Crowdsourcing Without Data Bias: Building a Quality Assurance System for Air Pollution Symptom Mapping Toward an SDG Indicator

Marta Samulowska
Uniwersytet Warszawski Wydzial Geografii i Studiow Regionalnych
Szymon Chmielewski
Uniwersytet Przyrodniczy w Lublinie
Edwin Raczko
Uniwersytet Warszawski Wydzial Geografii i Studiow Regionalnych
Michał Lupa
Akademia Gorniczo-Hutnicza imienia Stanislawa Staszica w Krakowie Wydzial Geologii Geofizyki i Ochrony Srodowiska
Dorota Myszkowska
Uniwersytet Jagiellonski w Krakowie Collegium Medicum
Bogdan Zagajewski (bogdan@uw.edu.pl)
Uniwersytet Warszawski Wydzial Geografii i Studiow Regionalnych https://orcid.org/0000-0001-7882-5318

Research

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Abstract

The United Nations (UN) sustainable development goals (SDGs), a strategy to guide the world's social and economic transformation, highlight the issue of urban air pollution in SDG 11. Open data, as an output of citizen science (CS), are needed to supply and improve the SDG indicator system. Therefore, we propose a CS framework to extend the paradigm of urban air pollution monitoring from particulate matter concentration levels to air quality-related health symptom load, and foster the development of a tier-3 SDG indicator (which we call indicator 11.6.3). Building this new perspective for CS contributions to the achievement of SDGs, we address the problem of crowdsourced data bias as a prerequisite for better quality open data output. The aim of this study is to propose an air pollution symptom mapping framework for citizen-driven research and to find the most robust data quality assurance system (QAs) in this field. The method includes a GeoWeb application as well as data quality assurance mechanisms based on conditional statements, in order to reduce crowdsourced data bias. A four-month crowdsourcing campaign, released in Lubelskie voivodship (Poland), resulted in 1823 outdoor reports with a rejection rate of up to 28%, depending on the applied QA system (QAs). Testing the QAs variants, we find the most robust data bias solving method in survey-based symptom mapping. The framework output is shared via GeoWeb dashboards, including the 11.6.3 indicator evaluation. By familiarizing the public with citizen science, a city can track the progress of its SDG achievements and increase the transparency of the process through the use of GeoWeb.

1. Introduction

Urban air pollution is well-known to cause negative health impacts. Therefore, the monitoring of pollutant concentration levels plays a key role in understanding air quality and its effects on the subjective well-being (SWB) of citizens (Laffan 2018). SWB reflects the philosophical notion of a good life, as a proxy for assessing life satisfaction, momentary experiences, and stress. Kim-Prieto et al. (2005) also took into account contemporary health hazards, among which air pollution is a key factor (Ferreira et al., 2013, Signoretta et al., 2019). To promote public well-being while protecting the environment, the UN has targeted 17 Sustainable Development Goals (SDGs) and their indicators (Koch and Krellenberg 2018) to track the overall progress towards 2030. SDGs have become fundamental strategies to guide the world's social and economic transformation (Shi et al., 2019), putting emphasis on respecting natural resources and the needs of future generations. Of the SDGs, the 11th SDG is targeted at reducing the adverse per capita environmental impact of cities, including paying special attention to air quality; additionally, SDG target 3.9 aims to reduce the number of illnesses, among others, from air pollution (UN, 2015). The development of smart and sustainable cities can only be accomplished through inclusive growth, using smart people, technologies, and policies (Yigitcanlar et al., 2019). From the perspective of Smart People (Giffinger et al., 2007)—those who use smart devices to make their everyday living easier and health safer—we found it necessary to develop GeoWeb solutions to measure the adverse impact of cities on their inhabitants. Ensuring measurement credibility becomes a key scientific challenge in this context. To this end, we carried out research on the example of air pollution health symptoms, an emerging trend particularly related to odour (Arias et al., 2018) and green pollutant (Bastl et al., 2015) crowdsensing (Dutta et al., 2017, Feng et al., 2018). As crowdsensing (or, more generally, crowdsourcing) methods for health symptom mapping are subject to data bias (Zupančič and Žalik 2019), we developed and tested the quality assurance mechanism (QAm) framework (section 2.2), which can be transferred to similar health symptom-based studies. From a practical point of view, we use a case study crowdsourcing data set to track the progress on SDG 11 with the use of tier 3 SDG 11.6 indicators (Koch and Krellenberg 2018). The tier structure of the SDG indicator system defines tier 3 as a group of indicator candidates for which no agreed measurement methodology is available; we use this tier to propose a measure of citizen SWB with respect to adverse per capita air pollution impact.

Sparse or irregular monitoring station networks as well as limited access to the reference air pollution data underlies the need for CS activities in the field of air pollution monitoring. Personalized information on exposure to air pollutants, monitoring during acute events or at specific locations, partnerships with local governments, and educational and community-driven purposes are the key benefits of bottom-up environmental monitoring. CS enables the collection of data on much larger spatial and temporal scales and at much finer resolution than would otherwise be possible. The issue of urban air pollution crowdsourcing motivated the implementation of several citizen science (CS) programs, such as those led by Mapping for

Change, a community interest company in London (e.g., Pepys Air Quality Project, Science in the City Project, Love Lambeth Air; mappingforchange.org.uk/projects/), as well other international-scale activities such as those found at claircity.eu and citi-sense.eu (Castell et al., 2015), whenever hosted on GeoWeb (Komarkova et al., 2007, Haklay 2013, Jankowski et al., 2019). In this approach, citizens are required to act as sensors (Goodchild 2007), as “traditional data sources are not sufficient for measuring the SDGs” (Fritz et al., 2019). The SDG tier 3 indicator system is expected to use known quality crowdsourced data to track the progress of sustainable development. In this study, we specifically focus on urban air pollution and its health-related symptoms.

By default, urban air pollution is determined using a national, state, or local monitoring network of digital sensors measuring particulate matter (PM) 2.5 μm and 10 μm, NO_2, and SO_2 concentration levels. The link between air pollution and human health hazards has been proven both in the field of environmental science (Brągoszewska and Biedroń 2018, Weryszko-Chmielewska et al., 2018, Hano et al., 2019), as well as by medical research (Grzybowski and Mimier 2019, Warburton et al., 2019). However, anthropogenic-sourced PMs are not the sole factors of air pollutants (discussed in detail in Section 1.2). The first attempts to crowdsource urban air pollution data, understood as the compound effect of anthropogenic- and biophysical-sourced PM, were undertaken in the CS HackAir project (https://www.hackair.eu), as well the PollenApp (Bastl et al., 2015). Pan-European CS projects, such as D-NOSES (Distributed Network for Odour Sensing Empowerment and Sustainability; Arias et al., 2018), have shown that particular aspects of urban air pollution can be measured through the sense of smell of trained citizen scientists. In general, the use of a “sense of smell” is not a new approach in air pollution research. Its beginnings dates back to 1794, when Jean-Noël Hallé (the Chair of Public Hygiene in Paris) developed ‘smell walking and mapping’ as a methodology for identifying environmental hazards in industrializing cities (Kitson et al., 2019). Today, poor human olfaction is a 19th-century myth, derived from neuroanatomist Paul Broca’s hypothesis that the evolution of human free will requires a reduction in the proportional size of the brain’s olfactory bulb. In fact, such a reduction in size has been shown to not be accompanied by a reduction in the number of neurons it contains. Thus, humans have excellent olfactory ability (McGann 2017). This ability provides a scientific basis for research in the field of mammalian space sensors (Nummela et al., 2013, Meister 2015), multisensory landscape perception (smell-scape; Porteous 1985, Gorman 2017, Xiao et al., 2018), and odour crowd-sensing (Arias et al., 2018).

Contemporary scientific odour pollution mapping (Eltarkawe and Miller 2018) is carried out by the use of geo-survey (Engel et al., 2018) or a field olfactometer, a calibrated measurement tool (Walgraeve et al., 2015, Motalebi Damuchali and Guo, 2019), which dilutes air samples such that the human sense of smell can sense the odour intensity at a minimum threshold of concentration. Olfactometer calibration aims to reduce the subjective nature of odour sensing. Preliminary results of field olfactometer mapping have been reported by Walgraeve et al., (2015), Badach et al., (2018), and Kitson et al., (2019); however, this measurement tool has not yet been recognized as citizen science equipment. Moreover, citizen science has been recognized as a separate method of odour measurement (Bax et al., 2020).

Despite the subjective measurement nature of the human sense of smell, human-sensed CS (sCS) meets the high-quality method expectations (D-NOSES meets VDI (germ. Verein Deutscher Ingenieure, eng. The Association of German Engineers) 3940 standard). Human-sensed measurements of ambient air pollution, as well as the symptoms it causes, provide a promising source of spatial information. However, the unstructured nature of crowdsourced data (Capineri et al., 2016, Kamp et al., 2016, Moreri et al., 2018) requires data quality assurance (QA) protocols (Wiggins et al., 2011, Kosmala et al., 2016), as well as trust and reputation modelling (TRM; Bishr and Mantelas 2008) procedure development.

To the best of our knowledge, using QA for the purpose of air pollution symptom mapping (APSM) has not yet been investigated. Our goal was to address the challenge of crowdsourced APSM framework design with the use of a GeoWeb platform (Section 2.3) and to solve the data bias problem by using a quality assurance logic-rules-based system (QAs; Section 2.2). By assessing the rejection rate of reports affected by data bias, we provide evidence of reliable air pollution monitoring expressed as the severity of human health symptoms caused by combined factors of anthropogenic and biophysical ambient air pollutants (Grewling et al., 2019). Extending the paradigm of air pollution referenced by the WHO in terms of six main air pollutant (Sheng and Tang 2016) concentrations levels and their public health impacts (WHO 2005) to air pollution symptoms

(APSs), we indicate new possibilities for citizen-driven research and social inclusion in environmental and health-related issues, as experienced by sustainable cities. We also contribute to the development of an sCS data quality methodology. Furthermore, the quality of the spatial data determines its usability in the field of SDG indicators (OWA 2015, Hecker et al., 2018).

1.1. Sustainable Development Goal Partnership on Urban Air Pollution

Sustainability is an interactive process, maintaining a dynamic balance among six dimensions—land, natural environment, institutions, technology, economics, and humans—where change within one dimension has an impact on the others (Dockry et al., 2016). These changes and impacts may occur globally, which is why GIScience (Goodchild, 2009) plays a leading role in achieving the global SDGs.

The general idea for the SDGs has been expressed, by Brundtland et al. (1987), as the need to “meet the necessities of the present generation without harming the future generation's capacity”. We consider health symptoms caused by air pollution as one of the indicators of the current ecological footprint of humanity on the environment. In 2000, Brundtland’s idea was formulated as the Millennium Development Goals by the UN (Sachs, 2012). Over the next 15 years, the idea was emphasized as the interconnected environmental, health, social, and economic aspects of development (Schleicher et al., 2018) in SDG 2030. Out of the 17 SDGs, the 11th SDG refers to sustainable cities and communities and the third SDG refers to public health. In both cases, poor air quality caused by ambient air pollutants (in particular, referring to SDG target 11.6) is a key issue, which provided the motivation for this research. The Organization for Economic Cooperation and Development (OECD) predicts that, by 2050, air pollution will be the main reason for human mortality (Marchal et al., 2012). Therefore, we focused on urban air pollution as a case study with the starting point of health symptoms caused by human exposure to air pollutants. This concept highlights the relationship between urban habitats and SWB of citizens, as well as the interdependence of the particular SDGs. The issue of air pollution requires spatial information provided thoroughly by a modern spatially variable society (Enemark and Rajabifard, 2011, Ionita et al., 2015). This underlines the need to implement a local partnership between air pollution monitoring agencies, researchers, and the local community, who all breathe the same air. Therefore, high quality geospatial data, in terms of air pollution, is expected to be used for monitoring global progress towards achieving the SDGs.

The need for open geospatial technologies for measuring SDG 11.6 has been discussed by Choi et al. (2016), where special attention was paid to sCS as a public–academic partnership, where citizens collect data, which is then used by research institutions and themselves. By engaging in APSM, the project members, as citizen scientists (Bonney et al., 2016), facilitate the implementation of the SDGs to become an integral part of social innovation.

1.2. Extending the Paradigm of Urban Air Pollution

In the field of environmental research air quality, information on the quality (i.e., clean or polluted) of air is reported as an air quality index (AQI; Liu et al., 2019). AQI tracks six major air pollutants, inhalable particles (PM_{10}), fine particulate matter ($PM_{2.5}$), ozone (O_3), sulfur dioxides (SO2), nitrogen dioxides (NO_2), and carbon monoxide (CO; Sheng and Tang, 2016). The spectrum of pollutant sources includes those related to the development of human civilization (anthropogenic pollutants; Grewling et al., 2019), as well those from natural sources, which questions the belief that everything that is natural is healthy (Liang, 2013). Ambient air pollution concentrations above the approved limits (Kelly and Fussell, 2015, Zwozdziak et al., 2016) can cause certain health symptoms. Conversely, health symptoms can reflect air pollution. However, health symptoms resulting from inhalation of polluted air are also stimulated by natural-sourced biophysical PM such as pollen, mold spores (Bastl et al., 2017, Grewling et al., 2019), and volcanic emissions (Joseph et al., 2019), causing human health problems such as respiratory allergies including allergic asthma, which is regarded as an important disease (Baldacci et al., 2015, Di Menno di Bucchianico et al., 2019, Grewling et al., 2019). In terms of air quality, aerobiologists focus on plant species whose pollen is most harmful for pollen allergy sufferers (e.g., birch, alder, mugwort, grass, and so on) and emphasize that their co-occurrence with PMs is affected by other factors, such as increasing urban air temperature (Grewling et al., 2019).

