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Air Quality Monitoring in Coal-Centric Cities: A Hybrid Approach

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Abstract: Despite the increasing time sensitivity of climate change, many cities worldwide still heavily rely on coal. The extraction, processing, transport, and usage of coal lead to deteriorated air quality, resulting in complex environmental and public health problems for the local communities. Mapping different pollution sources in coal-centric cities is not trivial due to the hyperlocal nature of air pollution and the often low-density network of air quality monitors. This study explores the air quality issues surrounding coal-centric cities using a combination of qualitative and quantitative data from reference-grade air quality monitors, low-cost sensors (LCSs) deployed on citizens' vehicles, and community engagement activities. It explores how LCSs can be used to characterize air quality at a high spatio-temporal resolution and how this information can be used to decode people's perceptions of air quality issues and elicit local knowledge. We evaluated our approach in Sparwood (Canada), and Oskemen (Kazakhstan) which are very different cities, but are both heavily dependent on coal. LCSs have been proven an efficient tool to identify pollution hotspots that traditional reference monitors miss, while workshop-based activities making use of data maps and coding tools have successfully elicited information about pollution sources from non-experts, helping collaborative sense-making and informing new LCS deployment strategies. Understanding air quality in coal-centric cities as a complex socio-technical phenomenon can enable the coal industry, city officials, and residents to engage in addressing air quality issues.

Keywords: environmental science; mining towns; coal-centric towns; air quality; internet of things; community engagement

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1. Introduction

Despite ongoing global efforts towards decarbonization, coal continues to hold a significant role in the world's energy mix [1] and remains a crucial economic contributor to numerous cities and towns worldwide. However, the process of mining, processing, and burning coal can have substantial impacts on social, economic, and environmental aspects [2,3]. Coal mining operations often lead to acid mine drainage, containing high levels of toxic metals that negatively affect water sources [4,5]. Additionally, mining and mineral processing can contribute to elevated levels of particulate matter (PM) pollution and increased noise levels due to drilling, blasting, crushing, collection, storage, and transportation along the supply chain. Furthermore, mining can have social consequences on communities previously established in mining regions [6]. Beyond the local impacts on communities, burning coal emits greenhouse gases (GHGs), which contribute to climate change. Coal-burning power plants provide approximately 36.7% of the electricity demand worldwide, with coal being the primary energy source in countries such as Kazakhstan (54% of the mix) and South Africa (71%) [7]. Transitioning to non-fossil fuel sources is often challenged by high costs and lock-in mechanisms [8]. Nonetheless, local economic benefits often lead regions to embrace coal-related industries while implementing regulations to mitigate their impact on public health [9].

Mapping pollution sources in coal-centric cities is a challenging task. In industrial and mining-intensive areas, PM pollution typically consists of a significant amount of coarse aerosol, often referred to as dust [10]. These larger particles are considered *hyperlocal* as they tend to deposit closer to their emission source compared to smaller particles; therefore, they can hardly be monitored without a dense network of AQ monitors, leading to high costs. Further, while some sources including mine blasting and coal burning in power plants are evident, others are less visible, such as coal transportation between processing plants and delivery to customers. A high-resolution map of air quality (AQ) can offer valuable insights into pollution sources. Such environmental data may help enforce air quality standards, facilitate the implementation of targeted mitigation strategies for local pollution sources, as well foster community engagement around environmental issues.

Typically, cities use static reference monitors to produce air pollution estimates. However, these monitors are costly, ranging from USD 50,000 to USD 100,000, resulting in a sparse network. Previous research has shown that particulate matter (PM) can vary significantly over short distances, even just a few meters [11,12]. Consequently, fixed monitors may struggle to accurately capture the spatial variations of fugitive emissions, often referred to as "dust events" [13].

