrogen oxides (NOx), carbon monoxide (CO) and sulphur dioxide (SO_2). Therefore, estimation, monitoring, and mapping the spatial and spatiotemporal variability of these pollutants are of health, economic and societal importance. The use of ground-based or *in-situ* based methods for estimation have come a long way. Yet, these methods are limited in terms of spatial and temporal coverage, and are not cost effective.

The application of satellite remote sensing for monitoring aerosols and tropospheric trace gases has existed since the late 70’s (Griggs 1975, Carlson and Wendling 1977, Mekler et al. 1977). Early applications include the use of AVHRR, Landsat, GEOS, TOMS products/instruments to monitor aerosols and tropospheric trace gases. Recall Fraser (1976) derived, with the aid of satellite measurements of nadir radiance from Landsat-1, the mass of particulates in a vertical column of dust outflow from North-Western Africa. The Saharan dust has been in focus of aerosol optical depth estimation from radiance measured aboard the NOAA 3 satellite by the VHRR (Carlson and Wendling 1977).

Since the launch of TOMS instrument in the 1978, there has been profound improvement in satellite remote sensing of tropospheric trace gases. The lack of scientific understanding of the implications of aerosols on climate initially impeded retrieval efforts for aerosol optical properties. Now, is it clear how atmospheric aerosols induce climate dynamics. Not only have the scientific tools for sharing and application improved, but also the development of new sensors and retrieval algorithms.

In the Table 2, we present a non-exhaustive summary of available sensors and their products useful for air quality and climate studies

Table 2 Satellites, sensors and climate and air pollution parameters

Instrument	Platform/Agency	Period	Resolution at nadir (km)	Global Coverage	Spectral range (µm)	Trace gases	Aerosol Optical properties	Climate measures
GOME[5]	ERS-2/ESA	1995-2003	320 x 40	Yes: 3 days	0.23-0.79	NO_2, HCHO, SO_2, O_3: (0.5-1.5)	AOD	
POLDER	ADEOS-II							
MOPITT[6]	Terra/NASA	2000-	22 x 22	Yes:3.5 days	4.7	CO_2: (0.5-2)	NA	
MISR[7]	Terra	2000-	18 x 18	Yes: 7 days	4λ: (0.45-14.2)		AOD	
MODIS[8]	Terra/NASA	2000-	10 x 10	Yes: 2 days	36λ: (0.14-14.2)		AOD	
MODIS[8]	Aqua/NASA	2002-	1 x 1	Yes: 2 days			AOD	
AIRS[9]	Aqua/NASA	2002-	14 x 14	Yes: 1 day	3.7-16	SO_2 CO: (0.5-1.5)	NA	
SCIAMACHY[10]	ENVISAT/ESA	2002-2012	60 x 30	Yes: 6 days	0.23-2.3	NO_2, HCHO, SO_2,CO, O_3:(0.5-1.5)	AOD	
OMI[11]	Aura/NASA	2004-	24 x13	Yes: 1 day	0.27-0.50	NO_2, HCHO, SO_2, O_3: (0.5-1.5)	AOD, AAOD, AI	
TES[12]	Aura/NASA	2004-	8.5 x 5.3	Yes: 2 days	3.3-15.4	CO: (0.5-1.5), CH_4, CO_2, NH_3, O_3: (1-2)		
CALIOP	CALIPSO	2006-	40 x 40	NO	0.53-1.06		>30	
GOME-2[13]	METOP/ESA/ EUMETSAT	2006-	80 x 40	Yes: 1 .5 day	0.24-0.79	NO_2, HCHO, SO_2, O_3: (0.5-1.5)	AOD	
IASI[14]	METOP/ESA	2006-	50 x 50	Yes: 0.5 days	3.6-15.5	SO_2, CH4, CO_2, NH_3, CO: (0.5-1.5), O_3:(1-2)	NA	
AATSR	ENVISAT	2002-	10 x 10	Yes: 5 days	555,659, 865,1610		AOD	
VIIRS		2011	0.75		0.41-12.5		AOD,AT, AE, AOT, APSP	
OCM	Oceansat-1	2009	1 x 1: Global area coverage	Yes: 2 days	0.402-0.885		AOD	LST, NDVI, EVI,
TANSO-FTS[15]	GOSAT/ JAXA	2009-	10 x 10	Yes: 3 days		CH_4, CO_2	NA	
TROPOMI	Sentinel 5/ESA	2017-	7 x 7	Yes: daily	0.27-2.3	SO_2, CH_4, CO_2, CO, O_3, NO_2, HCHO		

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2.3 Existing climate and air quality services and end user applications

Since a couple of years companies started providing specific air quality and/or climate related services for end users and customers, such as governments, private business, and citizens. Services in this context are particular databases, tools and applications provided via the web or as a smartphone app. They are typically based on large climate or air quality related spatial data sets which are processed, and adapted to end user needs in order to bridge the gap between latest scientific and technological developments and real-world decision-making. Satellite data of air quality or climate parameters as well as of other relevant parameters (e.g. land use/cover, vegetation) is often merged for these applications with data sets form other sources, such as ground based measuring. Companies such as Acclimatise (http://www.acclimatise.uk.com/), Hermess (http://www.hermess.nl/) or [s]&[t] (http://www.stcorp.nl/) are examples of companies offering particular services.

European Union's Earth Observation Programme (Copernicus) provides since long already various services mainly based on satellite data in the fields land use, climate change, emergency, security, environmental monitoring (https://www.copernicus.eu/en/services). The European Air Quality Portal (http://aqportal.discomap.eea.europa.eu/) facilitates the reporting of official air quality information from EU Member States and other EEA member and co-operating countries. LOTOS-EUROS (https://lotos-euros.tno.nl/) is an open-source chemical transport model (CTM) that provides a number of applications supporting scientific research, regulatory programmes and air quality forecasts. The NSL monitoring tool (https://www.nsl-monitoring.nl/) provides a map viewer for the entire Netherlands showing levels of air pollution along main roads corridors. Riga airTEXT (https://www.copernicus.eu/en/use-cases/airtext-air-quality-information-glance) makes air quality forecasts for the residents of Riga, Latvia, available up to three days ahead online (www.rigaairtext.lv) and via a free phone app. AIR-PORTAL (https://airportal.stcorp.nl/) is a new service that shows air quality levels at high resolution, and allows users to perform online specific analyses of the data for selected urban areas in Europe.

3. Air quality and climate data: User inventory and fields of applications

The following sectors and fields of applications using air quality and climate data derived from satellites will be distinguished in the study.

- Climate studies (atmospheric climate parameters)
- Epidemiologic and public health studies related to air quality (relative risk assessment, disease mapping)
- Spatial and urban planning (air quality planning, air quality regulations, climate change adaptation planning)
- Environmental monitoring and management (unconventional extraction and emissions, long-term trends, etc.)
- Air dispersion modelling

It needs to be mentioned, that between the different fields of applications identified here various links, synergies and overlaps exist. For instance air quality, particularly air dispersion models, are often used in public health studies, the latter makes often use of results from environmental monitoring studies, and urban planning and public health sometimes collaborate for creating healthy urban areas. One main difference is that some of the fields already make regular use of satellite data while other fields, such as urban planning, hardly use satellite data so far and if so, only indirectly by using results of air quality models. Main reason are the different scales at which these applications operate, from global to regional for environmental monitoring studies to sub-local/neighbourhood level of health inequalities or air quality planning.