Bastl et al. (2015, 2017) described pollen as one of the “green pollutants”, which are significant components of the atmosphere and are relevant to air quality information for pollen allergy sufferers. This distinction is important for the comprehensive understanding of APS. Air pollution is specified as the concentration of pollutants measured in physical values (e.g., micrograms per cubic meter), whereas air quality refers to AQI, as well as to classifications, opinions, and feelings, including the experiences of citizens in terms of air - and air quality-related SWB (Laffan, 2018, Signoretta et al., 2019). This broad understanding of air quality is accepted in ecosystem services science, where poor air quality is referred to as an ecosystem disservice (Escobedo et al., 2011, Sacchi et al., 2017). This concept extends our understanding of air pollution from pollutant concentration levels to personal health symptoms caused by pollutant inhalation. The quantity and severity of symptoms can explain the air quality; however, consensus about the terminology involving urban air quality has not yet been reached and researchers typically distinguish air pollution through pollen exposure (McInnes et al., 2017). There is no symptom classification for air quality yet. Regardless, both factors shape air quality. Future research is required to understand and quantify the interaction of co-exposure to both types of air pollutants and its impact on the severity of human health symptoms (Robichaud and Comtois, 2019).

Symptom mapping is a prerequisite for the spatial explanation of both dependencies. First attempts of citizen symptom mapping related to green pollutants have been undertaken by Bastl et al. (2017) and Werchan et al. (2017). Their research proved that citizen symptom load can be mapped efficiently using crowdsourced data; however, the sources of the symptoms cannot be clearly determined. The symptom load index is not directly correlated with annual pollen loads and has a strong correlation to allergen content (Bastl et al., 2017), with an (often daily) linear correlation (Bastl et al., 2017, Bédard et al., 2020). Finding that relationship is beyond the scope of this paper; however, crowdsourced symptom data have shown potential as an indicator of the effects of urban air pollution on citizen well-being. This raises the possibility for new tier 3 SDG indicator, as monitored following a standardized CS method. The unstructured nature of crowdsourced data requires rigorous QA mechanisms. In this study, our aim is to identify QA system for APSM and provide a GeoWeb framework to stream high-quality data in order to facilitate a tier 3 SDG indicator system. So far, this data stream does not exist. By sharing trusted and open data on air pollution symptoms, our findings can be used for aerobiological and health risk forecasting research.

1.3. Contribution of Citizen Science to Improvements in Air Pollution Mapping

According to Haklay (2013), geographical citizen science overlaps VGI, especially in the geographical context of citizen-driven research. GeoWeb plays an essential role in this field. However, it is crucial that CS and VGI should not be seen as equal, as the main purpose of VGI is to produce geographical information, whilst citizen science aims to produce new scientific knowledge (Connors et al., 2012, Eitzel et al., 2017). Citizens engaged in scientific research projects become citizen scientists (Silvertown, 2009) who, depending upon their personal interests, motivation, education level, and experience in previous projects, engage with different levels of participation and expect to see the results of their research contribution. They contribute in the project by collecting and analysing data, but may also be involved in defining research questions or even interpreting results (Dickinson et al., 2010, Haklay, 2013, Kar et al., 2016). Considering the scope of citizen participation, Haklay (2013) has defined four levels of CS: crowdsourcing (first level), distributed intelligence (second level), participatory science (third level), and extreme citizen science (fourth level). Citizen involvement in environmental projects on air pollution is usually based on collecting and analysing sensor data in the form of online maps. In this way, knowledge is produced. The fundamental questions about the harmful health effects of air pollutant have been asked, so these activities are typified as CS level 1 and CS level 2. Of course, higher levels (depending on the engagement of members) are not excluded. In the case of odour crowdsourcing, which requires training as well as expecting measurement insights back from members, a collection method can be devised (i.e., level 3). Reviewing the most relevant air pollution citizen science activities (Table 1), the typology of participation engagement can be assigned to be basic on the project description; however, this does not limit the engaged members to achieve the next levels through the re-use of data, scientific collaboration, and report publishing. Our study was based on the first level of CS, where citizens are engaged in the process of crowdsourcing APS data to monitor progress toward the achievement of SDGs 11.6.3, producing a new scientific knowledge of APSM together with researchers. CS provides a solution to research problems while also educating citizens (Bonney et al., 2009). Before starting to collect data in this study, citizens were educated about the research problem and project aims and were trained how to use the associated

tools properly. By attending workshops, the citizens gained knowledge and new skills, and followed the progress of the project in real-time. By sharing their conclusions and opinions during the social campaign, they had a direct impact on the optimization of methods used.

So far, smartphones have not been considered appropriate equipment for measuring urban air pollution. This is due to the fact that the built-in sensors of smartphones, by default, do not allow users to measure air pollutant concentrations. Therefore, bottom-up activities considering air pollution have usually relied on external, low-cost sensors (initially only capable of PM measurement, these sensors can now also sense all major pollutants, including volatile organic compounds). In an attempt to involve smartphones users into air pollution monitoring, efforts have been made to determine the PM concentration with the use of a mobile app which takes images of clear blue skies (AirTick project), with an average of day time PM1 concentration level up to 87% (Zhu et al., 2018). Other approaches have used spectropolarimeters as add-ons, such as within the iSpex project (Snik et al., 2014), to measure PM concentration level. The idea of using a smartphone camera to measure air pollution has been adopted by the HackAir project (Kosmidis et al., 2018). Furthermore, the most recent smartphone cameras and flash function-based development of a fine dust measurement system called FeinPhone (Budde et al., 2019) suggests that low-cost PM sensors may become default equipment in next-generation smartphones. Low-cost and relatively good result correlations with reference air pollution stations (Karagulian et al., 2019) allows users to set up citizen science initiatives and involve local communities into global problem solving. The most relevant of these projects are listed in Table 1, which is an extension of the review carried out by Moumtzidou et al. (2016). The relatively simple design of citizen science sensors makes them suitable for do-it-yourself (DiY) workshops. Creating local workshop groups, usually co-ordinated by a local Media Lab, allows the establishment of communities which are emotionally involved in self-created monitoring networks, which becomes the basic mechanism motivating the continuation of the local monitoring project. Furthermore, the growing awareness of air pollution hazards has led to the development of personal sampler devices (e.g., PlumeLab) designed to be mobile and facilitating real-time monitoring of exposure to air pollution; such new smart devices could be used effectively in citizen science activities. Coupled with the application to health symptom recording, they could progress our understanding of air pollutants, their co-existence, and their relationships with human health (Bédard et al., 2020). Citizen measurements were formerly conducted in a stationary manner through the use of passive diffusion tubes (Palmes et al., 1976) or wipes for pollution measurement; at present, such measurements can successfully be carried out in a mobile way through the use of smart sensors. Loreto et al. (2017) emphasized that modern participatory sensing, which is one of three sub-categories of citizen cyberscience (Grey, 2009), has witnessed significant progress related to the fast development and social networking tools of ICT (Information and Communication Technologies), which “allow effective data and opinion collection and real-time information sharing processes”. In that context, Guo et al. (2015) and Capponi et al. (2019) introduced mobile crowdsensing (MCS), which focuses on sensing and collecting data with mobile devices and aggregating data in the cloud. However, there are pollutants which are still exclusive for IoT 'sensor dust'. A great challenge of contemporary CS measurement is odour sensing, which affects both indoor as well as outdoor air quality. Human-sensed air pollution monitoring seems to be an emerging trend.

Table 1 A review of relevant citizen science initiatives for air pollution monitoring. Explanation: GeoWeb: M – mobile app, W – web app, e – educational resources; Sensors: D – digital toolkit of low-cost sensors, DiY – do-it-yourself sensors, Md – measured by mobile devices (surveys, video, image, voice), Hs – human senses; Feedback to Citizen Scientists: Rt – real-time mapping, Pc – personalized communication, Ms – map screening, Ru – re-use of data; No info – information is not available. Sources: Air Quality Egg (airqualityegg.wickeddevice.com/); PlumeLab personal sampler (plumelabs.com); Smart Citizen Kit (smartcitizen.me); Aircitizen (aircitizen.org); AirCasting (habitatmap.org); Sensebox (sensebox.de); CitiSense (co.citi-sense.eu); CaptorAir (www.captor-project.eu).

Project name	Aim of the project	Pollutants	GeoWeb	Sensors	Feedback to the citizens
Group of projects: Air Quality Egg; Smart Citizen Kit; AirCitizen; Plumelabs; AirCasting; SenseBox	The education and inclusion of local communities in air pollution monitoring with the use of low-cost sensors and open-source WebGIS	$PM_{2.5}$; PM_{10} $SO_{2;}$ $NO_{2;}$ CO; $O_{3;}$ VOC	W, e	D	Rt
CitiSense (CityAir App)	To build European network of low-cost DiY air pollution sensors	$PM_{2.5}$; PM_{10} SO_2; $NO_{2;}$ NO; O_3	W, M, e	DiY; Hs (AQ perception)	Rt
Luftdaten; AirsensEur (Gerboles et al., 2015)		$PM_{2.5}$; PM_{10} SO_2; $NO_{2;}$ NO; O_3	W, e	DiY	Rt
D-Noses (Arias et al., 2018)	To create a community map of odour and provide a bottom-up approach to tackling odour pollution issues.	Outdoor odour	W, M, e	Hs (trained volunteers)	Ms
IAQ self reporting (Similä et al., 2019)	Collect long-term perceived indoor air quality data and symptoms to monitor school air quality.	Indoor odour	M	Hs	Pc users push notifications
Innovation Program for Environmental Monitoring (IPEM; Wesseling et al., 2019)	To build a crowdsourced system that provides citizens with detailed environmental data and enriches the Dutch environmental monitoring network.	$PM_{2.5}$; PM_{10} SO_2; NO_2	W	Dt	Ms
CaptorAir	Three-year project aimed at monitoring ozone pollution in Spain, Italy, and Austria with the use of low-cost sensors	O_3	W	Dt	Ms

In this research, we specify the “citizens as sensors” and participatory sensing concepts, where the senses, subjective impressions, and perception of humans are the only sensors used in the project; therefore, we propose this as human-sensed CS. Moreover, by developing a QA mechanism for sCS, this study contributes to bottom-up air pollution monitoring and open data credibility.

Personal symptom observations are an everyday practice of pollen allergy sufferers. They have access to smartphone applications such as Patient’s Hayfever Diary (PHD; available as “Pollen App”; Bastl et al., 2015), MASK (Mobile Airways Sentinel Network) Allergy Diary (Bousquet et al., 2017), or other digital allergy diaries (Voorend-van Bergen et al., 2014, Bastl et al., 2017) which help to monitor, analyse, and understand personal health symptoms. In this study, we wanted to involve the personal symptoms observations of citizens. The bottom-up approach is consistent with the CS definition: co-operation of citizens (non-experts) and scientists (professionals) for the solution of research problems in a specific area of science (Kar et al., 2016).

1.4. Importance of Data Quality in Crowdsourced Air Pollution

Data quality issues include errors and biases. Factors affecting the data collected through citizen perceptions result in data biases. Citizen Science requires the collaborative contributions of multiple contributors (Haklay et al., 2010), but the assumption of multiple contributors is insufficient to provide high-quality data. Therefore, data quality protocols are an essential part of crowdsourcing-driven research. Although participatory research faces methodological challenges such as biases in data collection (Nimbalkar and Tripathi, 2016, English et al., 2018), CS has been proven to be a source of trusted geospatial data (Sheppard and Terveen, 2011, Lin et al., 2015, Kosmala et al., 2016, Fritz et al., 2017, Parrish et al., 2018), including for health risk mapping (Maantay, 2007, Keddem et al., 2015, Palmer et al., 2017) and risks caused by poor air quality (Bastl et al., 2017, Penza et al., 2017, Khasha et al., 2018, Kankanamge et al., 2019). The data quality determines its usefulness (Choi et al., 2016, Chmielewski et al., 2018). Thus, the unstructured nature of crowdsourced data requires rigorous data QA protocols (Flanagin and Metzger, 2008, Antoniou and Skopeliti, 2015, Foody et al., 2018, Moreri et al., 2018, Wu et al., 2018).

In CS air quality projects, data quality assurance methods have been developed for combining low-cost personal digital or mobile sensor data with data from the official air pollution monitoring stations or local-scale air pollution models (Van den Bossche et al., 2015, Miskell et al., 2017, Schneider et al., 2017), or even with data mined from social media posts (Jiang et al., 2015, Sun et al., 2017, Zheng et al., 2018). To optimize the data quality of digital sensors, pre- and post-sampling calibration adjustments are typically applied, such as temperature corrections and filter equilibrations (Gillooly et al., 2019). Castell et al. (2017) and Spinelle et al. (2017) emphasized that the field calibration of the low-cost devices remains a challenge.

Sensor measurements are still valuable, despite their limited precision and accuracy. Low-cost sensors should be only considered good enough for the intended objective (Williams et al., 2014) and, as part of the trust and reputation modelling (TRM) procedure, should include metadata for characterizing the exact qualities of the recorded data (Clements et al., 2017). The D-NOSES project (Arias et al., 2018) proved that the sense of smell of individuals can be calibrated through training on odour pollution and workshops exploring odour perception in the D-NOSE method.