Low-cost sensors (LCSs) are increasingly utilized to complement regulatory monitoring networks [14–16], providing high-resolution data in areas where people actually reside [17]. However, using LCSs comes with the challenge that the data they produce may be more error-prone compared to reference-grade sensors. Currently, no LCS meets the data quality requirements for regulatory monitoring purposes [18] and conventional calibration procedures often cannot be applied to LCSs due to cost or technology barriers [19]. However, recent research works have shown that the inclusion of independent information such as reference instrument data and satellite observations [19] combined with machine learning models [20] can lead to calibration methods that significantly lower data uncertainty.

The biggest potential of LCSs lies in democratizing air pollution monitoring due to their low-cost and widespread use among the public. LCS-based approaches can engage communities in monitoring their environment, complementing traditional methods conducted by governments, companies, and research institutes, and by leveraging citizen science techniques [21,22] to include non-experts in research efforts. Community engagement in air quality monitoring offers several benefits. It increases public participation in scientific research [23], supports citizen involvement in environmental policy making [24], helps identify environmental disparities and spatio-temporal patterns [25], and fosters lifelong learning [26] when citizens are trained to collect and understand data. These positive impacts are of particulate relevance for disadvantaged communities as as shown in where an LCS network established in disadvantaged communities revealed different workshifts, outdoor activities, and an overall high exposure to pollution among residents. These findings have been linked to differences in the built environment such as greeness, street geometry, walkability and pavement quality [25]. Finally, by facilitating wide-spread and decentralized sensing, LCS initiatives have the potential to contribute to an "environmental data openness". This approach, the release of open datasets, comes with several benefits for both academic research and grassroots advocacy, including innovation and general smart city development. Despite that, the progress in open data initiatives has been slow, not just in developing countries but also in large and wealthy cities [27]. LCS projects have also been recently surveyed based on their applications in urban environment [14], drives and challenges linked to their implementation [28], and enabling technologies [29].

This paper investigates opportunities stemming from combining traditional environmental sensing strategies with LCSs and community engagement techniques. It explores how LCSs can be used to characterize air quality at a high spatio-temporal resolution to detect pollution hotspots. In turn, this information is used to decode people's perceptions of air quality issues and elicit local knowledge towards pollution source identification. As part of this study, a mobile LCS sensing platform has been designed, fabricated, and deployed on community vehicles in two coal-centric cities. Different methods to enable community members to understand the data collected have been designed and evaluated during in-person workshops. Drawing from our experience collaborating with a diverse group of environmental scientists, mine workers, computer science students, and citizens, we offer insights into the challenges and opportunities of implementing environmental sensing programs in coal-centric cities.

2. Context of the Study

Our approach has been applied to two coal-dependent cities: Sparwood (Canada), a mining town with the country's second-largest coal reserves of 215 million tonnes, and Oskemen (Kazakhstan), where coal-fired power plants provide most of its electricity consumption. These cities were selected as they represent two distinct impacts of coal, one during mining and the other during energy production.

Even though both cities are heavily dependent on coal, their air pollution profile is different. Sparwood is a coal mining town, indicating mining dust and the operation of fossil fuel vehicles are the major emission sources; this leads to higher coarse particulate matter concentrations [30,31]. In Oskemen, the city consumes coal to power its metallurgy industry, which leads to fine particulate matter emissions from fossil fuel combustion. Therefore, we highlighted PM_{10} pollution in Sparwood and $PM_{2.5}$ in Oskemen.

The characteristics of the two cities are compared in Table 1.

Table 1. Characteristics of Sparwood (Canada) and Oskemen (Kazakhstan).