3.1 Use of satellite data for climate studies

After the launch of the vanguard-2 satellite in 1959, satellite remote sensing has become a leading research method in climate studies (Yates 1977, Li 2011). Unlike ground control stations, satellite remote sensing easily allows observations of space-time terrestrial, oceanic and atmospheric processes. Despite the lack of planning for continuity of measurements of many of the key climate variables, it is evident that the future of the global climate observing system depends critically upon a major satellite component. Satellites now provide a vital means of obtaining observations of the climate system from a near global perspective and for comparing the behaviour of different parts of the globe. Despite the concerns about the suitability of satellite data for monitoring and understanding climate change (Christy et al. 1997), satellite data are widely used for developing prevention, mitigation and adaptation measures to cope with the impact of climate change across the atmospheric, oceanic and terrestrial domains (Joyce et al. 2009). The value of climate related satellite data goes beyond climate change and systems studies. For instance, the value of a validated, routinely produced global precipitation product would not be limited to weather and climate forecasts but would also have a considerable impact on agricultural planning, forestry and water management (GCOS 2011). Nevertheless, some possible biases remain in satellite data, such as satellite images being contaminated by clouds or atmospheric aerosols. Hence, in situ data are also critical for not only satellite calibration and validation but also for any final bias corrections needed at the time of any analysis (Reynolds et al. 2002).

The Global Climate Observing System (GCOS) enumerates essential climate variables (ECV) under the three main domains. The ECVs of the atmospheric domain, either over land or sea, includes surface wind speed and direction, precipitation, upper-air temperature, upper-air wind speed and direction, water vapour, cloud properties, Earth radiation budget (including solar irradiance), carbon dioxide, methane and other long-lived greenhouse gases, and ozone and aerosol properties, supported by their precursors. The oceanic domain has fewer ECV's, which include sea-surface temperature; sea-surface salinity; sea level; sea state; sea ice; ocean colour. The third domain, the terrestrial domain, includes lakes; snow cover; glaciers and ice caps, ice sheets, albedo, land cover (including vegetation type), fraction of Absorbed Photosynthetically Active Radiation (FAPAR); Leaf Area Index (LAI); above-ground biomass; fire disturbance; soil moisture.

According to the GCOS, 26 out of 50 listed essential climate variables (ECVs) are significantly dependent on satellite observations. Climate studies require long term and large spatial coverage data. The limited availability and spatial coverage of ground control stations naturally appeals for the use of satellite data for climate studies. Satellite data provides an independent way to investigate global temperature trends, particularly at the ocean surface and in the atmosphere (Yang et al. 2013). Currently, the key operational issues of satellite data for climate studies, as indicated by the GCOS, are continuity, homogeneity and overlap of satellite observations; enhanced orbit control; calibration and instrument characterization, and validation of products; sampling strategy; and sustained generation of products, data analysis, and archiving. Yang et al. (2013) have categorized the ECV's into three important study areas of climate studies; global warming, snow and ice, sea-level changes, solar radiation, aerosols, water vapour and precipitation, and clouds studies. In this study on available satellite data and products and user needs for climate studies and reflect on operational issues that have been raised in relation to that. current studies.

Ground control stations are limited in both coverage and scale, hence inadequate to monitor the earths changing climate, making satellite remote sensing a vital resource. Majority of the ECV's can be monitored using satellite remote sensing. Taylor (2012) pointed out that satellite sensors do have the required accuracy for monitoring cloud trends. This supports the conclusion drawn by Kahn et al. (2011) that finer spatial resolution requirements must be considered for future satellite observations for temperature and water vapour. Important limitations also include the technical characteristics of the sensors themselves. Some satellites cannot stand the test of time in terms of the loss of radiometric sensitivity. How well the uncertainties associated with the sensors are catered for is therefore critical, especially the accompanying drift with time. In fact, Lea et al. (2012) concluded that the Spectral Irradiance Monitor's radically different solar variability characterization is a consequence of undetected instrument sensitivity drifts, not true solar spectrum changes.

Temporal resolution of the satellite data has been a recurring limitation in our review that limits the utilization of remote sensing data for climate studies. We agree with the proposal by Joyce et al. (2012) for the provision of constellation of small satellites that observe the same location over a given time interval. In addition, retrieval methodologies can lead to either underestimation or overestimation of particular climate/air quality parameters. For instance, in a follow-up study (Benestad et al. 2009), a nearly negligible percentage was found to be the contribution of solar radiation on climate change after Scafetta et al. (2006) had estimated 25–35% of the 1980–2000 global warming.

3.2 Relationships between the atmospheric observation of climate and air quality parameters

There is documented evidence on the interplay between air pollution and climate. Aerosols in particular are deemed crucial for long-term climate predictions. Bartlett et al. (2017) indicate that anthropogenic aerosols have significant climate impacts against a background of greenhouse gas-induced climate change. The interplay between aerosols and climate dwells on the emission sources, atmospheric properties, processes and chemistry, and mitigation options (von Schneidemesser et al. 2015). Vehicles, for instance which are common emissions sources of particulate matter in the atmosphere, also emit greenhouse gases like nitrogen and oxides. Suspended fine solid or liquid particles, aerosols, do not only pose air quality problems but also have several climate forcing properties. The climate-inducing property of aerosols depends on its response or interference with incoming solar radiation, either through absorption or scattering. The radiation absorbed by black particle contributes to warming the atmosphere, and that scattered by other aerosol components tends to cool the earth's surface (Ramana et al. 2010, Banerjee et al. 2018, Schwartz and Andreae 1996). The aerosol optical property (AOD) has often been the focus of estimating aerosol quantity in the atmosphere, which is derived from observations recorded by visible and infrared optical sensors on board various satellites. Tropospheric ozone, a secondary air pollutant, is formed by the accumulation of and combination of nitrogen oxides. The biophysical reactions between some greenhouse gases like ozone and short lived air pollutants like aerosols is likely to immerge as the most important climate impacts (Unger and Pan 2012). Improvements in energy efficiency as mitigation options influence both air quality and the earth climate. This influence, however, will not necessary be advantageous for both. For instance, the use of wood biomass burning as alternate residential heating though reduces CO2 emissions could significantly increase particulate matter emissions (Haluza et al. 2012). Air pollution studies such as modelling the spatial distribution of particulate matter or aerosol have contributed significantly to the understanding of such atmospheric climate dynamics. Thus, studying the dynamics of aerosols links together, either explicitly or implicitly, the dynamics of the climate.

While many studies have associated satellite retrieved AOD with PM concentrations, few have associated the climate forcing properties of AOD with climate variation. Zhang et al. (2016) evaluated the degree at solar radiation forcing from a smoke plume introduces daytime surface cooling using MODIS retrieved AOT and estimated smoke-aerosol induced daytime direct surface cooling efficiency to be $\sim -1.5\ ^\circ C$ per 1.0 AOT. Benedetti and Vitart (2018) observed that the interactive aerosols have the capability of improving the sub-seasonal prediction at the monthly scales for the spring/summer season. That said, numerical predictions of aerosol properties have become important input data source for both regional and global climate observers. As a result of increasing attention paid to the effects of aerosols in climate dynamics, Li et al. (2009) articulated key uncertain factors in the retrieval of AOD for some widely used satellite aerosol products including the AVHRR, TOMS, MODIS, MISR. To better understand cloud formation variability, Tuccella et al. (2019) incorporated the indirect effects of MODIS retrieved aerosols in a Weather Research and Forecasting (WRF) model. Ali et al. (2019) observed increasing trends of MODIS retrieved AOD with cloud properties. Although these studies have conducted at the local levels, they indicate the high potential to further explore the effectiveness of AOD properties for climatic predictions.

Current literature has not clearly defined the metrics of user needs for AOD inventories or models necessary for enhanced climate predictions. This could be attributed to the different temporal and spatial scales of climate predictions. Additionally, the context of user needs of aerosol modelling for climate predictions places much emphasis on emissions scenarios, hence requirements will be different (Benedetti et al. 2018). The requirements also differ for global and regional modelling and applications, although certain requirements may apply to both regional and global applications. Conclusions from Cowie et al. (2015) and Bergametti et al. (2017) suggest that hourly or better time resolution is required to model the desert dust aerosols given the short lifetime. Requirements for better vertical resolution is deemed necessary though no provision for the exact metrics has been discussed in literature, to the best of our knowledge, as are those for particle size distribution and multiple wave lengths. An ideal spatial resolution requirement has been argued to be as good as the modelling requirements. For global modelling, a required spatial resolution of 50km is acceptable; higher resolution presents additional benefits but not without computational challenge (Wang et al. 2014). The use of population as proxy in current modelling approaches has led to the suggested requirement of 10 km spatial resolution for global modelling and less than 1 km for regional and urban models given that the scale of emission sources are very small (Benedetti et al. 2018, Mailler et al. 2017). The radiative efficiency of aerosols which depends on properties such as size and composition play a significant role in their cloud condensing capabilities. This instigates user needs for particle size resolution, translated into particle size apportioning.