The starting point for data quality assurance in CS is education and the provisioning of technical information and resources (Wiggins et al., 2011, Gillooly et al., 2019), in order to increase citizen knowledge about the issues of air pollution and to improve their environmental awareness and motivation to provide air quality monitoring supporting activities (Commodore et al., 2017, Penza et al., 2017, Kosmidis et al., 2018). Of the range of crowdsourced data quality measures discussed in the academic literature by Haklay (2010) and Foody et al. (2018), among others, attribute accuracy and completeness are essential. Furthermore, those aspects of geographic data quality have also been recognized by international standards of spatial data quality. The ISO 19157 (2013), which handles the diverse perspective of data quality, defines a set of standardized data quality measures, including completeness of data, positional accuracy, and temporal accuracy, which are all grouped as so-called data quality elements (DQEs; Fonte et al., 2017). Each DQE is, then, further evaluated and the result of the evaluation is documented and reported (Foody et al., 2018). The principles of the aforementioned ISO 19157 (2013) served as the basis for the proposed APSM data quality framework. Air pollution-related health symptoms were recorded with the use of survey questions. The survey design allowed us to select and reject attribute table contradictions, in order to reduce data bias, such as user response inconsistency, location inaccuracy, and duplicate time–space-related reports.

By combining several logic-based data quality assurance mechanisms (QAms), we tested the robustness of the QAms to find the strongest QAm set and build a ranked data quality assurance system (QAs).

To achieve the SDG 11.6 target, reliable sources of spatial data are needed. We did not solve the problem caused by the non-air pollution-related factors which affect human symptom severity, which act synergistically with air pollution to contribute to spatial database robustness on health-related symptoms (Chehregani et al., 2004, Karatzas, 2009, Sofiev and Bergmann, 2013, Bastl et al., 2015, D'Amato et al., 2015).

The goal of this study was to answer the question of quality assurance mechanism implementation in the GeoWeb-based APSM. For this purpose, we propose a dedicated air pollution symptom mapping (APSM) framework for the following QA mechanisms: start-check, sequence, cross-validation, repeating, and time-loop check (see Section 2). Our research question

was: Which QAs best reduces data bias in APSM? The sources of data bias include contradictory entries in the geodatabase attribute table recorded as answers supplied to the specially created APSM survey. By answering the research question, we aim to underline the importance of CS for the achievement of the SDG 11 and 11.6 targets.

2. Materials And Methods

For our participatory APSM project, we followed the CS development framework of Bonney et al. (2009), starting from the research question and project team formulation through to CS action execution and the dissemination of project findings (Sect. 2.1. and 2.3.). However, we focused on addressing data bias (Sect. 2.2.) to improve the symptom-based air pollution mapping data quality, as a contribution to the achievement of SDGs through the provisioning of spatial information, as well as social inclusion in sustainable development.

2.1. Building the Project Team and Field Data Collection Strategy

Having defined the scientific question, we formed the project team, which was based on the following roles recommended by Bonney et al. (2009):

- Scientist: responsible for formulating the research question, crowdsourced data protocol design, co-operation with citizens, and answering the research question.
- Educator: responsible for training the participants.
- Technologist: provides GeoWeb tools to the project members. Technologically, the project is based on the cloud and configurable applications are built using the “puzzle” idea in ArcGIS Online (AGOL; Esri Inc., Redlands, CA, USA; Fargher, 2018).
- Evaluators: researchers and medical doctors who work in the field of air quality (including pollen allergy) related to daily symptoms. They are engaged in the app testing process.
- Citizens: collect APSM data and follow the results through web map apps.

To turn students into citizen scientists (Harlin et al., 2018), we engaged teachers and students. The crowdsourcing campaign was planned for one academic semester starting in February and finishing at the end of May. Starting the campaign in the first quarter of the year is crucial, as pollutants and pollen occur simultaneously at the beginning of the year; especially gaseous pollutants which can act as “adjuvants”, exacerbating pollen allergenic potency and immunoreactivity (Ring et al., 2001). At the beginning of the campaign, the group of citizens involved in the project was formed, which included students and non-academic participants. The students of different faculties of the University of Life Sciences in Lublin (Poland) were invited as volunteers. The core of the group consisted of students co-operating within their scientific student organization. The project was continually open to everybody. The researchers and Ph.D. students of the University of Warsaw (Poland) were responsible for the technological part of the project. Together, they formed the community channel for data and apps sharing, which was implemented in GeoWeb.

Before the field data collection campaign, the scientific student organization of the Spatial Management Faculty of the University of Life Sciences in Lublin organized workshops for the citizen scientists, who learned about the research project assumptions and were trained on handling the mobile and web apps (details about apps provided in Sect. 2.3). The workshops, trainings, informing, and research project promotion among citizens lasted for the first month. They learned that the mobile app requires initiation just after being turned on, in order to fix the GNSS (Global Navigation Satellite System) positioning accuracy. Other educational materials were made available in the narrative web apps. They were asked to collect data during their daily outdoor activities, preferably once per day. If they observed air pollution-related symptoms, they were asked to report them as soon as possible. If they caught a cold or were sick, they were expected to stop collecting data until they recovered. The project assumptions and rules for collecting data were included in the mobile app, as an introduction to the study. The wider user guide version was available, at any time, to the citizens in the web mapping application.

After completing the survey in the mobile app, the user was geolocated such that the observed individual symptom severity was presented as a point on the map immediately after it was sent to the cloud.

Our study referred to the patterns of citizen activity characteristic for CS specifics (Seymour and Haklay 2017). As such, we implemented a dedicated module for citizen motivation improvement, which was based on the monthly activity ranking of users, presenting a number of submitted APS reports, which were available to citizens in real-time. Users were assigned award titles, according to the following number of reports sent per month: 1–5, Beginner; 6–10, Pretty Involved; 11–20, Super Engaged; and > 20, Excellent Citizen Scientist. A user activity tracking module was included in the operations dashboard app (details in Sect. 2.3), which listed the 10 most active citizens, presented as their nicknames (checked to be consistent using the PIN provided by the citizen in the first survey) together with their award titles, as well as their number of reports in the last month. This mechanism helped to increase user engagement, as the ranking list was public and allowed for competition between the citizens.

2.2. Data quality assurance methods for Air Pollution Symptom Mapping

Following other studies of human health symptom severity, such as SLI (Symptom Load Index) research in pollen allergy sufferers (Kmenta et al., 2014), we used a questionnaire sheet. However, we extended the group of potential citizens to all those who suffered from air quality-related health symptoms. The form included a set of close-ended questions about citizen air pollution symptom severity and quality of well-being associated with the symptoms, complemented by a citizen (APSM project member) allergy profile question. To receive the recurrent results, we asked the same question several times, which is standard practice in classic surveys (Albuam and Oppenheim, 1993, Schaeffer and Presser, 2003, Boynton and Greenhalgh, 2004, Wiggins et al., 2011). To alleviate the problem of data bias in the citizen-driven mapping, we used a method based on specific conditional statements implemented in the survey questions. The proposed method includes data forms, which are the basis of the developed conditional statements. The data stored in the database were displayed as a text data type in the mobile app, which is simple and intuitive for the user. The data were also coded in the database in the short integer data type (except for question 12 (Q12), which was coded in text data type), and were used for data analysis and statistics (Table 2).

Table 2
Questionnaire for citizen air-quality-related symptoms observations, including data forms.

Question No.	Question Type	Question	Answer	
			Mobile App	Database coding
Q1.	Single choice	How do you feel today?	Good	1
			Average	2
			Bad	3
			I have no opinion	0
Q2.	Single choice	Sneezing. If you are currently experiencing this symptom, please choose the level of severity.	Mild	1
			Moderate	2
			Strong	3
			No symptoms	0
Q3.	Single choice	Nose itching. If you are currently experiencing this symptom, please choose the level of severity.	Mild	1
			Moderate	2
			Strong	3
			No symptoms	0
Q4.	Single choice	Runny nose. If you are currently experiencing this symptom, please choose the level of severity.	Mild	1
			Moderate	2
			Strong	3
			No symptoms	0
Q5.	Single choice	Watering eyes. If you are currently experiencing this symptom, please choose the level of severity.	Strong	3
			No symptoms	0
			Mild	1
			Moderate	2
Q6.	Single choice	Scratchy throat. If you are currently experiencing this symptom, please choose the level of severity.	Mild	1
			Moderate	2
			Strong	3
			No symptoms.	0
Q7.	Single choice	Breathing problems. If you are currently experiencing this symptom, please choose the level of severity.	Mild	1
			Moderate	2
			Strong	3
			No symptoms	0

Question No.	Question Type	Question	Answer	
			Mobile App	Database coding
Q8.	Single choice	Do you rub your eyes?	Yes, seldom	1
			Yes, quite often	2
			Yes, very often	3
			No	0
Q9.	Single choice	Could you assess the level of your current self-comfort?	Low–Average–High	3–2–1
Q10.	Time range	How long have you been in this location?	1 min to more than 2 h	1–120+
Q11.	Time range	For how long have you felt your symptoms?	1 min to more than 2 h	1–120+
			No data	0
Q12.	Multiple choice	Which pollen allergens are you allergic to?	Birch–Alder–Hazel–Grass–Pine–Plantain–Mugwort–Nettle–Ragweed–Other–No allergens	Bi–Al–Ha–Gr–Pi–Pl–Mu–Ne–Ra–Other–No

2.2.1. Data Quality Assurance Methods Applied During Data Collection Process

We initially adopted three QA methods in the mobile survey app, in order to improve data quality during the data collection process. These methods were based on the quality measures of ISO 19157 (2013): positional and temporal accuracy, data completeness, and consistency. The first QA method eliminates identical reports sent from the same location within a certain time interval (5 minutes) from the database, in case the same report was duplicated. Reports lacking geolocation were excluded from the database by the second QA method. The third method controlled the GNSS positioning accuracy of the reported APS observations, under the assumption that reports with horizontal accuracy error greater than 100 meters were outliers, which were eliminated in the data collection stage. If the surveys were accepted under the three QA methods described above, they were finally checked with the completeness quality measure. Surveys which were not completed, in terms of the obligatory questions, were automatically blocked against submission through the mechanism configured in the app.

2.2.2. Logic-Based Data Quality Assurance Mechanisms Implemented After Data Collection Process

The proposed QA framework for APSM includes five QA mechanisms, which work as combinations of specific conditional statements. The logic formula for each conditional statement was built to filter and eliminate data bias—identified as false data—such that false results were returned (Table 3). The QA mechanisms of start-check, sequence, cross-validation, repeating, and time-loop check were proposed, with one or two levels of robustness (Table 4), and were finally combined into a QA system (Table 5). These QA mechanisms were implemented in the database after the data collection process was finished. The conditional statement algorithms were combined into QA mechanisms, some of which were proposed and studied in two robustness variants, and implemented in the APSM. To date, such a method has not been implemented in an sCS air pollution-related symptom mapping project. As a data quality assurance framework for APSM, we propose a data quality assurance system (QAs) which is the combination of each QA mechanism, depending on the QA mechanism robustness variant. The choice of the QA system variant depends on the project character: Each QA mechanism works independently and, so, can be implemented to the APSM project separately or in any combination, if needed.

Table 3

Conditional (Con.) statements, the basis of the quality assurance (QA) mechanisms.

Conditional statement number	Logic Formula
Con.1	$if[(Q1 = 0)or((Q1 = 1)and(any(Q2:Q7) = 3))]thenfalse,$
Con.2	$if[(Q1 = 0)or((Q1 = 3)and(all(Q2:Q7) \neq 3))]thenfalse,$
Con.3	$if[(Q1 = 0)or((Q1 = 1)and(any(Q2:Q7) > 1))]thenfalse,$
Con.4	$if[(Q1 = 0)or((Q1 = 3)and(all(Q2:Q7) \neq 3))]thenfalse,$
Con.5	$if[all((Q2:Q4)or(Q6:Q7)) = 1)and(Q5 = 3)]thenfalse,$
Con.6	$if[all((Q2:Q4)or(Q6:Q7)) = 3)and(Q5 = 1)]thenfalse,$
Con.7	$if[all((Q2:Q4)or(Q6:Q7)) = 0)and(Q5 = 2)]thenfalse,$
Con.8	$if[((Q5 = 0)and(Q8 = 3))or((Q4 = 0)and(Q8 = 3))]thenfalse,$
Con.9	$if[((Q5 = 0)and(Q8 \neq 0))or((Q4 = 0)and(Q8 \neq 0))]thenfalse,$
Con.10	$if[((Q9 = 1)and(Q1 = 3))or((Q9 = 3)and(Q1 = 1))]thenfalse,$
Con.11	$if[((Q9 = 1)and(any(Q2:Q7) = 3))or((Q9 = 3)and(all(Q2:Q7) \neq 3))]thenfalse,$
Con.12	$if[((Q9 = 1)and(Q1 \neq 1))or((Q9 = 2)and(Q1 \neq 2))or((Q9 = 3)and(Q1 \neq 3))]thenfalse,$
Con.13	$if[((Q9 = 1)and((any(Q2:Q7) = 3)or(any(Q2:Q7) = 2)))or$ $or((Q9 = 3)and(all(Q2:Q7) \neq 3))]thenfalse,$
Con.14	$if(Q11 \geq Q10)thenfalse,$
Con.15	$if[(Q11 = 1)or(Q11 > 120)]thenfalse,$
Con.16	$if[(all(Q2:Q7) = 0)and(Q11 \neq 0)]thenfalse,$
Con.17	$if[(all(Q2:Q7) \neq 0)and(Q11 = 0)]thenfalse.$

The core principle for the research is the logic-based data quality assurance procedure. The start-check, cross-validation, and time-loop check mechanisms are based primarily on the medical assumptions included in logical rule framework. The other QA mechanisms, sequence and repeating, are purely logical and result from social and psychological survey methods for monitoring, the typical respondent answering process, and data quality control (Weijters et al., 2013).