Characteristic	Sparwood	Oskemen
Location	Southwestern Canada	Eastern Kazakhstan
Population	∼4000	∼320,000
Population Density	21.5 inhabitants/km^2	644.7 inhabitants/km^2
Climate	Continental. Avg. Temperature 37 °F, H: 73 °F, L: 11 °F	Continental. Avg. Temperature 40 °F, H: 82 °F, L: −3 °F
Economy	Coal mining	Heavy industries: mining, metallurgy, electricity generation
Median Household Income	103,538 CAD	Not publicly available
Average Age	39 years	33 years
Percentage Population < 15 years	19.26%	19.3%
Percentage Population > 65 years	12.2%	9.9%
Major Environmental Pollutants	$PM_{2.5}$, PM_{10}	SO_2, NO_2, $PM_{2.5}$
Average $PM_{2.5}$	6.9 µg/m^3	70.9 µg/m^3
Average PM_{10}	10.4 µg/m^3	94.9 µg/m^3

2.1. *Sparwood, Canada*

Sparwood, located in Southwestern Canada, has relied heavily on steel-making coal mining since the late 1800s. The town is home to approximately four thousand citizens, with a population density of 21.5 inhabitants per km^2. Sparwood is situated in the Elk Valley region, which covers approximately 70,000 km^2.

The region has a rich history in mining and forestry, with metallurgical coal mining playing a pivotal role in driving massive economic growth since the first large mining company, the Crowsnest Coal Company, was established in 1889. Economic prosperity continued to soar, particularly after the post-World War II industrial boom, attracting individuals from across North America and beyond to relocate and contribute to the region's increasing wealth.

As per census data, Sparwood boasts a median household income of CAD 103,538, which is approximately 60% higher than the Canadian median of CAD 61,400 [32]. The average age of Sparwood residents is 39 years, with 19.26% of the population below the age of 15 and 12.2% over the age of 65 [33]. Notably, one-third of Sparwood's labor force is directly engaged in mining activities. Apart from mining, the region is renowned for its outdoor recreation and tourism opportunities, including winter sports, hiking, and fishing.

The Elk Valley region is well-known in the environmental science community for its selenium pollution in water sources [34–36]. Additionally, air pollution, particularly dust, has become a growing concern for the residents of Sparwood. According to a 2020 community report compiled by an independent group of experts ([37], pp. 36–42), the air quality objectives for the area in 2018 were not met. Although the annual limit for $PM_{2.5}$ (particulate matter with diameters less than 2.5 μm) measured by a network of eight reference monitors was slightly below the British Columbia Air Quality Objective (7.8 $\mu g/m^3$ with a limit of 8 $\mu g/m^3$), the daily limit of 25 $\mu g/m^3$ was exceeded sixteen times, as recorded by the air quality monitor located in a downtown area.

In the study, 76% of Sparwood residents rated the air they breathe as unclean and unhealthy. Additionally, 74% of the survey respondents agreed or strongly agreed that mine-related dust is negatively impacting their quality of life. The presence of dust and dirt on streets, private decks, and patios serves as visible indicators of poor air quality and remains a frequent topic of discussion among Sparwood residents. On 19 August 2018, the recorded data showed an all-year high average daily concentration of 102.44 $\mu g/m^3$. In response to these events in 2018, a local mining company established an air quality forum where Sparwood residents raised their concerns regarding air pollution [38]. The average asthma rate in the population is 11%, while the rate of Chronic Obstructive Pulmonary Disease (COPD) is 8%; both are in line with national averages [39].

The mining company has implemented various mitigation measures to reduce pollution levels. Water, mulch, and chemical suppressants have been used to minimize dust generation, which includes wetting roads and specific areas around the mine known for dust emissions. Workers' vehicles are also washed before leaving the mining sites for their home commute. However, these measures are typically applied only when the outdoor temperature is above freezing, which occurs for about five months each year [40].

Blasting on the mine pits occurs approximately every three days between 12:30 and 4:30 p.m. MST. The blasting schedule considers wind direction forecasts to minimize the risk of dust migration toward the town. Additionally, wind fencing is in place to act as a dust catchment measure.

The town of Sparwood has delegated the task of monitoring air pollution to the mining company via a third party. The company also runs a social responsibility program which consists of collecting citizens' feedback and complaints via anonymous feedback boxes, emails, and phone calls. Although feedback is collected at the regional scale, 90% of the 109 complaints received in 2018 as part of this program comes from Sparwood residents. Most complaints received were about dust events [13], which are high-intensity pollution events where dust is visible as airborne plumes or as deposition over residents' properties (cars, decks, house façades).