3.3 Use of satellite data in health related studies

There are numerous studies on the health effects of air pollution. We identified review papers between 2010 and 2018 on air quality, related to satellite data and health. Some studies are directly related to modelling health impacts, others are focused on air quality model building with a more indirect purpose to use it in health effect studies. In some studies in-situ data is used for assessing health effects, and satellite data is mentioned with its pros and cons.

In health studies, the most important reason for the use of air quality data is to estimate the exposure of humans to air pollutant concentrations, in order to link this exposure to health outcomes, morbidity or mortality. Depending on the type of study, individual exposure or population exposure is needed, and either short-term or long-term exposure data is required. Hoek (2017) extensively reviewed methods for assessing long-term exposure to outdoor air pollutants, amongst which satellite data. Satellite data has the limitation of measuring an entire vertical column while the interest is in breathing height. Ozone cannot be measured at surface level by satellites, because the levels in the stratosphere are very high compared to those at the surface. For NO_2 and PM there is a moderate correlation between satellite observations and in-situ measurements at background locations. The spatial variability of NO_2 is too high to map NO_2 on a grid of 1x1 km. Limitations of satellite data are the temporally and spatially varying relationship between column and surface concentrations, the spatial resolution, cloud cover interference, and characterization of a single time of the day. Sorek-Hamer, Just, and Kloog (2016) found similar results and add that AOD on its own does not represent the size distribution and toxicity of particulate matter.

The global coverage of satellite products and the resulting ability to apply the same method to the entire globe makes satellite data an interesting method for global comparisons of exposure (Matthias et al., 2018; Molina et al., 2010; Monks et al., 2015; Sorek-Hamer et al., 2016). Other field of application are exposure studies in rural areas or developing countries where no in-situ measurements exist (Marlier, Jina, Kinney, & DeFries, 2016), and as a complementary approach for large areas (Marć, Tobiszewski, Zabiegała, Guardia, & Namieśnik, 2015). Satellite data is however mostly used in developed countries, with the resources and knowledge to process the data (Prasad, Gray, Ross, & Kano, 2016). Jerrett, Gale, and Kontgis (2010) argue that the technology exists to use LiDAR at 1x1 meter resolution, but that the accuracy is currently limited by oversensitivity to coarse particles. For cohort studies, satellite data has a good temporal resolution and the advantage of long historical records (Vedal, Han, Xu, Szpiro, & Bai, 2017). To improve temporal resolution for short-term exposure estimation, geostationary satellites can be of great benefit. These satellites obtain data at hourly or sub-hourly resolution, and even near real-time data acquisition is possible (Sowden, Mueller, & Blake, 2018; Zhu et al., 2015).

Land use regression (LUR) models are typically used to model exposure at a finer resolution using land use covariates and in-situ measurements. Using satellite images directly for exposure estimates gives some sources of uncertainty and error, due to the measurement height, the derivation of $PM_{2.5}$ concentrations from AOD, the lack of spatial precision, and interference by cloud cover and nearby water (Samoli & Butland, 2017). Satellite images and dispersion model outcomes can however be integrated into land use regression models to model NO_2 and $PM_{2.5}$ at 100x100m scales. With growing interest in artificial intelligence and deep learning, also the interest in combining different data sources for exposure estimation is growing (Vopham, Hart, Laden, & Chiang, 2018).

For climate-related health effects, urban heat islands (UHI) are of interest. Satellite data, especially on land surface temperature (LST) is commonly used in studies on urban heat islands: e.g. 46% of the studies on UHI in South Asia were based on satellite observations (Kotharkar, Ramesh, & Bagade, 2018). Satellite images have increasingly been used since 2000, because of free availability of data. The main limitations for this application are the time of overpass, presence of cloud cover, viewing geometry, and spatio-temporal resolution. Mushore, Odindi, Dube, Matongera, and Mutanga (2017) propose to integrate high spatial resolution satellite data with high temporal and low spatial resolution in-situ sensors in the future. In the future, the variability in seasonal and long-term urban thermal patterns should be monitored.

Weigand et al. (2019) show in a recent publication that modern earth observation data are an important data source for research on environmental justice and health. The study highlights potential benefits of remote sensing data to environmental justice research. Among them are the derivation of micro-climatic properties and land surface temperature estimates, the characterization of the urban structure and density as well as the distribution of air pollutants. Furthermore, the assessment of certain health impacts, which cannot be directly derived from physical measurements, can greatly benefit from highly accurate proxy information on e.g. the degree of urbanity, urban structure or urban heat islands.

3.4 Use of satellite data in urban planning

The field of urban planning encompasses all technical and political processes concerned with the development and design of land use and the built environment in urban areas and regions, including transport and technical infrastructure such as transportation, communications, and water, energy and wastewater distribution networks. Results of these urban planning processes are development strategies and plans at different scales from sub-local (block, neighbourhood level) to regional that outline and demarcate the future development of urban areas.

Air quality and climate issues in cities have become significantly more important in recent years in urban planning related activities. On the one hand this is because of the increasing impacts on cities from environmental stressors that manifest in heat stress and heat islands in certain parts of the inner cities as well as high levels of air pollution affecting the living quality in many cities. On the other hand this is also because of the increasing insight that many human activities taking place in cities significantly contribute to their ever increasing environmental stress and that the future shape and structures of cities and urban regions will have significant effects on the reduction of this stress. The latter resulted in an increasing collaboration between urban planning and public health, while increasing climate stress in cities lead to manifold studies and projects on urban climate adaptation, e.g. by means of ecosystem services and nature based solutions for cities.

To reverse the above described trend, the European Commission approved a directive to improve the air quality in its member states in 2008. They need to develop air quality plans (AQP) for zones and agglomerations where air quality limit values are exceeded, in order to implement pollution control strategies and meet the legal requirements (Miranda et al. 2015). The law enforcement relies on a monitoring and reporting system to inform the European Commission and the public. For the various air pollutants so called air quality targets and methods of assessments are prescribed in the EU directive (see Gemmer and Bo 2013). The EU directive distinguishes between so-called limit values and target values. Limit values are legally binding but allow limited short-term exceedances. A target value has to be attained as far as possible by the attainment date and compliance is checked but not legally binding (Gemmer and Bo 2013). Other institutions dealing with air quality issues, such as the WHO, have published other air quality standards and guidelines, which are often more strict and ambitious then the EU directive, but not legally binding. (WHO 2017).

Pollution by particulate matter (PM), nitrogen dioxide (NO_2) and Ozone (O_3) are the most important air quality stressors in cities nowadays. Levels of air pollution vary very much within cities at small scale due to diverse urban forms of the city. For example, average concentrations of air pollutants are generally considerably higher at street locations compared to urban background with average ratios of 1.63 for NO2 and 1.93 for NOx and 1.14, 1.23 and 1.42 respectively for $PM_{2.5}$, PM_{10} and PM_{coarse}, in Europe (Nieuwenhuijsen et al. 2016). Sources of air pollution in cities are next to the amount of motorized, fuel based transport, also residential heating based on fossil fuels, and the density of industrial production. Next to this, also various physical factors of the urban form contribute to the spatial variation of air pollution within cities, such as the density and height of buildings, the availability of green space and water (green and blue infrastructure), and the availability of air corridors enabling a better ventilation of the city (Nieuwenhuijsen et al. 2016).

Air quality data used for air quality planning in cities often results from in situ measurements with either active or passive collectors, usually in combination with air quality modelling (see section 3.6). The 2008 European Air Quality Directive (AQD) (2008/50/EC) encourages the use of models in combination with monitoring in a range of applications (Thunis et al. 2016). However, Miranda et al. (2015) found that some cities in Europe do not include the use of air quality models, considering the monitoring network as spatially representative of the study domain (e.g. Lisbon Region, Riga, Malta).