Table 4

Quality assurance mechanisms implemented in the citizen air pollution-related symptoms questionnaire, with less (“1”) and more (“2”) robust variants.

QA mechanism	QA mechanism code	QA mechanism components: conditional statement combination
Start-Check	SC1	Con.1 or Con.2
	SC2	Con.3 or Con.4
Sequence	Sq	Con.5 or Con.6 or Con.7
Cross-validation	CV1	Con.8
	CV2	Con.9
Repeating	Rp1	Con.10 or Con.11
	Rp2	Con.12 or Con.13
Time-loop Check	TC	Con.14 or Con.15 or Con.16 or Con.17

The start-check mechanism was used to verify the report consistency at the beginning of the survey, excluding reports whose symptom severity answers are not consistent with the general well-being question. The quality assurance method of applying a general question about the issue preceding the detailed questions was used by Bastl et al. (2015) and Bousquet et al. (2017); however, these studies did not report success in using this conditional statement. We examined this in two variants: Variant 1 is less robust and assumes that the report is consistent when the citizens assess their current comfort as *good* (1), then the answers to Q2–Q7 should be between *no symptoms* (0) and *moderate symptom severity* (2). If the answer for Q1 is *poor self-comfort* (3), then at least one question between Q2–Q7 must be answered as *strong symptom severity* (3). Variant 2 is stricter and assumes that the possible answers for Q2–Q7 can only be *no symptoms* (0) or *mild symptom severity* (1) when the current comfort is rated as *good* (1). If the answer for Q1 was *poor comfort* (3), the same conditional statement was used as in variant 1. For both variants, the reports with the answer *I have no opinion* (0) for Q1 were excluded.

Table 5
Quality assurance system variants applied for Air Pollution Symptom Mapping (APSM).

QA system (QAs) variant	QA system components: QA mechanism combination
QAs_1	SC1 or Sq or CV1 or Rp1 or TC
QAs_2	SC1 or Sq or CV1 or Rp2 or TC
QAs_3	SC1 or Sq or CV2 or Rp1 or TC
QAs_4	SC2 or Sq or CV1 or Rp1 or TC
QAs_5	SC2 or Sq or CV1 or Rp2 or TC
QAs_6	SC2 or Sq or CV2 or Rp1 or TC
QAs_7	SC1 or Sq or CV2 or Rp2 or TC
QAs_8	SC2 or Sq or CV2 or Rp2 or TC

The sequence mechanism was applied to exclude user “automatism” in providing answers, which is often caused by a citizen giving rash answers or not reading the questions. Therefore, each report with all questions answered by responses with the same place in the sequence (e.g., every first answer for each question) were eliminated from the database. The QA mechanism is based on the method of rearranging the order of possible answers (Albuam and Oppenheim, 1993, Garbarski et al., 2015) for one question in the sequence of similarly asked questions. The standard order of the answers for questions Q2–Q7 was: 1, 2, 3, 0. The Q5 question was an exception, with an answer order of: 3, 0, 1, 2. If the citizen repetitively chose the first answer for questions Q2–Q7, then the QA mechanism excluded the report. The same rule was applied to reports with the third answer for questions Q2–Q7 and for the last answer in questions Q2–Q7.

The cross-validation mechanism was used to reject responses by using three essentially related questions. If the answer to the additional question was not consistent to the one of the two previously answered related questions, the report was excluded. The APS mentioned in Q8 should be related to runny nose (Q4) or watering eyes (Q5) symptoms. The mechanism was tested in two variants: Variant 1 assumes that *no runny nose* (Q4 = 0) and *watering eyes* (Q5 = 0) *symptoms* eliminate reports with *very often rubbing eyes* (Q8 = 3) observations. Variant 2 is much stricter and additionally excludes reports with *often* (Q8 = 2) but also *seldom rubbing eyes symptom* (Q8 = 1).

The repeating mechanism determines the consistency of the report, according to the other previously answered questions, by asking for the same question but in a different way. If the repeated answer is not consistent with the former one (Albuam and Oppenheim, 1993, Wiggins et al., 2011), the report was excluded from the database. This was used with Q9, which repeated the content about the citizen’s self-comfort in Q1. The mechanism was examined in two variants: According to variant 1, the report was eliminated if the minimum or maximum answer codes of Q1 and Q9 were the opposite (e.g., the answer code 2 for Q1 was consistent for Q9 answer codes 1, 2, or 3). Variant 2 was more robust, assuming that the answer codes from Q9 and Q1 have to be the same, with each exception from this rule excluded from the database. The mechanism was used to compare the answer to Q9 with the answers of the severity symptom questions (Q2–Q7). When the answer for Q9 was *poor self-comfort* (3) and none of questions Q2 to Q7 were answered as *strong symptom severity* (3), the report was excluded. The conditional statement for Q9 answered as *high level of comfort* (1) was examined in two variants: In the first variant, a report with at least one answer in Q2–Q7 representing *strong symptom severity* (3) was eliminated when the answer for Q9 was coded 1. According to the second variant, if the reported symptom severity in any of Q2–Q7 was assessed as *moderate* (2) or *strong* (3) while Q9 was answered with 1, then the report was eliminated.

The time-loop check mechanism was used to eliminate the reports that did not align to the geolocation of the citizens, according to the length of their stay in a place in comparison to the duration of their symptoms. Previous studies (Arvidsson et al., 2004, Galli et al., 2008, Gauvreau et al., 2015) have shown that human allergic reactions to pollen range from 10 to 20 minutes, usually resolving after 1–2 h for an early phase reaction, and 3–4 hours with resolution after 6–12 hours, sometimes even 24 hours, for a late phase reaction. The late phase reaction is preceded by an early phase reaction. The early phase reaction is characterized by symptoms like allergic rhinitis (including sneezing, itching, and rhinorrhea; Skoner, 2001, Baldacci et al., 2015), while the late phase is connected with nasal congestion and obstruction (Ferguson, B.J. 2004, Baldacci et al., 2015). For anthropogenic-sourced air pollutants PM_{10} and $PM_{2.5}$, the reaction time (according to the pollutant type) ranges between 2 and 10 minutes for the most sensitive subjects and resolves after 30 minutes (D’Amato et al., 2002, Kampa and Castanas, 2008). For the purpose of APSM, we adopted the time range for the duration of the human reaction to air pollutants

as between 1 minute and 2 hours. This mechanism assumes that all reports with a time loop value higher than the duration the user remained in the place were eliminated. We excluded all reports with symptom observation lengths equal to one minute. Reports with symptoms observed for more than two hours were excluded as well, as such information indicates a late-phase reaction, which is not connected with the current geolocation of the citizen.

When the database was completed, the technologist connected the database as an AGOL service (REST) to the desktop solution and prepared the data set through the implementation of the logic-based QA mechanisms. To analyse the robustness of the QA mechanisms, as well as the survey result statistics, we used the R statistical software (R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, www.R-project.org). Finally, the analysis results were published back to the cloud and presented in the public web mapping application. The results were reported as a percentage of the observations eliminated by the most robust QA mechanism combination, presenting the total robustness of implemented QA system.

2.3. GeoWeb Development Method

The GeoWeb platform, which was the technological basis of this project, in order to maintain project openness, consists of a mobile app for field data collection based on the configurable Survey123 for ArcGIS application (Survey123; Esri Inc., Redlands, CA, USA) and a data mapping module including dashboards (web mapping applications based on AGOL components; see Fig. 1). The mobile app (A) includes the APS survey for field data collection. The educational and technical training materials (B) are provided in a narrative web mapping application (Esri story maps templates), which are served through REST services. The collected data is sent to the geodatabase through the REST services and the raw data are presented in the dashboard app (C) in real-time. Then, the raw data is QA-checked in the database using ArcGIS Desktop integrated with the REST services and the R statistical software (D), which is used for analysis of the QA mechanisms and QA system variant robustness. The QA-checked data is returned to the database and presented as the APSM results in the open web mapping applications, including dashboards (C).

The tools for the APSM project are based on GeoWeb. We used ArcGIS platform components, which were available to the technologist as a puzzle structure, which allowed for direct customization of the applications to implement the APSM assumptions and requirements. For the project, we configured the mobile app and a set of web apps was publicly shared for citizens.

2.3.1. Mobile App for Crowdsourcing

The mobile app was based on the Survey123 for ArcGIS components and is available at the public link: https://arcg.is/0HWXrO. The survey consists of six information pages to facilitate its use and clear navigation (Fig. 2a). It is available in two languages: Polish and English (Fig. 2b). The app starts with an introduction with a short user guide (Fig. 2c), in order to explain the research rules and how to use the survey app (page 1), followed by user basic info (nickname, four-digit PIN, and student/non-academic status; Fig. 2d), helping the users in the citizen group to control the data collection process (page 2). The next pages (3–5) include 12 APSM questions which are completed with the user geolocation and the date of the report (page 6). All obligatory questions are marked with a red star (Fig. 2e). The third page focuses only on the general well-being level of the citizen (Fig. 2f), which is the basis for the start-check mechanism. Then, the citizens answer questions about their individual symptoms using drop-down lists of answers (Fig. 2g). In the summary (page 5), the citizens specify their level of well-being, choosing from a star rating scale; where one star means the lowest and three stars indicate the highest level of well-being (Fig. 2h). Then, using the calculator appearance widget, the users report the length they have stayed in their location and the symptoms have been observed for. These values are expressed in minutes, provided for question 11 (Fig. 2i). Question 11, regarding the length of the observation of symptoms, is fixed in the app as relevant only when any APS are observed. If Q2–Q7 are answered as "*no symptoms*", then Q11 does not appear in the survey. On the last page of the app, a map widget is presented to mark the current location and date (Fig. 2j). Here, app users are told that all reports with horizontal positioning accuracy error greater than 100 m are automatically eliminated, as these values are considered as GNSS positioning accuracy outliers. When completing the survey, the user can check the current location status at any time (i.e., latitude, longitude, and horizontal accuracy; Fig. 2k). The default date is set to the current date. The geolocation defaults to the current GPS location of the user, as well. When the survey is completed, a bottom-right submit tick is made active and the report is ready to send to the cloud geodatabase.

2.3.2. Field Data Collection Module: Mobile App

The questions proposed for the survey in Sect. 2.2 were included in the configurable Survey123 application. The mobile survey was divided into individual pages, in order to help the user to quickly navigate between questions without scrolling down the whole form. An offline mode was provided so users could choose whether to use an internet connection when collecting data. All survey fields were obligatory. We used a user authorization option with an alphanumeric nickname and 4-digit PIN at the beginning of the survey, in order to help follow the reports of each citizen while also providing them anonymity. Q1 to Q9, concerning well-being and symptom severity aspects, were implemented as single-choice questions. Q10 and Q11 were displayed using a calculator functionality, facilitating the entry of time data expressed in minutes. Q12 was expressed as a multiple-choice collection. The last section of the mobile survey contained a map, where the mobile app user could set their geolocation. The last field in the app was used to determine the current date of the symptoms observed.

The field data collection module was available for free, with the option of creating the survey app icon on the smartphone screen. It was available in two languages—Polish and English—and users could choose their desired language when filling in their responses. To start using the survey, we advised users to download the Survey123 for ArcGIS app from Google Play (Google LLC, Mountain View, CA, USA) or the App Store (Apple Inc., Cupertino, CA, USA) to their mobile device. Then, using the public survey link, the form was downloaded to the app. The link for the survey could also be entered into a web browser.

2.3.3. Air Pollution Symptom Mapping Module: WebGIS App

The APSM web interface included two dashboard apps: one for real-time raw data presentation and another for QA-checked results presentation, which were published after the field data collection campaign. The real-time data on APSM were presented with a point symbolized map accompanied by an indicator summarizing the current number of reports and activity curves of the users. The dashboard displayed the user activity ranking widget, which was a list of user nicknames ordered in a bar chart ranking their monthly activity (Sect. 2.1). The second dashboard included a point symbolized map and statistics of the QA-checked symptom severity data. We assumed that the dashboard presented the results of data checked with the most robust QA system. The application allowed citizens to choose layers for each symptom. The dashboard presented the proposed tier 3 SDG indicator for the SDG 11.6 target. The statistical data corresponded to the current map range. The dashboard also contained information about the percentage of data reports rejected by the most robust QA system.

The dashboard presented the proposed tier 3 SDG indicator for the SDG 11.6 target. We propose 11.6.3 as the next SDG (tier 3) indicator, which measures subjective well-being as identified by citizens, to be no health symptoms are caused by air pollutants. This indicator is weighted per 100,000 population. Contrary to air pollution-related hazard medical research (e.g., 11.6.2), SDG1 1.6.3 reflects the well-being of citizens as a result of unpolluted air and no nuisance from breathing city air. SDG 11.6.3 is defined as the ratio of the percentage of surveys reporting “no APS symptoms” for each APS question (Pn) to the total number of city inhabitants (Nc). The indicator is measured monthly, due to the variation of air pollution level throughout the year.

$$SDG_{11.6.3} = \frac{P_n}{N_c} \times 100{,}000,$$

where P_n is the percentage of reports without any symptom observed and N_c is the total nu2.3.4. Air Pollution Symptom Mapping: results sharing through Web apps mber of city inhabitants.