The city lacks an independent air quality working group, but it does have a Socio-Community and Economic Effects Advisory Committee (SCE-EAC). This committee comprises members from both the mining company and the town of Sparwood and serves as an advisory agency for both the district and the mining company.

2.2. Oskemen, Kazakhstan

Oskemen, also known as Ust-Kamenogorsk, serves as the capital city of Eastern Kazakhstan, with a population of just over 320,000 [41]. Despite a decrease in population density over the last 50 years, it remains significantly higher than Sparwood, with 644.7 inhabitants per km^2 compared to Sparwood's 21.5 inhabitants per km^2. Established in 1702, the city lies nestled in the foothills of the Altai mountains and is traversed by the Ulba and Irtysh rivers. Throughout its history, Oskemen has been shaped by heavy industries such as mining, metallurgy, and electricity generation, dating back to the Soviet era when it served as a fort and trade center connecting Mongolia and China.

Oskemen is home to several research institutes, including Eastern Kazakhstan Technical University (EKTU). The city's median age stands at 33 years, with 19.3% of the population being below the age of 15 and 9.9% over the age of 65 [42]. While the region is renowned for its industrial activities, it also boasts parks, museums, and natural beauty.

The prevalence and continuous operation of heavy industries in Oskemen have led to severe air pollution, resulting in negative environmental and public health consequences. Reports indicate that in 2019, the local SO_2 level was 4.5 times higher than the WHO's 24 h average limit, and the local annual average NO_2 also exceeded WHO standards [43]. Additionally, hazardous air pollutants detected in the region include selenium, lead, cadmium, arsenic, hydrogen fluoride, and chlorine [44].

The state-run *Kazhydromet* service, situated in the Ministry of Ecology, Geology, and Natural Resources of the Republic of Kazakhstan, provides some air quality information in Oskemen with seven monitoring locations listed [45]. However, the overall air quality profile in Oskemen remains relatively poorly monitored and studied, potentially due to the lack of robust monitoring protocols and infrastructure. To address these knowledge gaps, citizen science initiatives such as AirKaz are emerging, utilizing a network of low-cost monitors distributed throughout several cities. The scarcity of public land use, energy use, and socio-economic data further hinder the application of traditional empirical or physical air quality models.

At the national level, Kazakhstan heavily relies on coal, with 40% of all households surveyed for the Households Living Conditions Survey by the Committee of Statistics of the Republic of Kazakhstan using coal for heating, cooking, and other needs. Moreover, approximately half of all energy consumption in Kazakhstan can be attributed to coal use [46]. Coal burning constitutes a significant portion (66%) of electricity and heat production, releasing large quantities of hazardous air pollutants [47]. Notably, Kazakhstan ranks second in the world for per-capita coal consumption, with each person in the household sector consuming around 157 kg of coal [48].

Cities with power plants burning low-quality coal, with an ash content exceeding 40%, such as Nur-Sultan and Almaty, experience the highest PM_{10} values in Kazakhstan. In contrast, in the cities of Eastern Kazakhstan, including Oskemen, where coal with an ash content of 15–20% is used, PM_{10} concentration tends to be lower. However, Oskemen's air pollution is likely a combination of factors, with coal playing a role, but heavy industry contributing to the majority of pollutants.

3. A Hybrid Methodology for Air Quality Sensing in Coal-Centric Cities

This paper explores combining the existing networks of AQ reference monitors in Sparwood and Oskemen with two novel methods: (i) custom-designed mobile LCSs deployed on community vehicles and (ii) community engagement workshops with mapping and coding activities.

The first method focuses on enhancing the spatio-temporal resolution of air quality data by opportunistically deploying sensors on road vehicles: mining company vehicles used by employees for both work-related and personal purposes in Sparwood, and students' personal vehicles in Oskemen. This approach has been shown to effectively improve the characterization of rapidly changing phenomena, such as dust events and hotspots [49], complementing the data obtained from reference monitors.