In the scope of air pollution mitigation strategies, integrated assessment modelling (IAM) methodologies have received increasing attention both in the scientific literature as well as in the European air quality directives (Thunis et al. 2016). IAM include tools that allow a user to design air quality plans taking into consideration the impacts of different policy options.

Data of air quality and climate directly derived from satellite sensors is hardly being used in urban planning/air quality planning related studies up to now. However, recent scholars identify the opportunity for using satellite data for either for informing air dispersion models or for data fusion methods which take a variety of data sources such as ground based monitoring, air quality modelling, satellite retrieved data and/or any other spatially distributed data relevant to air quality into account.

3.5 Use of satellite data for environmental monitoring

Environmental monitoring studies observe, among others, factors of air quality and climate parameters at global to regional scales. Due to its rather coarse scales, environmental monitoring of air quality makes frequent use of satellite borne air quality data. Current applications can be distinguished into rather short-term changes of air quality parameters resulting from single or unexpected events and the monitoring of long-term trends of ambient pollutant concentrations. The former includes, among others, tracking of pollutant plumes from agriculture and wildfire (Duncan et al. 2014), emissions and transportation of dust and aerosols resulting from mining activities (Csavina et al. 2012), monitoring of regional differences of black carbon from biomass based cooking (Soneja et al. 2016), and identification of oil and natural gas emission sources (Field, Soltis, & Murphy, 2014). Monitoring of long term trends in air quality is mainly used for developing environmental indicators (Hsu et al. 2013), which in turn then can be used to inform high level policy and decision making (de Sherbinin et al. 2014). With respect to the latter, the authors stress the need also for solid ground truth datasets to bolster the applicability of satellite-based indicators, because “decision makers may still be understandably hesitant to rely on satellite-based indicators without comparisons” (de Sherbinin et al. 2014).

Satellite data is very useful for monitoring the distribution and transport of particulate matter at continental scale (Youssouf et al., 2014). Chen et al. (2017) evaluated the impacts of biomass burning on air quality, health and climate. For this purpose, satellite data has advantages over in-situ measurements. Satellite images can be used for different aerosol optical and physical properties, precursors and trace gases, and measure an entire vertical profile. They allow for observation of the number of fires, locations of fires, smoke-plume distribution, injection height, fire radiative power, long-range transport, and mapping of burnt areas. Rehman, Ahmed, Praveen, Kar, and Ramanathan (2011) however showed that studies on black carbon (BC) emissions from biomass burning and fossil fuels based on satellite images often underestimate the real concentrations. The reason behind this is that there is only one measurement a day available, outside BC peak time. There is a need for understanding of small-scale variation and the link between indoor and outdoor pollution to improve emission profiles from remote sensing applications (Soneja, Tielsch, Khatry, Curriero, & Breysse, 2016). Liu, Pereira, Uhl, Bravo, and Bell (2015) systematically reviewed 61 papers on physical health impacts from non-occupational exposure to wildfire smoke, of which 11 papers were using satellite imagery for exposure assessment. Most studies use at least five years of data. In the future they expect more advanced models based on satellite images.

Monitoring pollutant plumes is also done in the case of mining operations, where the importance of metals and metalloids in atmospheric dust is studied (Csavina et al., 2012). There, the main interest is in particle diameter and composition, as this relates to the distance travelled in the environment. For future research, the priority is on fine size particles, which pose the highest health risks. Satellite imagery is also used for identification of oil and natural gas emission sources and identifying areas with elevated concentrations. Improvement of spatial resolution and vertical sensitivity would improve monitoring of unconventional oil and natural gas production in the future (Field, Soltis, & Murphy, 2014). For monitoring atmospheric aerosols, MODIS Deep Blue is popular because of its long-term operation, high accuracy of AOD measurements, and twice daily coverage of the earth. For monitoring within cities a finer spatial resolution is however required, in combination with a good accuracy (Kanniah et al., 2016). A finer spatial resolution is also required for modelling small-scale dynamical processes for evaluation of the contribution of anthropogenic and natural dust sources to emission rates (Ginoux, Prospero, Gill, Hsu, & Zhao, 2012). For hydrological dust sources, longer time series are needed. AOD performance is dependent on individual tiles of satellite imagery.

Smoke plumes can also be detected using RGB satellite imagery, and linked to in-situ measurements of air pollution. Based on the satellite images, visible plumes are drawn by hand by analysts. A limitation is that the plumes are invisible during cloud cover and during the night. Also only 1 or 2 times a day an image is visible, while the plume moves and may cover a larger area (Larsen, Reich, Ruminski, & Rappold, 2018). Aerosol composition is of importance for human exposure and health. Future needs for forecasting atmospheric composition include measurements of aerosol mass, size distribution, chemical composition, AOD at multiple wavelengths, absorption AOD (AAOD), ratio of vertically integrated mass to AOD, and the vertical distribution of aerosol extinction (Benedetti et al., 2018).

Satellite data is also used for air quality forecasting in the US. Satellite imagery is accessed on a daily basis by state air quality agencies, combined with surface monitor information to produce a daily report that forecasts air quality during the summer wildfire season (Duncan et al. 2014).

3.6 Use of satellite data for air dispersion modelling

Air dispersion models are used to determine the origin and transport pathways of the air mass or atmospheric trace gases prior to its arrival at a given place. The main purpose of air dispersion models is to incorporate emission data and basic meteorological/atmospheric data with numerical processing to estimate concentrations of pollutants over space and time. In contrast to land use regression, dispersion models have the added advantage of identifying the sources of emissions, although they are both able to assess exposure to such gases. Typical users of air dispersion models are practitioners, either from the health sector analysing changes of air quality and impacts on health outcomes (e.g. certain diseases or mortality), or from urban planning assessing environmental or health impacts of a planned intervention, e.g. the building of a new transport connection.

The use of dispersion models to assess exposure to trace gases has increased steadily over the years. The role of satellite data as either source input data or for parameter estimation validation for dispersion models has long been known. Back in the 70's, Kibler and Suttles (1977) compared measured LIDAR sensor data with dispersion-model outputs through a numerical estimation procedure to yield parameter estimates that best fit the data. Lioy et al. (1980) also analysed the atmospheric distribution of sulphate using backward trajectory, satellite imagery and ground station measurements. Singal (1993) used a Gaussian dispersion model to compute pollution concentration downwind of an emission source with the help of SODAR determined data.

Dispersion models are based upon physical principles and actual emission data. Relying generally on Gaussian plume equations, dispersion models require pollution, meteorological, and emission data. Routinely collected data are unavailable for most countries, and even among those countries, that have collected such data, these are spatially sparse. Data from satellite remote sensing has become a great alternative. The relevance of satellite data for air quality and dispersion models is its quick and easy access to the sources term, i.e. an assessment of the rate at which the pollutant is injected into the atmosphere. As noted in Jerret et al. (2005), the use of satellite remote sensing for exposure assessment appears to be a promising avenue for future research, particularly in low-income countries that may lack the resources to implement extensive ground monitoring programs. The required pollution, emission, and meteorological information can be extracted from satellite data, which are readily and largely available.

As highlighted by El-Harbawi et al. (2013), the four main factors that influence the transport, dilution, and dispersion of air pollutants can be grouped as emission or source characteristics, nature of pollutant material, meteorological characteristics, and, effects of terrain and anthropogenic structures. Either of these factors are accessible and extractable from satellite data. In what follows, we focus on exemplary air quality dispersion models that incorporate satellite data as either source term or for evaluation purposes.