To define the minimum monthly number of reports required for inference, we carried out a significance test for a proportion. Statistical tests were carried out both before and after implementation of the most robust QA system (QAs_8), specifying the statistical error for the test of proportion, with the assumption α = 0,05; confidence level 95%; and fraction 0.3, which corresponds to the faction of the population reporting allergic symptoms in Poland (Samoliński et al., 2014, Krzych-Fałta et al., 2016). We dynamically presented the collected data set in the time slider web app. This app allowed citizens to track not only the variability in symptom severity, but also user activity within the duration of the project.

2.3.4. Air Pollution Symptom Mapping: results sharing through Web apps

The resulting web app is available (at https://arcg.is/1iDD18) as an open application for each person interested in the project results. The site is primarily used to provide result feedback for the citizens engaged in the study. The app was configured based on the Map Series template and consists of five applications, which can be open by selecting five buttons: 1, Introduction to the project; 2, Field data collecting app; 3, Real-time data (before logic-based QA check); 4, APSM results (after logic-based QA check); and 5, APSM time slider (Fig. 3).

The first app—introduction to the project (Fig. 4)—is based on the Esri Story Map Cascade template, which is used for building narrative web mapping apps by combining images, maps, and multimedia context with narrative text (https://storymaps-classic.arcgis.com/en/app-list/cascade/). The application has an educational function for the citizens involved. It provides educational materials about air pollution and the APSM project idea, as well as extended mobile and web app tutorials and technical knowledge. Button number 2 links to a web version of the Survey123-based application for data collection.
Within the field data collection campaign, the reports were mapped, in real-time, in a point symbolized data layer. Each point represented the location and code attributes of an individual symptom severity observation reported by a user through the mobile app. The mapping module, based on a set of web apps, was responsive and compatible with the Survey123 app. Co-operation between the Survey123 mobile app and the web mapping module was based on the typical WebGIS architecture (Lupa et al., 2017). The application presents the raw data collected before the QA process and contains the operations dashboard-based interface which consists of five modules: a map with the raw data APSM reports collected during the crowdsourcing campaign (Fig. 5a), a legend (Fig. 5b), an indicator counting the total number of reports (Fig. 5c), a histogram of the citizen activity from the beginning of the crowdsourcing campaign to the current moment (Fig. 5d) which changes dynamically, according to the map, and a citizen activity ranking, divided for each month and cumulatively (Fig. 5e), as described in Sect. 2.1.
The time slider app is based on the Esri Time Aware configurable template. It includes a map of point-symbolized QA-checked reports accompanied by a time slider tool, which displays the increase of collected data over the entire duration of the crowdsourcing campaign. The time slider can move automatically (with a play button) or can be moved manually to the required date (Fig. 6).

3. Results

The QA framework is key for useful and effective sCS and, so, the results mostly focus on the implemented QA mechanisms and the robustness analysis of the QA system variants for air pollution-related symptom mapping. On the other hand, the results focus on the achievement of the proposed SDG 11.3.6, based on the APSM framework. We first focus on the field data collection campaign, which provided us the input for our analysis. The citizen activity curves indicated the varying and regularly decreasing activity of the citizens. For the QA robustness results, our key focus was the eight QA system variants, the combinations of five logic-based QA mechanisms, which rejected from 18.3–28.6% of reports with data bias. As a result, we created GeoWeb tools, based on the ArcGIS platform, which were configured and customized to the study requirements; these were proposed, finally, as an APSM framework.

3.1. Data Collection Campaign Outcomes

The method was adopted in the city of Lublin and Lubelskie voivodship, located in Eastern Poland. The data collection campaign lasted for one academic semester, from February to May 2018. At the beginning of February, we started the crowdsourcing campaign, recruited citizens, and informed of and promoted the research project among them. We created a group of citizens involved in the project, comprised of 56 students of different faculties of the University of Life Sciences in Lublin, who were involved in the project as volunteers; of which, 30 Spatial Management students were the core citizen group of the project. A total of 18 non-academic citizens joined the research and collected data together with the student group. They became members of the CS-Community-UW (Citizen Science Community of University of Warsaw) Group (https://arcg.is/WeqfK), which was set up to share all project data, materials, and apps in GeoWeb, in order to provide continuous access to the results. The group was managed by researchers and Ph.D. students of the University of Warsaw and educators, together with the student organization of Spatial Management of the University of Life Science in Lublin. The citizens participated in workshops and trainings until the end of February and received access to educational materials and instructions through the Esri Story Map Cascade app template, which is a web mapping app template for building narrative apps. During the data collection campaign, 1936 APS reports were sent by citizens to the cloud, which were used as the input to the QA mechanism-developed database. When citizens collected data, their activity was controlled and updated every month in a user activity module implemented in the dashboard app (Sect. 3.3.2). Analysis of the activity curve indicated that citizen activity peaked for 11 days at the beginning of the campaign (39–48 reports per day) and then decreased. After this, activity stabilized at between 4 and 29 reports per day, with two peaks of 32 and 34 reports per day (Fig. 7). The students were

more active than non-academic citizens. The most active student collected 25 reports in April, whereas the most active non-academic citizen collected 7 reports in March.

3.2. Robustness of data quality assurance mechanisms

During the initial stage of data set filtering, 19 outliers with no geolocation were eliminated. Another 68 APS records were excluded as they were duplicate reports at the same geolocation within a short (5 minute) interval. The horizontal positioning accuracy varied from 0 to 100 m, where 93% of reports had a horizontal accuracy between 0 and 30 m. We filtered 26 outliers which had a horizontal accuracy error exceeding 100 m, which were rejected. As a result, 1823 reports of the 1936 remained and were used as the object of our logic-based QA implementation study. After the implementation of the QA mechanisms in the database, their robustness was analysed.

According to Table 6, the three most robust QA mechanisms for our specific case study were: repeating in two variants (more robust, repeating2 (Rp2); less robust, repeating1 (Rp1)) and start-check in the more robust variant (SC2). The repeating2 mechanism excluded 23.1% of reports, repeating1 eliminated 10.6% of reports, and start-check2 eliminated 6.9% of reports. Most data bias resulted from inconsistencies in the repeated questions.

Table 6
Data quality assurance mechanism robustness.

QA mechanism		**Reports**				**QA mechanism robustness rank**
Name	**Code**	**Accepted**	**Rejected**	**Total**	**Rejected (% of total)**	
Start-check	**SC1**	**1752**	**71**	**1823**	**3.9**	**5**
	SC2	**1698**	**125**	**1823**	**6.9**	**3**
Sequence	Sq	1806	17	1823	0.9	8
Cross-validation	CV1	1769	54	1823	3.0	6
	CV2	1716	107	1823	5.9	4
Repeating	Rp1	1629	194	1823	10.6	2
	Rp2	1401	422	1823	23.1	1
Time-loop Check	TC	1771	52	1823	2.9	7

Three QA mechanisms—start-check, cross-validation, and repeating—which were implemented in two variants (i.e., less robust and more robust) were analysed in terms of the report reduction in each variant. For the start-check mechanism, the two variants reduced 71 of the same reports, while start-check2 eliminated 54 more reports than start-check1. Cross-validation1 and cross-validation2 reduced the same 54 reports, while cross-validation2 additionally eliminated 54 observations. For the repeating mechanism, repeating1 and repeating2 were compatible for 194 reports, while repeating2 was 12.5% more robust than repeating1, excluding 228 additional APS reports (Table 7).

Table 7
Data quality assurance mechanism variant compatibility.

		Start-check2		Cross-validation2		Repeating2	
		Accepted	Rejected	Accepted	Rejected	Accepted	Rejected
Start-check1	Accepted	1698	54				
	Rejected	0	71				
Cross-validation1	Accepted			1716	53		
	Rejected			0	54		
Repeating1	Accepted					1401	228
	Rejected					0	194

The largest data bias was related to the consistency between the general well-being question and its repeated query (repeating1: 10.6% and repeating2: 23.1%). This result could have been produced by the inaccuracy of the repeated question structure or by citizens misunderstanding the question. The start-check2 mechanism rejected 6.9% of reports, which means that the severity symptoms did not align with the general well-being assessment. The sequence mechanism was the least robust (0.9%), indicating that citizens rarely filled in the form automatically; that is, without carefully reading the answers. A high rejection rate was observed using the QA mechanisms start-check2 (6.9%), cross-validation2 (5.9%), and repeating2 (23.1%), which were between 46% and 57% more robust than their alternative variants (start-check1, cross-validation1, and repeating1, respectively). They rejected a higher percentage of reports. Due to its high rejection rate, start-check2 was found to also reject some consistent reports.

Table 8
Data quality assurance system variant robustness.

QA system variant	QA mechanisms combination	Reports				QA system robustness rank
		Accepted	Rejected	Total	Rejected (% of total)	
QAs_1	SC1 or Sq or CV1 or Rp1 or TC	1490	333	1823	18.3	6
QAs_2	SC1 or Sq or CV1 or Rp2 or TC	1325	498	1823	27.3	2
QAs_3	SC1 or Sq or CV2 or Rp1 or TC	1459	364	1823	20.0	5
QAs_4	SC2 or Sq or CV1 or Rp1 or TC	1445	378	1823	20.7	4
QAs_5	SC2 or Sq or CV1 or Rp2 or TC	1325	498	1823	27.3	2
QAs_6	SC2 or Sq or CV2 or Rp1 or TC	1422	401	1823	22.0	3
QAs_7	SC1 or Sq or CV2 or Rp2 or TC	1302	521	1823	28.6	1
QAs_8	SC2 or Sq or CV2 or Rp2 or TC	1302	521	1823	28.6	1

Finally, the QA mechanisms were combined into eight QA system variants (QAs_{1-8}; Table 8). Implementing each subsequent QA mechanism changed the database, considering the QA system functions. For this study, the most robust QA systems were QAs_8 and QAs_7 (28.6%) and QAs_2 and QAs_5 (27.3%), which best reduced the number of falsely filled reports in the survey. They increased the quality of the collected data, but rejected a percentage of reports that might have contained valid information. As a result, some valuable data would be lost. The least robust were QAs_1 (18.3%) and QAs_3 (20.0%), which could not identify all the reports with false data, thus decreasing the quality and validity of the research results. As mentioned above, two pairs of QAs variants reduced the same data set and replicated the result database (QAs_2 with QAs_5; QAs_7 with QAs_8), thus allowing their interchangeable use. To reduce replication in the results, the studied QA framework was limited to six QAs variants (with QAs_5 and QAs_7 removed). For another location (i.e., country, continent) and society structure, the robustness ranking of the six QAs variants could be different and the particular QA mechanisms could be more or less effective than in the considered case study in Lublin.

3.3. $SDG_{11.6.3}$ as the air pollution impact on citizen well-being indicator

The proposed SDG 11.6.3 indicator was calculated for the Lublin case study, for each month of the field data collection campaign (March–May 2018). Lublin city has a population of 340,000 people, which was the used for the SDG 11.6.3 calculation. The survey monthly statistics and SDG 11.6.3 are presented in Table 9, comparing the results before and after implementing QA_{s8}, the most robust QA system.

Table 9
Air pollution symptom mapping survey monthly statistics details.

	March*		April		May	
	Before QAs_8	After QAs_8	Before QAs_8	After QAs_8	Before QAs_8	After QAs_8
Total number of reports	889	660	542	377	392	298
Number of reports marked as "no symptoms"	350	292	210	188	194	181
Minimum number of reports (significance test for a proportion result)	322	322	322	322	322	322
The result achieved after (days)	15	20	17	25	25	-
Statistical error for test of proportion	3%	4%	4%	5%	5%	-
$SDG_{11.6.3}$	11.58%	13.01%	11.40%	14.67%	14.56%	-

According to the significance test for a proportion for Lublin city with 5% possible statistical error, the minimum number of reports is 322 per month. In March and April, the minimum number of reports was reached both before and after QA checking. In May, the minimum number of reports of reports was not achieved for the dataset after QA and, so, this data set was not included in further analyses.

The highest total number of reports was collected in March (889), where 350 reports were marked as “no symptoms (no APSs)”. This indicates that 61% of surveys in March reported APS. After the QA process, the total number of reports decreased by 26% (660) and the number of reports marked as “no APS” was reduced to 292; thus, the surveys reporting APS increased to 66%. The minimum number of reports was achieved after 15 days of field data collection. To achieve the same minimum number in the QA_{s8}-checked database, five more days were needed. The maximum statistical error for 889 reports, before QA checking, was 3%; while, after QA, it was 4%. The SDG 11.6.3 indicator in March for the reports before QA was 11.58%; while, after QA, it increased to 13.01%.

In April, 542 reports were collected, 210 of which were marked as “no APS”. QA_{s8} reduced the total number of reports by 31%, where “no APS” reports were reduced by 11%. Therefore, 50% of QA_{s8}-checked reports were marked as “APS” in April. A total of 17 days were needed to achieve the minimum number of reports before QA, and eight more days for QA-checked data. The maximum statistical error for this sample was 4% before QA and 5% after QA. The SDG 11.6.3 indicator for April was 11.40% for the data set collected before QA, and increased to 14.67% after QA. This means that the SDG 11.6.3 indicator, based on the data after QA, was higher by 1.55 percentage points in April than in March.