The second intervention aims to empower residents by encouraging them to supply qualitative feedback through a collaborative and participatory strategy [50]. It points at providing community members with the necessary knowledge, skills, and tools to enable them to identify and communicate qualitative insights related to air quality effectively. It encourages collaborative brainstorming and sense-making, aiming to improve the estimation of pollution sources and foster participation around environmental issues.

Our objective is to utilize these interventions to analyze aerosol sources, identify best practices, and uncover opportunities and challenges for future air quality monitoring campaigns. These findings will hold relevance and applicability for other coal-dependent towns.

3.1. Static Reference Monitors

The Elk Valley has a network of eight reference monitors, with four of them located in Sparwood. These monitors are maintained by a third-party provider; the data they collect are reported to the British Columbia Ministry of Environment and they are available upon request [51]. For our study, we specifically selected the monitors closest to Sparwood that measure aerosol pollution, including fine particulate matter with diameters less than 2.5 µm ($PM_{2.5}$), particulate matter with diameters less than 10 µm (PM_{10}), and total suspended particulate matter (TSP). Each monitor records 60 min averages of $PM_{2.5}$, PM_{10}, and TSP, which includes dust and larger particulates. Additionally, the monitors measure wind speed and direction, temperature, and humidity. We analyzed the measurements of the three different aerosol pollutants over an average day, week, month, and year over the course of 2019 to identify diurnal, weekly, and seasonal patterns of pollution to identify key sources. Using the package openair in R [52], we also produced bivariate plots of $PM_{2.5}$ and TSP of each pollutant with respect to wind speed and wind direction to identify the locations of key sources of pollution vis-a-vis each monitoring site.

There are five stationary air quality stations located in Oskemen operated by the state-run Kazhydromet service [45]. The stations are operated by the local governments and report minute-level PM_1, $PM_{2.5}$, and PM_{10}. Meteorological information, including temperature, air pressure, and relative humidity, is also reported at the stations. We analyzed the measurements of the three different aerosol pollutants over an average day, week, month, and year from April 2020 to July 2021. Notably, during this period the COVID-19 pandemic restrictions were in effect, leading to a nation-wide pause in commercial, industrial, and travel activities. As a result, there was a noticeable reduction in anthropogenic pollution, presenting a unique opportunity to capture one of the best air quality episodes in the region. Although the measurements between the two cities did not fall within the same time frame due to logistical reasons, we believe this analysis is valuable as it contrasts a normal scenario with a best-case scenario in coal cities; in both developed and developing countries.

3.2. Mobile LCSs

The LCS platform used in this study has been developed as part of MIT's City Scanner research initiative [53,54], which investigates the use of LCSs deployed on everyday urban vehicles (e.g., garbage trucks, taxies) as an opportunistic environmental monitoring platform. Because of the high costs associated with the deployment of regulatory-grade stationary air quality monitors, mobile and low-cost air quality sensors are growing as an important tool to increase the spatio-temporal granularity of air quality data at a fraction of the cost. For a review of different initiatives, see [16].

For this study, a new sensor prototype has been developed based on the original City Scanner design [55]. The prototype, named *Whiteburn* (Figure 1, top), was deployed on pickup trucks operated by the mine workers in Sparwood (Figure 1, center) and on passenger vehicles driven by students in Oskemen (Figure 1, bottom).

Figure 1. Whiteburn sensors (**top**) deployed in Sparwood, Canada (**center**) and Oskemen, Kazakhstan (**bottom**).