Rolph et al. (2009) used the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model to calculate the transport, dispersion, and deposition of the emitted particulate matter, and carried out model evaluation by comparing predicted smoke levels with actual smoke detected from satellites by the HMS and the Geostationary Operational Environmental Satellite (GOES) Aerosol/Smoke Product. Henderson et al. (2008) used aerosol optical thickness (AOT) and colour imagery product from MODIS for further evaluation. Their focus was to describe an approach that makes plume dispersion models more accessible for public health applications by simplifying and evaluating them with MODIS fire detection, aerosol, and true colour products. In northern Iraq, Bjoernham et al. (2017) showed that remote sensing through satellite images of SO_2 can be utilized to provide a rapid source estimate for dispersion modelling. As far back as in the 80's, the National Environmental Research Institute (NERI) in Denmark developed an OML ("Operationelle Meteorologiske Luftkvalitetsmodeller" – Operational Meteorological Air Quality Model) local-scale atmospheric dispersion model (Olsen 1995a, b). Using OML and satellite data, specifically tropospheric-ozone from OMI, Grigoraş et al (2016) assessed the surface-ozone concentration in Bucharest, Romania. They highlighted that estimated tropospheric-ozone from satellite can be used as input in OML model and that satellite data can improve the air quality assessment on local level. Lowry et al. (2016) have used the UK Meteorological Office Numerical Atmospheric-dispersion Modelling Environment (NAME) to investigate origins of air masses arriving at Egham, England, with both near-background and higher CO contents. Here, CO extracted from the Measurements of Pollution in the Troposphere (MOPITT) satellite data were used to assess the model consistency. De Hoogh et al. (2018) incorporated MODIS AOD observations and dispersion model estimates to develop and evaluate fine spatial scale land use regression models for four major health relevant air pollutants ($PM_{2.5}$, NO_2, BC, O_3) across Europe. Using evapotranspiration information extracted from MODIS, Rahman et al. (2019) showed that the sensible heat flux was dominating during dry periods and the latent heat flux was dominating during the wet periods, and the rate of dominance was controlled by the availability of water, vegetation dynamics and weather conditions. Based on AOD and AE extracted from MODIS and CALIPSO sensors, and hourly environmental monitoring measurements from Chinese cities and East Asian meteorological observation stations, Zhang et al. (2018) analysed the spatial and temporal characteristics of dust dispersion as well as its associated impact on the Asia-Pacific region. The authors investigated the transport of smoke aerosols and quantified the impact of Russian forest fires on Asia using AOD and NDVI from MODIS and CALIPSO. Yu et al. (2018) applied spatial average, inverse distance weighting, kriging, discontinuous tessellation, natural neighbour tessellation with interpolation, land use regression, downscaled MODIS-derived AOD, dispersion model, and chemical transport model to study the air quality dispersion in Atlanta, Georgia, USA.

Back and forward trajectory analysis have been used to aid identifying and selecting measurements taken under and outside of the volcanic SO2 plume using observations from OMI GOME-2 (Zerefos et al. 2017). The transport of NOx emitted in East Asia was also demonstrated using OMI satellite data and surface in situ measurements and Lagrangian particle dispersion model simulations (Lee et al. 2014). Langford et al. (2017) also examined the contributions of stratosphere-to-troposphere transport (STT) and transported AOD, O_3, and CO exceedances using MODIS. With GOME-2 and OMI data being readily available, a rapid source term estimation was made to determine the release rate of SO_2 from an industrial accident and was used for forecasting of SO_2 concentration in the region by use of dispersion models (Bjoernham et al. 2017).

Satellite remote sensing has a promising future for air dispersion modelling, particularly in low-income countries that may lack the resources to implement extensive ground monitoring programs. The role of satellite data is either as source input data or for parameter estimation validation for dispersion models. Synthesizing the various literature, we deduce that the prominent air quality variable for dispersion modelling is AOD. The AOD is retrievable from the majority of the sensors available, of which the retrievals from MODIS are most commonly used. Specific user needs and limitations relating to spatial and temporal resolutions have rarely been indicated in literature; perhaps because the atmospheric life-span of AOD is short (days to weeks) and highly localized in space (von Schneidemesser et al. 2015). Being either an input or validation source, the spatial resolution requirements for air dispersion models may be deduced from Thompson and Selin (2012). Here, no significant differences in model outputs were observed for 2, 4, and 12 km resolution, but over-prediction for 36 km resolution.

4 User needs for air quality and climate data

In the following, we present the main findings from the expert interviews structured by the main questions discussed with the experts and enriched with matching findings from the literature review. The codes given at the end of each statement indicate the various experts in anonymized form.

1) What are the main advantages of satellite based measurements of air quality and climate data?
   - Spatial temporal coverage and resolution for studies at national to regional scale (DE1, NL6), countrywide coverage of similar data acquisition (NL9, NL2, NL4)
   - Temporal resolution good for annual averages for long-term exposure studies (GH) and daily values are enough for legislation purposes (INT4)
   - In combination with model data, 1x1 km resolution possible (NL1) or even 100x100m in land use regression models (Samoli & Butland, 2017)
   - Important data source for background concentrations to improve models (NL1, DE2)
   - Validation and source apportionment when peaks are measured by low-cost in-situ sensors (NL6), e.g. local source or pollutant cloud
   - Detection of unknown air pollution sources in developing countries without emission inventories (NL3)
   - Monitoring of ozone layer and effect of ozone-depleting substances (NL3)
   - Availability of data within a few days (NL2)
   - Cubesat: (https://www.cubesat.org/): mini satellites, low cost, chance to launch a number of them, in order to achieve a better temporal coverage/resolution (NL11)
   - Standardized, uniform measurements worldwide (NL11) (Matthias et al., 2018; Molina et al., 2010; Monks et al., 2015; Sorek-Hamer, Just, & Kloog, 2016)
   - Large spatial coverage area on continental/global scale (Youssouf et al., 2014)
   - Cheap source of data in developing countries or rural areas where no in-situ measurements exist (INT4), e.g. for exposure studies (Marć, Tobiszewski, Zabiegała, Guardia, & Namieśnik, 2015; Marlier, Jina, Kinney, & DeFries, 2016) or detecting urban heat islands based on land surface temperature (Kotharkar, Ramesh, & Bagade, 2018)
   - Detection and forecasting of transboundary pollutant transport for source apportionment (INT4)
   - Long-term historical records of data (Kanniah et al., 2016; Vedal, Han, Xu, Szpiro, & Bai, 2017)
   - Measuring the entire vertical column at once (Youssouf et al., 2014) -> both an advantage and a disadvantage, depending on the application

2) What are disadvantages/shortcomings of satellite based measurements of air quality and climate data?
   - Data gaps when e.g. clouds are occurring (DE1) (Hoek, 2017; Kotharkar et al., 2018; Larsen, Reich, Ruminski, & Rappold, 2018; Rehman, Ahmed, Praveen, Kar, & Ramanathan, 2011; Samoli & Butland, 2017; Sorek-Hamer et al., 2016)
   - Lacking spatial resolution for more finer studies, e.g. at city level (DE1, NL7, NL2, NL1, NL4) (Hoek, 2017; Kanniah et al., 2016; Kotharkar et al., 2018; Samoli & Butland, 2017; Sorek-

Hamer et al., 2016), for validation purposes (NL5) and for modelling small-scale dynamical processes for evaluation of the contribution of anthropogenic and natural dust sources to emission rates (Ginoux, Prospero, Gill, Hsu, & Zhao, 2012)
- Measurements only once or twice a day is very crude particular for experts and practitioners from health and epidemiology resp. those developing and running air dispersion models, because they are typically interested in the change of air quality over the day or the exposure of the population to low air quality during peak hours (INT1, NL1, NL2, NL5) (Hoek, 2017; Kotharkar et al., 2018; Larsen et al., 2018; Sorek-Hamer et al., 2016)
- Relationship satellite images and ground-level concentrations not accurately defined and varies in space and time (NL1, NL7) (Ginoux et al., 2012; Hoek, 2017; Samoli & Butland, 2017; Sorek-Hamer et al., 2016)
- Sulphur (from ships) hard to measure because of water vapour interference (NL5)
- Measuring concentrations of pollutants (gases) at ground level not possible (NL11) because an entire vertical column is measured and because ozone levels in stratosphere are very high compared to ground level (Hoek, 2017)
- Nice to have a geostationary satellite to improve temporal resolution (Sowden, Mueller, & Blake, 2018; Zhu et al., 2015), but because of the height needed, the resolution is not very good (NL11, NL10)
- Interference of nearby water (NL1) (Samoli & Butland, 2017)