In May, the total number of reports reached 392 surveys, of which 194 reports were marked as “no APS”. The maximum statistical error was 5% and the SDG 11.6.3 indicator was equal to 14.56%; the highest in the data set before QA. However, as mentioned above, this data set could not be compared to the data after QA as the minimum number of reports was not achieved.

The implementation of QA_{s8} increased the SDG 11.6.3 indicator value by 1.43 percentage points for the March 2018 data set and 3.27 percentage points for that of April. It follows that the SDG 11.6.3 value for April 2018 increased by 30% after QA checking and, so, the value of air pollution impact on citizen well-being was significantly changed. The SDG 11.6.3 value for March was 1.55 percentage points lower than in April when analysing data after QA. Comparing the SDG 11.6.3 for March, April, and May in the data before QA, the increase of the indicator value is conspicuous, which may have resulted from a decrease in anthropogenic pollutant concentrations in urban air over these months, such that their simultaneous occurrence with pollen had a lower intensity.

The citizen scientists engaged in the project collected enough APS reports in March and April to calculate the SDG 11.3.6 value. Comparing these two months, the minimal number of QA_{s8}-checked reports in March was achieved after 20 days of data collection: in April, this was achieved after 25 days. In May, the collected data after the QA_{s8} process was not enough for significant statistical analysis. It seems that the activity and motivation of citizens became too low in this month.

Monthly values of the SDG11.6.3 indicator, as calculated on QA_{s8}-checked data set, were added to the GeoWeb dashboard app (Fig. 8), such that each user could track the progress of the SDG achievements, presenting the monthly impact of air pollution on their subjective well-being status. This information was presented together with the other APSM results of the whole crowdsourcing campaign, presented in terms of the spatial location of eligible symptom-related layers (Q1–Q8; Figs. 8a, 8b), the number of QA-checked reports (Fig. 8d), the general level of citizen comfort (Fig. 8e), individual symptom severity values (Q2–Q8; Fig. 8f), and the percentage robustness of the QA_{s8} implemented in the project.

4. Discussion And Conclusions

In this study, we introduced social innovation into the urban air pollution issue, where citizens act to assess air pollution using their symptoms, thereby extending the paradigm of air pollution. We considered the spatial context; therefore, a map was used to spatially model symptom severity. The web mapping application is public and provides information about air pollution in specific areas of the city, such that citizens can learn about which areas could positively or negatively impact their well-being, according to information about the severity of the symptoms observed by the APSM project members. The tier 3 SDG indicator (11.6.3) proposed in this study highlights the crucial role of sCS in achieving the SDG 11.6. The value of SDG 11.6.3 is presented in the open web mapping app, such that citizens can observe and compare the percentage indicator of the impact on their well-being in the city within individual months.

Although the potential for using crowdsourced data to monitor urban air pollution was demonstrated here, the minimum report sample can be considered as a limitation of the project. Citizen science is an emerging trend in Poland and, so, specific motivation mechanisms need to be elaborated, based on the citizen motivation recommendations developed in other projects (Nov et al., 2011, McCrory et al., 2017). As the APSM focuses on citizens who are interested in the effect of air pollution on their health and well-being, our study is wider than other projects which are dedicated only to people diagnosed with health problems. This means that the motivation mechanisms involved differ from those which are appropriate for patients (e.g., free medical consultations).

Crowdsourcing projects rely on a suite of methods to boost data quality and account for data bias (Kosmala et al., 2016). To gain better data quality in CS, three-step mechanisms are generally recommended: taking considerations before, during, and after the data collection process (Wiggins et al., 2011). The APSM method, using logical rules to reject inconsistent database entries, was successfully implemented after the data collection process. Depending on the expected data quality level, different mechanisms were tested. However, by choosing a single QA system (Table 5) and combining rejected reports with the username (nickname and PIN), each user's quality rank can be calculated. A user who passes the QA system could then be rewarded with truth and reputation statuses. Such citizen trust models have been proposed by Alabri and Hunter (2010), who developed a social trust metrics framework, and Langley et al. (2017), who applied a reputation model and used a reputation score system to determine the threshold for accepting volunteered data. This should be based, for each citizen, on the ratio of reports accepted by QA system to the total number of their surveys: the higher the ratio of accepted reports, the higher the level of citizen trust.

In conclusion, APSM data quality mechanisms implemented after the data collecting stage—but referenced to particular user's reports—could be used to develop a user motivation system (which, in the current study, was limited only to user activity). Furthermore, the technological implementation of QA systems as cloud services may enable the ranking of user trust and reputation during the data collection process. Then, not only the quantity but also quality of user reports can be analysed and their level of reputation could be assessed and presented during the campaign. In large-scale CS projects such as iNaturalist (iNaturalist.org), the trust and reputation of citizens is based on their activity: "The users community ensures that data is reliable, but it also gives the opportunity for fellow users to gain knowledge" (Nowak et al., 2020). The APSM project will be further developed with machine learning methods, which will allow us to train the QA models to classify true and false reports and filter them in real-time on the map. Moreover, during the collection process, another solution can be implemented: GPS trajectories. Currently, Q10 (Table 2) requires users to estimate how long they have stayed in a location. Using GPS or GSM data to characterize user mobility patterns and analyse user spatial trajectories could increase data quality and make the application smarter. Changes in user trajectories could also result in an individual push notification to maintain or cancel the APS, depending on the change of location. Finally, to gain better data quality, improvements before the data collection stage may also be proposed. The APSM was carried out as a Polish case study. As CS has been recognized as an emerging trend in Poland, we found it necessary to promote the sCS concept through the European CS platform (https://eu-citizen.science) and engage citizens in air pollution monitoring by organizing training sessions. What differentiates CS from other VGI activities is the fact that CS can be taken up by any volunteers who have undertaken standardized training. Learning how to observe one's own symptoms in reaction to air pollution, relating them with air quality information and green pollutant concentration levels, and regular symptom recording were considered prerequisite parameters for ensuring the quality of APSM.

From a practical point of view, the data quality (i.e., completeness, spatial accuracy, thematic resolution, timeliness, and logic consistency) should be suitable for the project purpose. The quality of CS data is expected to be similar to data collected by professionals. According to Wiggins et al. (2011), some general solutions for improving crowdsourced data quality include: volunteer training (workshops), using a large sample size, data filters, data mining algorithms, using a qualifying system, voting for the best, reputation scores, online data and metadata sharing, citizen contribution feedback, reuse of data, and replicate studies; however, the purpose of our study was to create a data quality framework.

This confirms that data quality control mechanisms are an indispensable element in any citizen-driven research, hence also being effective in CS activities such as that considered in this paper. The removal of falsely completed surveys increased collected data quality and usefulness. In our research, only 5.8% of data were eliminated due to positioning accuracy, either lacking geolocation or duplicated reports at the same geolocation. Farman (2015) identified 12% of crowdsourced data to have accuracy-related errors. Thus, we conclude that, in our sCS, this type of error did not pose a significant problem, in terms of data quality; however, subjective data bias definitely does. Still, the problem of human bias in data poses a problem which must always be considered during data analysis. Human bias introduced into data can be mitigated by using clearly stated survey questions, additional training, and limiting the scope of the survey. We found that up to 29% of all collected surveys regarding air pollution objectively contained useless or false information. Kosmala et al. (2016) reported subjective data bias at levels between 5% and 35%, depending on the simplicity of the tasks assigned to citizens; Hube et al. (2019) presented data bias at 15–17% in a crowdsourced data set; and Eickhoff (2018) pointed out an accuracy rate reduction by 20% due to cognitive data bias. We recognize that our percentage share of data bias was high, highlighting the absolute necessity of a QA mechanism framework for sCS health-related projects. As QA mechanisms are created through the use of logical rules, they are easy to understand and can be crafted to match particular (expected or observed) error types in collected survey data. We found that QA mechanisms can be used to remove surveys that contain clearly defined errors.

Out of the five employed QA mechanisms, the most robust were those aimed at removing inconsistent user answers in the survey (i.e., the 'repeating' QA mechanism). These results suggest that some of the methods employed might lead to a decrease in user engagement, as some users were not consistent with their own answers in the same survey. This finding may be due to a natural phenomenon associated with the human condition or to a survey questionnaire which lacks user engagement. Future surveys employing sCS as a data source might expect many haphazardly completed user surveys. As up

to 23% of all collected surveys were marked as containing errors highlighted by the repeating mechanism, at least this kind of QA should be applied to all further works using data collected with the help of CS.

The focus of our research was not on validation with digital sensors, but on eliminating logically inconsistent answers and technologically incorrect objects. To present, no QA mechanism framework had been formulated for APSM projects and, so, the proposed framework could be valuable for a wide group of projects that must manage a specific data subjectivity type: the subjectivity of human symptoms.

The APSM method can capture the moment when air pollution changes. The observed health symptom severity can be validated with air pollution concentrations measured by air quality monitoring stations. Having information whether citizens are diagnosed pollen allergy sufferers, by collating this information with the current concentration of pollen species, the chance for confirmation of air pollution impact on citizen well-being is higher.

The SDG 11.6.3 proposed in this paper is a new indicator, which proves that citizen science can have a meaningful contribution to the achievement of SDGs. Citizens, together with scientists, built a reliable model of the impact of air pollution impact on the well-being of citizens in their city. According to Fritz et al. (2019), SDG tier 3 indicators have high potential for future contributions to citizen science, where methodologies are still being developed or data gaps occur. However, they also pointed out that data quality is one of the greatest limitations in this area and, so, quality assurance mechanisms are a crucial challenge for obtaining CS data which can readily contribute to the achievement of SDGs. As a result of our research. we can confirm that not only QA mechanisms, but also citizen activity is necessary for CS contribution in SDG achievement. Despite crowdsourcing solutions being popular at present, we had difficulties in collecting the minimal number of reports for a statistically significant analysis. The results showed the decreasing activity of citizens, which led to not enough data to confidently calculate the SDG 11.6.3 value in the last month of the crowdsourcing campaign (May 2018). A total of 74 citizens participated in our study and, although they were invited to report their APS observations preferably once per day, there were not enough reports in May to reach the minimum number. We conclude that the group of citizens was too small and had limited motivation.

In the study, we applied a user activity rank model, which showed that citizen activity decreased over time; which is typical for a CS project (Geoghegan et al., 2016). The level of citizen engagement and motivation was the highest at the beginning of the crowdsourcing campaign (100 reports per day), dropping after 14 days. The two peaks in the last month of field data collecting campaign could have resulted from the motivational workshops with an educator where citizens rankings were discussed, thus increasing competition between the citizens (35 and 40 reports per day, May 2018). In summary, for a case study of Lublin or any city of similar size and structure, a citizen group larger than 74 people is needed and regular workshops are necessary to maintain their activity.

Due to the intuitive access and operation of the presented tools, such methods and tools are suitable for scientists, educators, and evaluators alike. The ability to reduce data bias in real-time is not possible without a programmed web-based mechanism functionality. AGOL configurable capabilities allow for data filtering, but the filters are too basic for the conditional statement combinations which form the QA mechanisms.

Conveniently, our database was set up on REST services, such that the QA mechanisms and their combinations could be implemented and analysed using desktop software, in direct connection with AGOL apps, which ensured the stability of the REST service-based data source. APSM modelling directly focused on the urban air pollution information shared with society and, as a result, represented the level of citizen well-being. Due to the proposed tier 3 SDG indicator, the data obtained with regards to the measured air pollution could be output as a spatial model of city well-being, which is crucial for SDG 11.6.