Each Whiteburn prototype captures:

- Particulate matter data (PM_1-$PM_{2.5}$-PM_{10}) at a rate of one sample every 2 s, using an Alphasense OPC-N3 optical particle counter [56]. The OPC-N3 costs USD ∼450, and works by using a 5 V, 175 mA, 658 nm laser to illuminate aerosol particles to measure the intensity of the light scattered. The sensor derives the number concentration of particles in different sized bins by calibrating the scattering coefficient with mono-dispersed, polystyrene (PSL) particles [57];
- Temperature and humidity data, recorded using am HST221 sensor [58];
- GPS coordinates of each measurement, captured using an SL876Q5 sensor [59].

The PM measurements produced by the OPC-N3 included in each prototype are error-prone because: (i) the particle composition in the locations of the deployments may be different from the composition of the aerosol used to calibrate the OPC-N3, (ii) the OPC-N3 cannot detect particles with diameters < 0.38 μm, and (iii) under conditions of relative humidity $> 80\%$, the particles adsorb moisture and appear larger to the OPC-N3, leading to errors [60]. Despite these errors, low-cost sensors are effective in detecting hotspots or high values of PM concentrations [12]. Even if such measurements are error-prone, if a high cut-off of $PM_{2.5}$ is chosen to identify potential hotspots, the true values are also likely to be high and a cause of concern.

A set of data cleaning and quality assurance processes have been developed, given the limitations of the low-cost sensors we use. The process builds on the United States Environmental Protection Agency's air sensor performance testing protocols [61,62]. In short, when the sensors operates with anomalies the records get flagged and eliminated. In addition, readings under high humidity (>90%) are eliminated, as low-cost optical particle counters are known to have skewed responses in this condition [12]. Lastly, records with readings out of the reasonable ranges (<1 μg/m^3 or >1000 μg/m^3 for $PM_{2.5}$) are deleted. In total, about 15% of raw data are excluded after data cleaning.

Each data sample acquired was tagged with a GPS location and timestamp, then streamed to a cloud database in real-time. The Whiteburn prototype poses little deployment requirements on the hosting vehicle and it is powered by a solar panel. It can be easily affixed and removed from the host vehicle using the provided magnets without modification or interference with the vehicle's routine operation. The production cost of each Whiteburn device is USD 2000, which is considered a low-cost instrument according to the EPA's guidance [63].

In Sparwood, two Whiteburn prototypes were deployed on pickup trucks driven by mine workers between November 2019 and March 2020, collecting roughly 60,000 data points. In Oskemen, one Whiteburn prototype on the private car of one student was deployed in October 2021, collecting circa 300 data points.

We detected hotspots using a technique proposed in [12]. Hierarchical clustering with a cut-off distance of 100 m between measurements is used as a measure of dissimilarity to cluster high $PM_{2.5}$ measurements (>100 μg/m^3) made in the same spatial area. We calculated the number of samples in each cluster (n), as well as the number of unique days (n_date) over which the measurements in each cluster were made.

3.3. Community Engagement Workshops

Qualitative information gathered through citizen engagement processes can complement quantitative data collected by both reference and low-cost sensing approaches, potentially enhancing the robustness of proposed solutions [64]. Including non-experts in scientific research can leverage well-established methodologies such as citizen science [22,65,66] and participatory research [67,68]. These methods foster collaboration between researchers, community members, and stakeholders to collectively examine, understand, and address various situations, leading to positive changes. In coal cities where air pollution is visibly present, such as dust and poor air quality, gathering qualitative insights from community members' experiences can inform researchers about high-priority research areas, health patterns, and quality of life concerns related to pollution, as well as highlight gaps in potential solutions.

In our work, we incorporated community engagement into two actions: a collaborative mapping activity with community members in Sparwood, and a mapping activity and coding workshop with college students in Oskemen.

3.3.1. Mapping Activity in Sparwood

In March 2020, the authors of the study conducted a workshop with Sparwood residents to obtain qualitative feedback on mining-related dust pollution. The workshop aimed to use data as means to foster reflection on air quality issues and leverage the local knowledge of residents to identify pollution sources.