3) Comparison of in-situ measurements vs. satellite based measurements of air quality and climate data

- It’s not so much a question of either or, but more of how to use both data sources together
  - E.g. AQ satellite data for background levels of air pollution together with ground based measurements for actual pollution levels (DE2, NL6)
  - AQ satellite data either as input parameter to or as for calibration of air quality/dispersion models.
  - Growing interest in combining datasets for exposure estimation with the growing interest in artificial intelligence and deep learning (Vopham, Hart, Laden, & Chiang, 2018)
  - Integrate high spatial resolution satellite data with high temporal but low spatial resolution in-situ sensors (Mushore, Odindi, Dube, Matongera, & Mutanga, 2017)

4) More details of current measurements of air quality and climate data required by users

- Better spatiotemporal resolution:
  - better spatial resolution required by health/epidemiology experts and researchers around important sources of pollutions (e.g. highways, industrial areas, ships) (DE1, NL2, NL5) and especially for pollutants with high spatial variability such as NO_2 (NL1) (Hoek, 2017) which are difficult to measure with low-cost sensors (NL7)
  - for models 1x1 or 2x2 km (NL3), for megacities in developing countries at least 1x1 km but preferably smaller (INT4), in European cities for urban planning and health impact

    - assessment issues ideally 100 x 100 m (INT1, NL7, DE3), or even 25 x 25 m (INT1), for transport planning 10-20 m (NL9)
    - hourly resolution needed for short-term health effect studies (NL1, INT1), modelling (NL2) and source apportionment (NL7), for better service provision and to reduce dependency on complex models (NL10)
    - at least more time stamps a day including traffic peak hours (NL1, NL2)
- data available over long periods of year measured with the same instrument (INT1)
- water/land differences (NL1)
- column/surface relation (NL1)
- real-time data for awareness and changing behaviour of general public (NL3, INT3)
- Measurement of air quality parameters 2 m above ground, i.e. at nose level (INT3)

5) Other pollutants/parameters required to be captured (by satellites)
- ultra fine particles (UFP) needed to be measured (DE1, NL6, NL4, DE2)
- secondary aerosols: particles which have not been directly emitted into the air as particles, but through a gas-to-particle conversion, nucleation or chemical process. (DE1)
- PM distinguished by source of pollutions (INT2, NL11), chemical composition (NL1, NL7, NL2, INT4) (Benedetti et al., 2018), vertical profile (NL2) (Benedetti et al., 2018) and size distribution (NL6) (Benedetti et al., 2018; Sorek-Hamer et al., 2016)
- Ammonia (NL2, NL4)
- CO_2 (NL2, NL4), ideally distinguished by anthropogenic and natural sources (NL2)
- Sulphur (but problem with water vapour interference) from ships (NL5) and from coal-fired power plants in South-East Asia (INT4)
- NO from coal-fired power plants in South-East Asia (INT4)
- O_3 at surface level (NL4, INT1)
- Methane from agricultural production (NL10)
- Black carbon (INT4)
- Mixing layer height MLH (DE2), see also Tang et al. (2016) "…to acquire continuous observations with high spatial and temporal resolution, ground-based remote sensing has become the most advanced approach to MLH measurement…
- Humidity: measurements from sat. rather sparse, profiles needed (NL11)
- AOD at multiple wavelengths and absorption AOD (Benedetti et al., 2018)

6) Current and future user groups and user needs/ new (fields of) applications
- exposure estimation (NL1)
- land use regression modelling of urban air quality variability (NL1)
- future: cyclist route planning for healthy routes (NL9)
- tackling air pollution problems on problematic roads (NL9)
- data assimilation: improving the spatial coverage of other datasets by incorporating information from satellite data (NL5, NL2) (Mushore et al., 2017)
- ship emission detection for coastline pollution regulations, combining satellite NO_2 data with ship tracking data from AIS (NL5)

- land surface temperature for monitoring urban heat island effects (NL5) (Kotharkar et al., 2018)
- future: air pollution-neutral city planning (NL7, NL4)
- air quality monitoring, impacts in relation to population density (DE1)
- source apportionment studies, i.e. measurements and tracking down of the sources of air pollution, e.g. transport, industrial production, biomass cooking, etc. (http://www.who.int/quantifying_ehimpacts/global/source_apport/en/) (INT2)
- vertical profiling (INT3)
- (near to) real time monitoring of air quality (INT3)
- evaluating policy effects, such as environmental zones in cities (NL1)
- If better data is available it would e.g. allow to detect emissions from certain incidences or events, such as a chemical disaster or volcano eruptions (NL10)
- With respect to methane, it would be good being able to detect how much is emitted where and when (NL10)
- Being able to track what is emitted where and when might be helpful also with respect to tracking emissions from ships, because that would help to enforce stricter regulations regarding emissions as they are currently discussed in the NL (polluter pays principle). (NL10)
- Monitor biomass burning: number of fires, locations of fires, smoke-plume distribution, injection height, fire radiative power, long-range transport, and mapping of burnt areas (Chen et al., 2017) and monitoring non-occupational exposure to wildfire smoke (Liu et al 2015)
- Monitoring pollutant plumes from coal-fired power plants (INT4), mining activities (Csavina et al., 2012), and unconventional oil and natural gas production (Field, Soltis, & Murphy, 2014)

7) New (commercial) markets, new business models

- climate services: Finance sectors/insurance using climate services for risk assessment, re-insurance (NL8)
- climate services: tourism sector not that much interested, don't want to burden their positive image (NL8)
- climate services: big data platforms (google, facebook etc.) as data providers, question whether data is provided open access or not, legal fights at courts pending (NL8)
- cyclist healthy route planning (NL9)
- city planning based on air pollution neutrality (NL7, NL4) and climate neutral developments (NL4)

8) Any other issues mentioned by the experts

- providing climate services as a new products/service needs to consider users having different levels of knowledge (layperson vs. expert users), and what effects does the use of such data have on them (NL8)
- also, the non-user, why do they not use it (they don't want it, they don't know it, they tried using it and have given up) (NL8)
- data on air quality is potentially politically sensitive, government might not want to spread/publicize the data or doesn't trust the data source (INT2, INT4)

- for long-term datasets, when new satellite is launched to replace an older one, period of overlap is needed for calibration and continuation of dataset (NL3)
- Satellite data is mostly used in developed countries, with the resources and knowledge to process the data (Prasad, Gray, Ross, & Kano, 2016)

5 Results and conclusions

In the following, we present the main findings from the research based on the expert interviews and the literature review we conducted with respect to user needs for air quality and climate data from satellites. The section is divided into two parts, first comes a rough quantification of used needs per field of application and parameter, then a general discussion and reflection on the main findings.

5.1 Quantified user needs per field of application and parameter

The following tables aim to summarize our findings in a sort of quantification of user needs per field of application with respect to the various air quality and climate parameters. The tables, depending on the application, deal with user needs in terms of spatial and temporal resolution and attribute accuracy, which is referred to as the accuracy of the air pollution measurements. The given recommendations are based on whether or not the data is accurate enough for a specific application. It needs to be mentioned, that the numbers in the tables need to be digested with care, because they represent a sort of snapshot based on interviews with selected experts, and therefore entail a certain level of uncertainty. In any case, there is no straightforward scientific evidence in a strict sense employed in the quantification for the different items in the table, such as spatial resolution, etc.

The most important parameters according to the experts are highlighted in yellow. Moreover, the tables shall not be read independently of the explanatory notes.