The Acronym List

Acronym	Defined in section	Meaning [section]
AGOL	ArcGIS Online	WebGIS platform by Esri Inc. [Materials and Methods]
AP	Air pollution	Air pollution refers to six major air pollutants: inhalable particles (PM_{10}), fine particulate matter ($PM_{2.5}$), ozone (O_3), sulfur dioxides (SO_2), nitrogen dioxides (NO_2), and carbon monoxide (CO). [Introduction]
APS	air pollution symptom	Human health symptoms related to air pollution, caused by combined factors of anthropogenic and biophysical ambient air pollutants [Introduction]
APSM	air pollution symptom (mapping)	Air pollution monitoring, expressed on the map as the severity of human health symptoms caused by combined factors of anthropogenic and biophysical ambient air pollutants [Introduction]
AQ	Air quality	Air quality refers to AQI as well as to classifications, opinions, and feelings (including citizen's experiences) of air- and air quality-related SWB. However, consensus about urban air quality terminology has not been reached and researchers distinguish air pollution through pollen exposure [49]. [Introduction]
AQI	Air quality index	AQI tracks six major air pollutants—inhalable particles (PM_{10}), fine particulate matter ($PM_{2.5}$), ozone (O_3), sulfur dioxides (SO_2), nitrogen dioxides (NO_2), and carbon monoxide (CO)—to describe the air quality with the use of an objective scale. [Introduction]
Con.1–Con.17	Conditional Statement no 1–Conditional Statement no 17	The 17 conditional statements which, in specific combinations, are the basis of the developed data quality assurance mechanisms (QAm). [Materials and Methods, 2.2]
CS	citizen science	Citizen-driven research, which citizens (non-experts) participate in by co-operating by researchers [Introduction, 1.3]
CV (CV1, CV2)	Cross-validation mechanism in variant 1 and variant 2	The cross-validation mechanism was used to reject responses using three essentially related questions. Mechanism studied and proposed in two variants of robustness. (variant 1 - less robust, variant 2 - more robust) [Materials and Methods, 2.2]
GeoWeb	geospatial web	Geographically related tools and web services for individuals and groups [Abstract, Introduction, Materials and Methods 2.3]
OECD	Organization for Economic Cooperation and Development	An international organisation shaping policies that foster prosperity, equality, opportunity, and well-being for all. [Introduction]
PHD	Patient's Hayfever Diary	Digital diary for pollen allergy sufferers. [Introduction]
PM	Particulate matter	A mixture of particle pollution; both solid and liquid droplets found in the ambient air. PM is characterized by particle size and chemical composition. The PM fraction of 2.5 μm or less ($PM_{2.5}$) is especially important for evaluating health as well as environmental risks [Introduction]
Q1–Q12	Question no 1–Question no 12	The 12 questions about air pollution-related symptoms and factors related to APS, but also additional information about subjective well-being asked to citizens in the mobile survey. [Materials and Methods, 2.2]
QAm	data quality assurance mechanism	Conditional statement-based mechanism for data bias controlling. Five data quality assurance mechanisms are proposed in this study [Introduction, 1.4; Materials and Methods, 2.2]
QAs	data quality assurance system	Combinations of the data quality assurance mechanisms. In the study, we studied and analysed eight QAs variants, depending on their robustness levels QAs_1–QAs_8 [Materials and Methods, 2.2]

Acronym	Defined in section	Meaning [section]
Rp (Rp1, Rp2)	Repeating mechanism in variant 1 and variant 2	The repeating mechanism determines the quality of the report, according to the other previously asked questions, by asking the same question but in a different way. Mechanism studied and proposed in two variants of robustness (variant 1 - less robust, variant 2 - more robust) [Materials and Methods, 2.2]
SC (SC1, SC2)	Start-Check mechanism in variant 1 and variant 2	The start-check mechanism is used to verify the report quality at the beginning of the survey and controls the report quality during the analysis of each symptom severity answer. Mechanism studied and proposed in two variants of robustness (variant 1 - less robust, variant 2 - more robust) [Materials and Methods, 2.2]
sCS	human-sensed CS	Citizen science measurement relying on one of the human senses [Introduction]
SDGs	sustainable development goals	(…) fundamental strategy to guide the world's social and economic transformation [Abstract]
Sq	Sequence mechanism	The sequence mechanism was applied to exclude user "automatism" in providing answers. [Materials and Methods, 2.2]
Survey123, cascade, time slider	Survey123 for ArcGIS mobile app, Esri Story Map Cascade app template, Esri Time Aware app template	Configurable mobile apps and web app templates based on ArcGIS.
SWB	subjective well-being	Reflects the philosophical notion of people's good life, a proxy of their life satisfaction, momentary experiences, and stress [Introduction]
TC	Time-loop Check mechanism	The time-loop check mechanism was used to eliminate the reports that did not align to the geolocation of the citizens, according to the length of their stay in the place, in comparison to the duration of their symptoms. [Materials and Methods, 2.2]

Declarations

Credit Author Statement: Marta Samulowska: project idea, QA method elaboration and development, GeoWeb development; Szymon Chmielewski: project idea, crowdsourcing campaign evaluation, crowdsourcing towards SDG, SGD indicators; Edwin Raczko: QA method development, R statistics software implementation; Michał Lupa: allergy symptom mapping idea, QA method verification; Dorota Myszkowska: air quality health symptoms, aerobiology and allergology issues; Bogdan Zagajewski: project idea evaluation, QA method verification. All authors prepared the manuscript.

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Figures

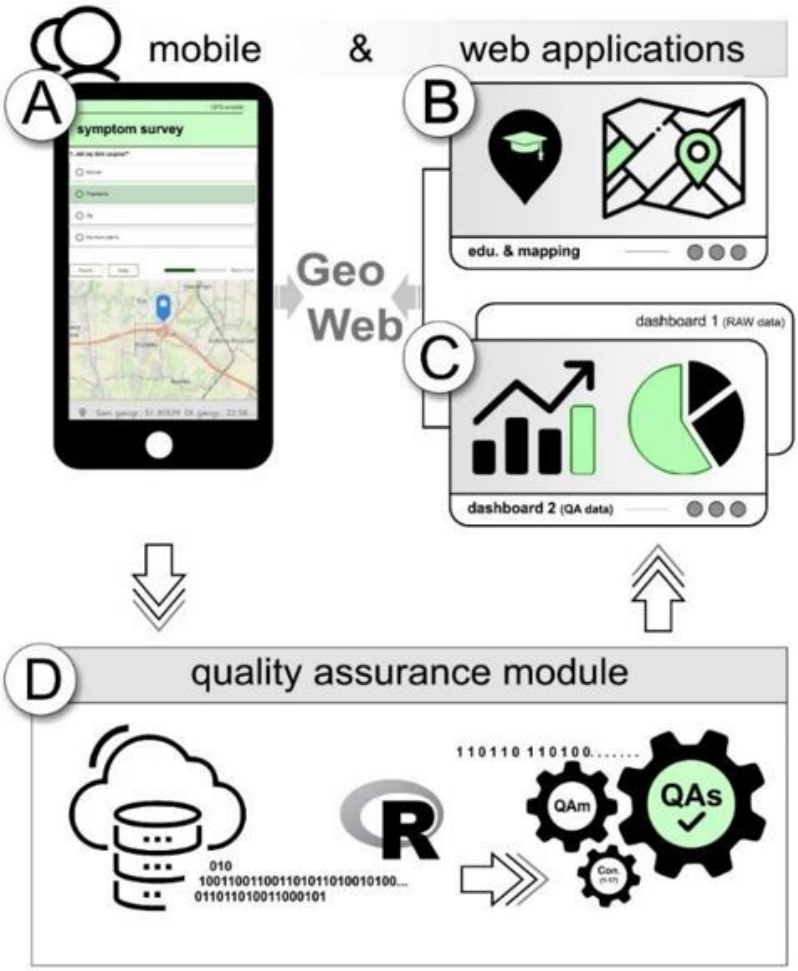

Figure 1

GeoWeb architecture implemented for the APSM project: A) mobile survey app for field data collection; B) web app with educational and training materials; C) dashboard app for monitoring data collection process and presenting APSM results; and D) quality assurance module.

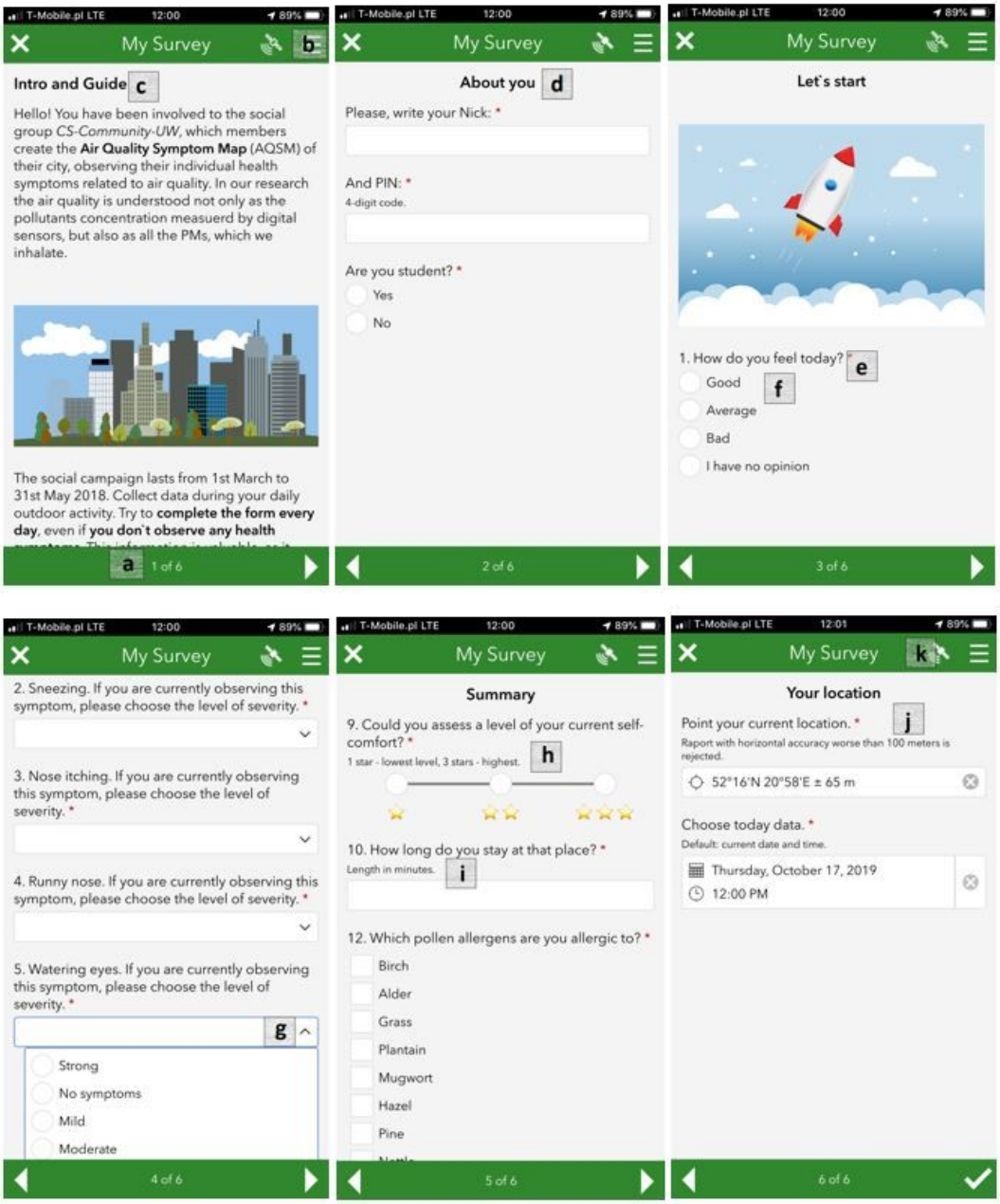

Figure 2

Six-page mobile survey app user interface: a. Six-page navigation; b. Choose language button; c. Introduction and user guide; d. User basic info; e. Obligatory question mark; f. General well-being question; g. Health symptom questions; h. Repeated well-being question; i. Length present in the place report; j. Location and date; and k. Current location status.

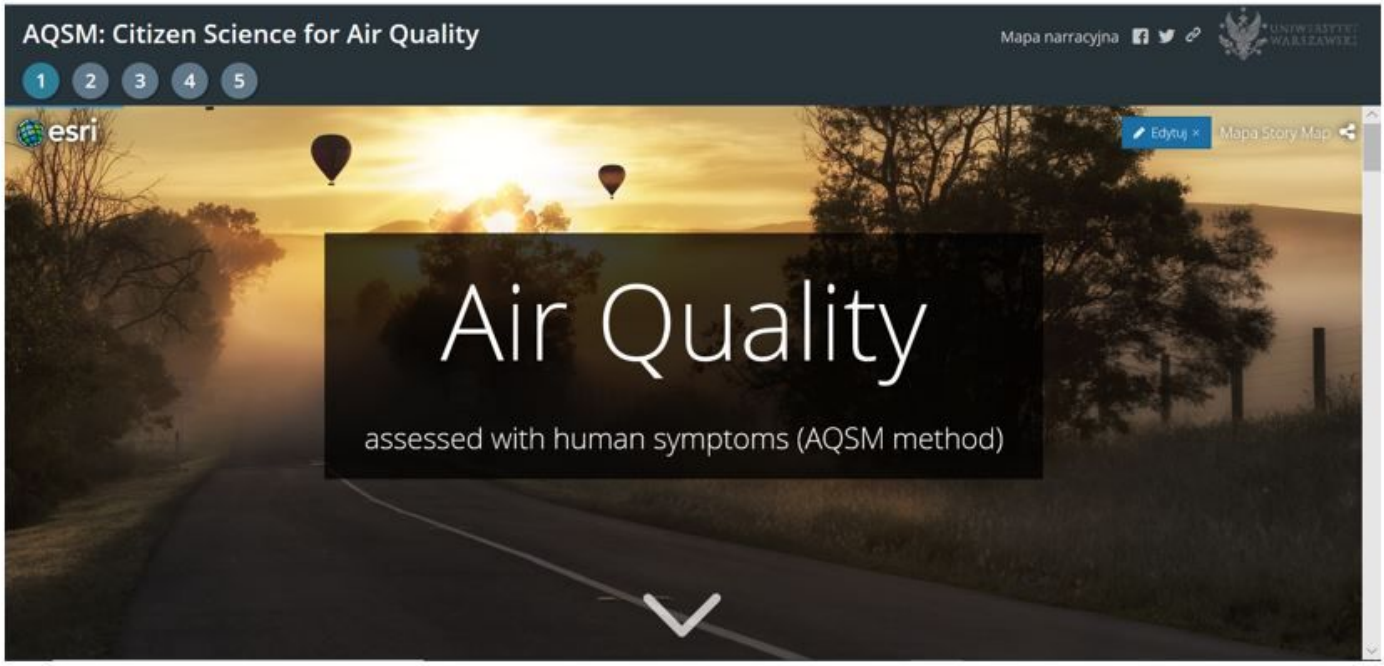

Figure 3

Web application for the APSM project: collection of five applications.