Epidemiology and health

$PM_{2.5}$, NO_2 and O_3 are the most important parameters for health effect studies in developed countries. Particular $PM_{2.5}$ and NO_2 work particularly well as so-called indicator parameters, to which many other parameter for air quality, to which others relevant parameters closely relate to. In developing countries $PM_{2.5}$ and NO_2 are most important due to wildfire burning and biomass cooking. For $PM_{2.5}$, which has a low spatial and temporal variability, the currently available satellite images are enough to reach the required 1x1 km resolution after downscaling. Ozone is hard to measure at surface level using satellite images. However, good in-situ measurements and chemical transport models (CTM) are available. The most important pollutant for which better data is needed, is NO_2. Land use regression (LUR) models can already reach a resolution of 100x100 m, but due to its very high spatial and temporal variability, better accuracy can be reached by more accurate and finer resolution input data to the models. This could consist of any satellite data with a higher spatial and temporal resolution than what is currently available.

Table 3 User needs epidemiology and health

Pollutant	Current situation	Required spatial resolution	Required temporal resolution	Attribute accuracy	More detail required	Remarks
PM_{10}	NA	NA	NA	NA	NA	Not the most relevant parameter for health effects
$PM_{2.5}$[1]	Downscaled to 1x1 km, LUR models 100x100 m	1x1 km		yes	Chemical composition	
Ultrafine particles (UFP)	Short-term monitoring campaigns	Within-city variability	Multiple times a day incl. peak hours	unknown		
NO_2	7x7 km or 1-2 monitors per city, LUR models 100x100 m	Street level variability	Multiple times a day incl. peak hours	yes		
O_3	1-2 monitors per city, CTM's	CTM, resolution OK	Multiple daytime measurements (night not relevant)	yes		Needed at surface level, good in-situ measurements are available in developed countries

Urban planning

For urban planning PM_{10} and NO_2 are currently the most relevant parameters, because these two are mentioned as standards in the EU air quality directive from 2008. Moreover, $PM_{2.5}$ is also highly relevant, because of its function as indicator parameter, as discussed above.

Data for the relevant air quality parameters is required at a rather small-scaled spatial resolution such as 100 x 100 m, because of the fine granularity of the urban form. However, this does not necessarily mean that the data for this has to come straight from satellite-based sensors. Deriving the information from suitable air quality models that makes of use satellite data is a more viable and cost-efficient solution. Temporal resolution for urban planning related purposes does not need to go below daily averages. More important is data on the source of the pollution, e.g. motorized transport or industrial production, and the vertical profile of the pollution, because this helps defining spatial planning interventions, which aim at reducing or relocating the emissions from these sources.

[1] The most important parameters in each table according to the experts are highlighted in yellow.

Table 4 User needs urban planning

Pollutant	Current situation	Required spatial resolution	Required temporal resolution	More details required	Remarks
PM_{10}[1]	Often used in planning as standard, data derived either from ground based monitoring (i.e. point data, a couple of sensors per city) or air quality modelling	100x100 m	Daily averages		Cities are obliged to use this parameters due to national or provincial planning law
$PM_{2.5}$	Not yet considered in planning, because of current planning law (standards) but also limited data availability	100x100 m	Daily averages		Is needed to be considered in health related planning according to health experts
UFP	Not yet considered in planning practice				
NO_2	Often used in planning as standard, data derived either from ground based monitoring (i.e. point data, a couple of sensors per city) or air quality modelling	100x100 m	Daily averages		
SO_2					Not that relevant
O_3					Relevant at surface level

Environmental monitoring and management

Environmental monitoring and management usually covering larger areas such as regions or countries is hardly done using in-situ measurements or models, but largely relies on satellite imagery already. Therefore, this table is slightly differently structured focusing on the application rather than on the single parameters. Applications include source apportionment studies, emission plume tracking and wildfire monitoring. The required spatial and temporal resolution depends on the size of the plumes and the speed of dilution and travel, but this is not of the highest concern. Generally, more information on particle composition and size distribution would improve source apportionment and impact assessment.

Table 5 User needs environmental monitoring and management

Application	Pollutants/ products of interest	Current situation	Required spatial resolution	Required temporal resolution	More detail required	Remarks
Smoke plume detection	RGB imagery	Manual drawing of plumes, 1-2 times a day	Available is 10x10km to 1x1 km, depends on sensor	Multiple times a day"		Plumes invisible during cloud cover or night
Wildfire monitoring	Aerosol optical depth (AOD), fine mode fraction (FMF), Ångström exponent (AE), PM, BC	1x1 km	unknown	Multiple time stamps a day, including peak hours to distinguish BC emission from traffic from those of other sources	Particle compositio n	
Mining activities pollution detection	Atmospheric dust, aerosols, PM	Tracking plume over several days	unknown	At least daily	Particle diameter and compositio n	
Detection of unconventio nal oil and natural gas production	NO, VOC, O_3, hazardous air pollutants (HAP), methane	8.5 x 5.3 km (Aura/NAS A TES)	Higher than currently available (8.5 x 5.3 km)	unknown	Vertical profile	
Atmospheric aerosol monitoring	AOD, FMF, AE	1.2x1.2 km, twice daily	In cities: higher than available	Twice daily is OK		

Air quality modelling

Current air quality models are able to model air quality at fine spatial and temporal resolutions, e.g. 1x1 m annual averages to 1x1 km hourly averages depending on the application. The accuracy of the models however depends on the quality of the input data and validation data. Satellite images are still of added value although they do not reach the spatial and temporal resolution of the final models. A better resolution of satellite images would, however, improve model accuracy. Satellite imagery of at least 1x1 km and with a temporal resolution of at least three images a day, would greatly improve current models. Here, pollutants of most interest are NO_2 and NH_3. Particulate matter is also of interest, but here the main focus should be on particle composition and vertical profile rather than improvement of the spatio-temporal resolution. SO_2 is of interest for ship emission detection. For this purpose, the 7x7 km TROPOMI images could be combined with AIS data for subgrid modelling in the future. The limited attribute accuracy due to interference with water vapour has however been noted.

Table 6 User needs air quality modelling

Pollutant	Current situation	Required spatial resolution[2]	Required temporal resolution	More detail required	Remarks
PM_{10}	1x1 m to 1x1 km model, hourly to annual average	cm's to 1x1 km	≥ 3 images a day	Composition, vertical profile	Sat. as input/ validation data
$PM_{2.5}$	1x1 m to 1x1 km model, hourly to annual average	cm's to 1x1 km	≥ 3 images a day	Composition, vertical profile	Sat. as input/ validation data
NO_2	1x1 m model	cm's to street level	≥ 3 images a day		Sat. as input/ validation data
SO_2	7x7 km satellite images combined with AIS data	OK after subgrid modelling with AIS data	unknown		Interest mostly in ship emissions
NH_3	1x1 km, hourly model	1x1 km	≥ 3 images a day		

5.2 Conclusions

Higher spatio-temporal resolution of air quality and climate data measured with satellite sensors required by multiple users.

A higher spatial as well as temporal resolution of satellite measurements of air quality and climate parameters is required according to various experts and for different reasons. A higher temporal resolution, i.e. e.g. in hourly time periods rather than one data point per day, is needed in order to monitor air quality levels during peak times, e.g. rush hours, or for short-term health effect studies, and in order to reduce dependency on complex models. Source apportionment studies are needed, i.e. measurements and tracking down of the sources of air pollution, e.g. transport, industrial production, biomass cooking, etc., The required spatio-temporal resolution of source apportionment studies highly depends on the application. Examples mentioned in the literature review and by the experts, include wildfire monitoring, ship emission monitoring, emissions of coal-fired power plants, detection of unconventional oil and natural gas production, and mining activities. A better spatial resolution of satellite data on air quality is required by researchers and practitioners working at city

[2] A spatial resolution of a few cm is a theoretically required resolution due to the applications, but in practice rather unrealistic, both from space and in-situ.

level in order to capture small-scale differences and temporal changes. Among other, this requirement refers to the use of such data in climate and air quality services, such as the AIR-Portal, which are becoming popular currently. While for modelling purposes a resolution of 1x1 or 2x2 km is sufficient, megacities in developing countries require at least 1x1 km but preferably smaller resolution. In European cities, where typically also other data sets are available at finer scales, ideally a resolution of 100 x 100 m, or even 25 x 25 m for route planning would be nice to have.

Other pollutants for air quality needed to be taken into account.

Several experts identified the measuring of ultrafine particle (UFP, diameter less than 100 nm) as one of the main future needs, because they are ubiquitous in urban air and an acknowledged risk to human health, particular in cities. Although the average exposure to outdoor UFPs in Asian cities is about four-times larger than that in European cities (Kumar et al. 2014), UFPs are an important health threat in Europe as well. UFPs are mostly of interest to epidemiologists rather than policy makers, as there are no legal bounds to UFP concentrations (yet), nor thresholds set by the European directive. This leads to a vicious circle: a lack of official measurements by authorities leads to lack of health effect studies on UFPs, which is the main reason why no thresholds have been established, and therefore no legal obligations nor official measurements. Innovative approaches of how to forecast UFPs by combining satellite and in situ measurements are given in Crippa et al. (2017). Another major requirement referred to by a large number of experts is the distinction of PM by source of pollutions and chemical composition, as well as vertical profiles and size distribution of PM (Benedetti et al., 2018; Sorek-Hamer et al., 2016). These would be useful for source apportionment, health effect studies, and targeted policy decisions to reduce air pollution both in cities and in rural areas. The measurement of ozone (O_3) at ground level is another future requirement identified by some of the experts, although it is acknowledged that the ozone levels in the stratosphere are much higher than those at surface level, making it practically impossible to establish a relationship between the measurements taken by the satellite and those measured at surface level. Besides the pollutants related to urban activities, there would be an advantage of satellite images to obtain accurate measurements of pollutants related to farming activities, such as methane and ammonia. These are only sparsely measured by official monitoring networks, while satellites can cover larger areas.

Satellite remote sensing remains a vital resource in climate studies

Satellite remote sensing remain a vital resource in climate studies since majority of the essential climate variables (ECV's) can be monitored through by satellites. This is against the background that ground control stations are limited in both coverage and scale, hence inadequate to monitor the earths changing climate. Current satellite sensors do have the required accuracy for monitoring cloud trends. However, finer spatial resolutions are essential for future satellite observations for temperature and water vapour. Temporal resolution of the satellite data has been a recurring limitation in our review that limits the utilization of remote sensing data for climate studies (see above). Important limitations of current measurements also include the technical characteristics of the sensors themselves. Some satellites cannot stand the test of time in terms of the loss of radiometric sensitivity, and hence causes drift in observations. Especially in climate change studies, the continuity of historical datasets is of major importance.

Satellite remote sensing has a promising future for air dispersion modelling.

Satellite remote sensing has a promising future for air quality dispersion modelling, particularly in low-income countries that may lack the resources to implement extensive ground monitoring programs. The role of satellite data is either as source input data or for parameter estimation validation for dispersion models. Synthesizing the various literature, we deduce that the common air quality observation for dispersion modelling is AOD. The AOD is retrievable from majority of the sensors available of which the retrievals from MODIS is the most commonly used. Specific user needs and limitations relating to spatial and temporal resolutions have rarely been indicated in literature perhaps because the atmospheric life span of AOD is short (days to weeks) and highly geographically localized.

Satellite and in situ based measurements of air quality are complementary and are ideally to be integrated.

In many of the studies the experts referred to in the interviews it's not so much a question of either using satellite data or in situ measurements, but rather more of how to integrate high spatial resolution satellite data with high temporal but low spatial coverage of in-situ sensors (Mushore, Odindi, Dube, Matongera, & Mutanga, 2017). For instance, air quality satellite data can be used for measuring background levels of air pollution, while ground based measurements help to identify actual pollution levels in certain location. Another example of integration of both sources is for forecasting UFPs by combining satellite and in situ measurements as given in Crippa et al. (2017).

Services based on air quality and climate data are increasingly developed by commercial businesses and lead to new applications.

Climate and air quality services, i.e. especially online tools and applications, that make use of satellite data among other data sources, are increasingly developed and provided by commercial companies. Goal of many of these services is to provide reliable, tailor-made, and readily accessible climate and air quality data at high resolution to decision makers. Examples are AIR-Portal (https://airportal.stcorp.nl/), wind and solar power forecasts (http://www.hermess.nl/assimilating-earth-observation/), airTEXT (https://www.copernicus.eu/en/use-cases/airtext-air-quality-information-glance) robust climate data targeted information products (https://iri.columbia.edu/resources/enacts/), and a climate risk screening tool (Acclimatise Aware, http://www.acclimatise.uk.com/analytics/applications/). Basic concept of many of these services is that they use available data from various services, among them satellite data, run complex models to add value to the data, e.g. by downscaling the spatial and temporal resolution, and then provide the results in user friendly online applications, either for free or based on contracts and licences. There is also an interest in the use of air quality and climate data for new applications. For example, insurance companies gain interest in air quality data for health risk assessment and climate data for building damage risk assessment.

However, while such tools and applications are increasingly being developed these days, serious questions in relation to it such as “What are the revenue schemes for such services, who is paying for it, and who is earning money from it”, are still unanswered. Various court cases are currently addressing the question: who is entitled to use and to valorise the data and the services, e.g. meteorological forecasts.

In Global South countries more expertise is needed on interpretation of satellite data.

Developing countries still have the highest levels of air pollution due to large amount of traffic in megacities, lack of regulations on car exhaust filtering, mainly fossil fuel based energy production and heavy industries. While threshold values, regulations and official monitoring networks to check on those are common practice in developed countries, they are much less common practice in the Global South. Satellite data can be useful to fill those gaps where no monitoring networks exist. However, the expertise to process and interpret the satellite data is mostly found in the developed countries. Besides that, governments do not trust data from low-cost sensors or satellites when not proven accurate compared to ground truth measurements. They are also likely to point to pollutant sources in neighbouring countries and explain their own high pollution levels by transboundary pollutant transport. Satellite data can make these issues more insightful, but accurate data and good data quality assessment are required.

Air quality and climate data and services based on these are highly political/sensitive issues.

Availability and access to detailed climate and air quality data and services based on these is often a sensitive political issue, particularly in global south countries. Eventually policy makers are not willing to make data available, that discredits programmes and interventions, or results are being discarded for being incorrect. In the (winter) tourism sector, climate data and services are e.g. eventually refused in order to not discredit the image of the location. Moreover, with respect to air quality and climate services open for the public, also user capabilities to understand the information need to be considered.

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7 Annexes

7.1 Interview guide

Guiding questions

First section: Their current work related to air quality and the use of data within that

1. What is/are your (current, past, future) activities/analyses for which you/your group/institutions/agency use/s) data on air quality?
2. Is the tasks/activities/ analyses you use air quality data for an obligatory (statutory) one or not, how often/regular do you do this
3. What air quality data do you use for that (what pollutants, at what spatial resolution, what temporal resolution, measured at what height, etc.)
4. Where is the data coming from (own data or third parties), what's the source of the data, from which year, etc.?
5. How do you get the data, what format, how frequent, how timely, real-time?
6. Have you ever worked with or considered air quality from satellite data? Why (Q7) /why not (Q8) using them?
7. If yes: for what advantages do you choose to work with satellite data?
8. If not: because of which aspect don't you use satellite data? (what pollutants, at what spatial resolution, at what temporal resolution, measured at what height, etc.)

Second section: requirements for new/better air quality data

1. Are you happy with the data quality (in all respects)? What do you think could be better about the data?
2. If you have better air quality data would you do tasks/activities differently resp. would you do other tasks/activities?
3. Any upcoming/future challenges/tasks burning questions/issues for which data or air quality might be needed (if not addressed in previous question already)
4. If you can wish: what kind of air quality data would you like to have / what is needed to do your tasks/activities best (what pollutants, at what spatial resolution, at what temporal resolution, measured at what height, etc.)?
5. Do you see other needs or other potential users of improved air quality data?
6. Any other issues you would like to mention?