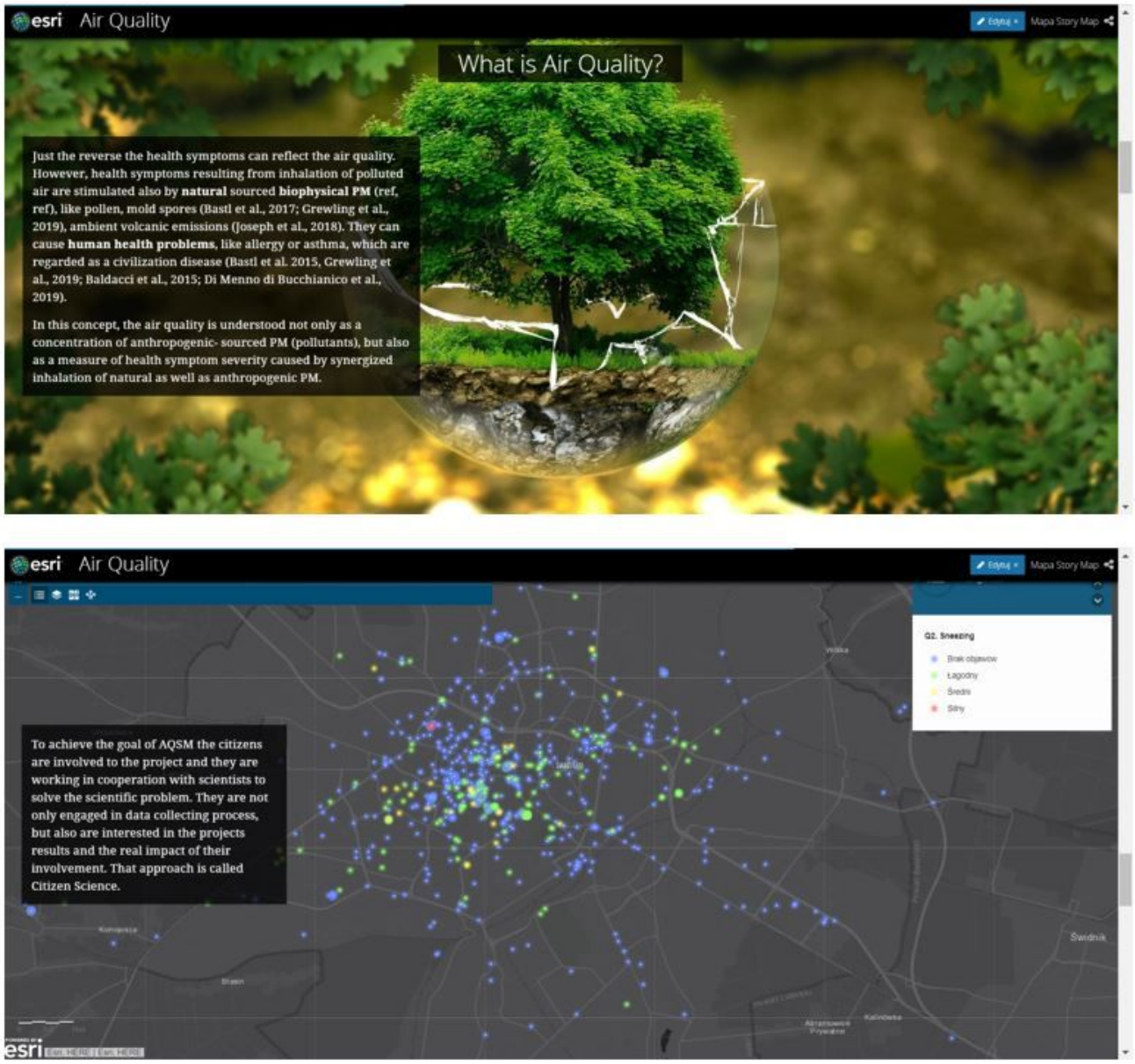

Figure 4

Educational part of application: cascade story map.

Figure 5

Web mapping application presenting collected data (before QA check) in real-time, operations dashboard: a. Map; b. Legend; c. Indicator of current number of the reports; d. Citizen activity histogram; and e. Citizen activity ranking.

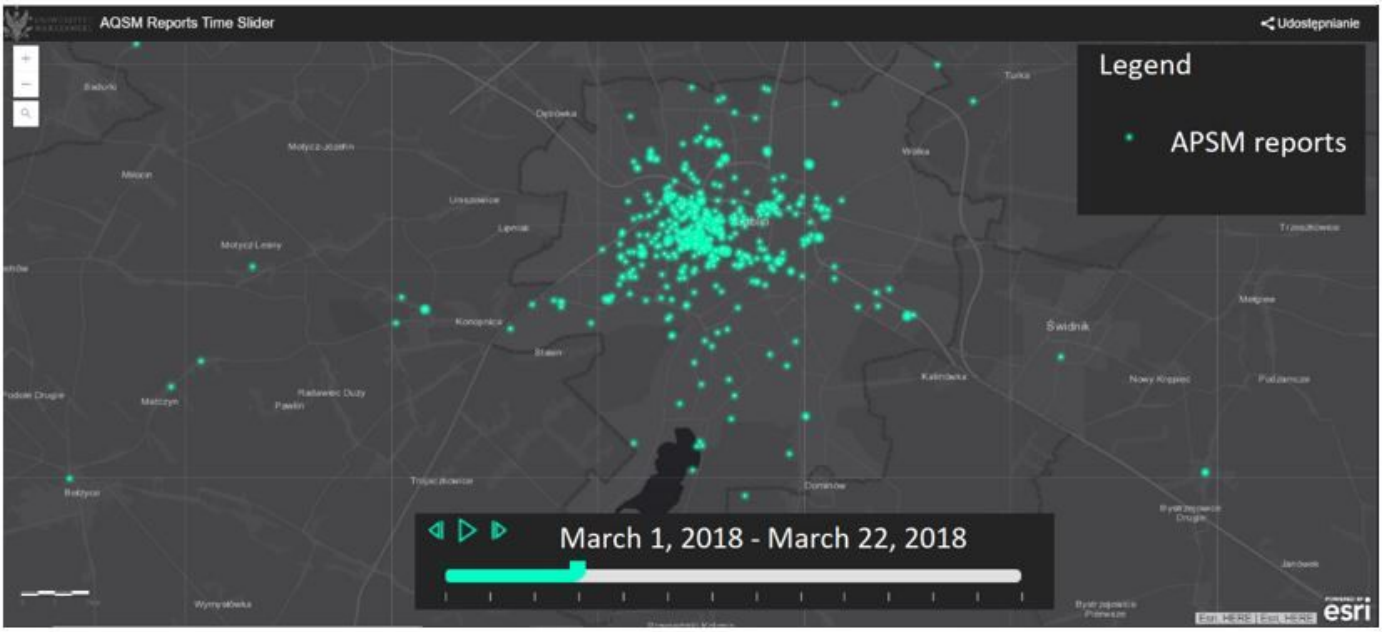

Figure 6

Time slider app following the data collection process over time.

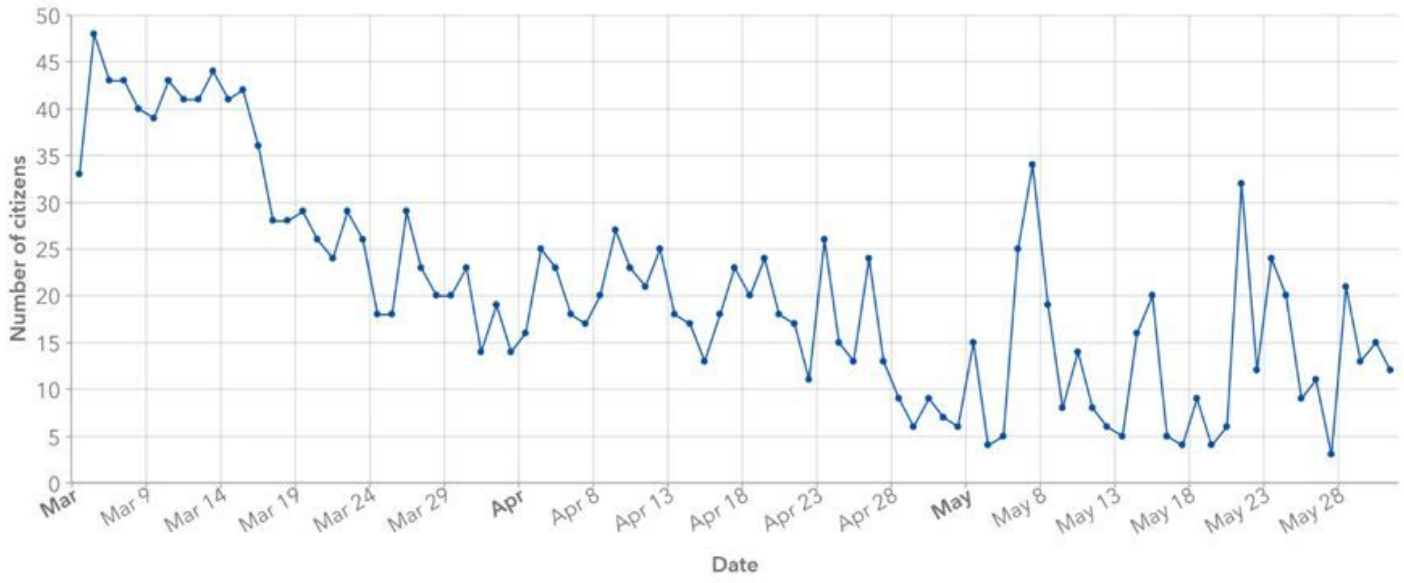

Figure 7

Citizen activity curves during the field data collection campaign.

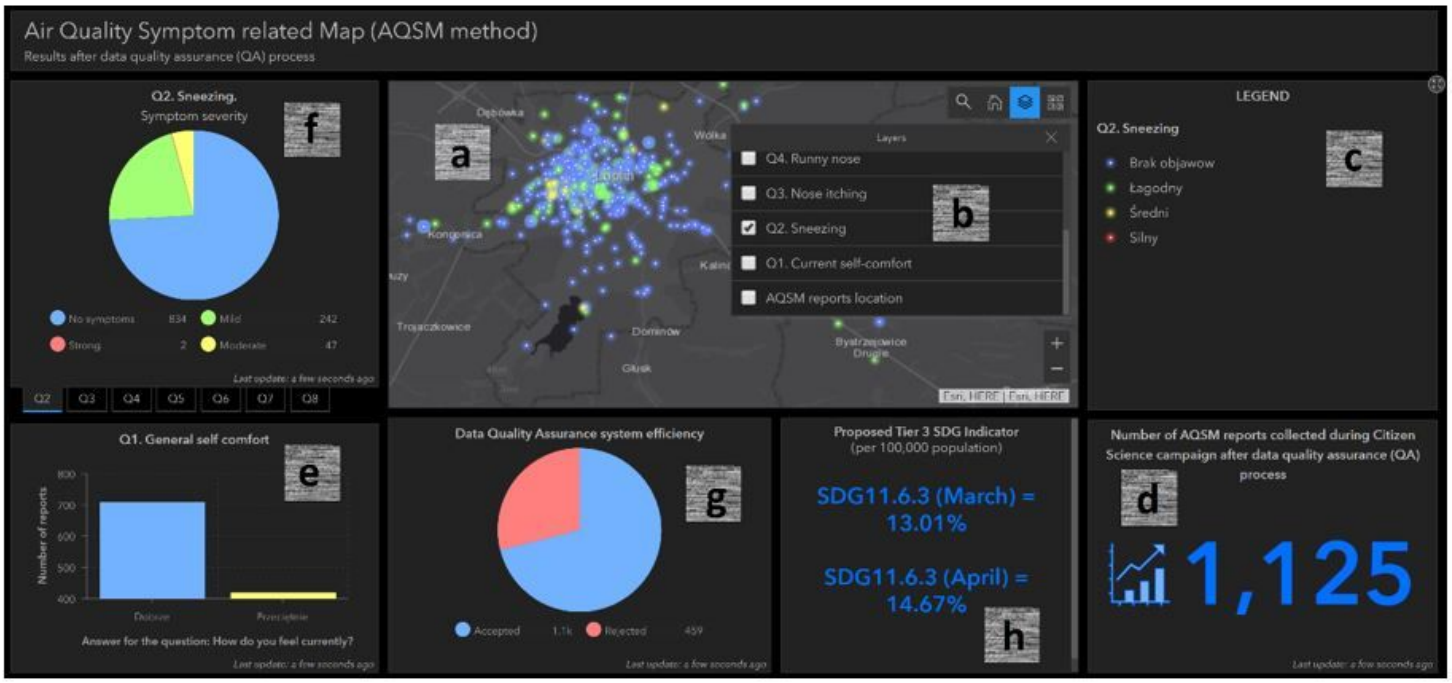

Figure 8

Web mapping application, presenting results of QA-checked data using QAs8, operations dashboard: a. Map; b. Layer list; c. Legend; d. Indicator of QA-checked reports; e. Bar chart of citizen general comfort; f. Pie chart of citizen symptom severity; g. Pie chart of QA system robustness; and h. Proposed tier 3 SDG 11.6.3 indicator.