The event was a collaborative effort with a mining company, which enlisted nine volunteers (five men and four women) with previous experience in similar initiatives. Although participants were not required to disclose their occupation or other demographic information, some participants mentioned being healthcare employees. The workshop proceeded in three phases. First, participants were asked to mark potential pollution source locations on a map of Sparwood, drawing from their empirical experiences as residents (Figure 2, left). This map served as a basis for discussing air quality perceptions, the impact of dust on daily activities, and coping strategies developed by citizens and by the mining company. Next, a sheet with GPS-located PM_{10} values collected by the Whiteburn prototypes was overlaid on the map (Figure 2, right). Participants were encouraged to compare these data with their empirically identified pollution sources, noting any correlations with high PM_{10} levels in the data map.

The workshop was audio-recorded and consent for the use of the data for research purposes was given by all participants. The conversations among participants and between participants and facilitators were transcribed and analyzed using thematic analysis methods [69]. Results are reported in Section 4.

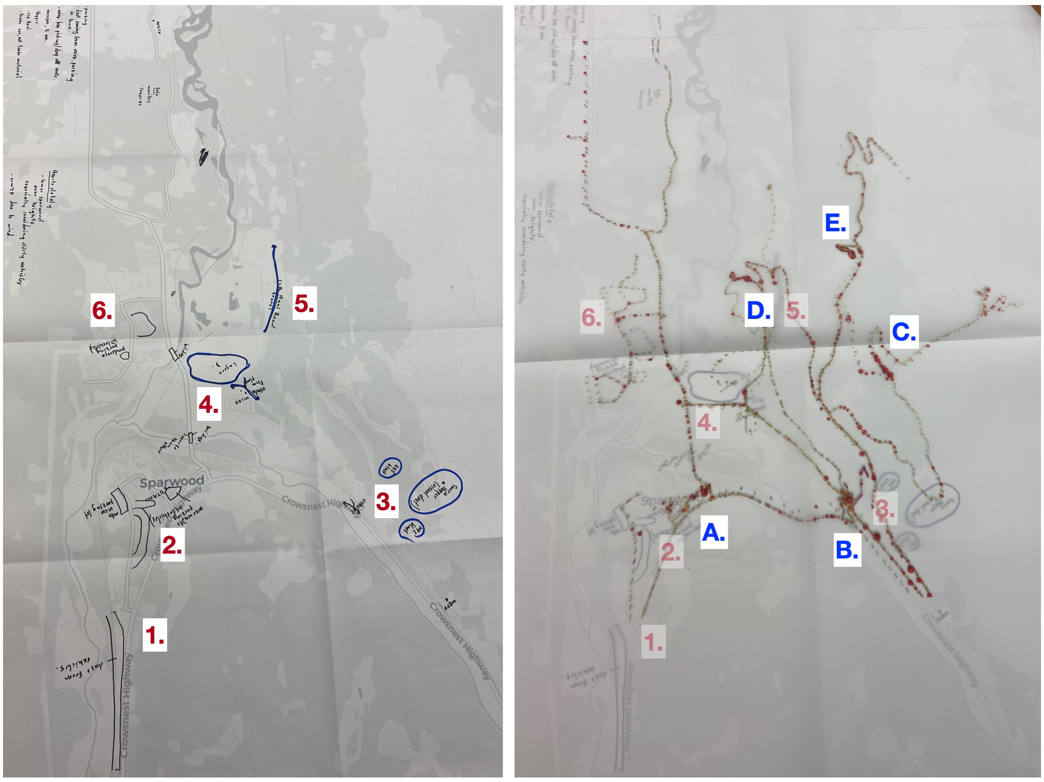

Figure 2. A map annotated by residents with the location of six pollution sources (**left**) and showing five hotspots identified using PM_{10} data collected by the mobile sensors (**right**).

3.3.2. Mapping and Coding Activity in Oskemen

In Oskemen, qualitative feedback was gathered from college students at the Eastern Kazakhstan Technical University (EKTU), during a workshop held in December 2021. The workshop included a lecture and hands-on mapping and programming activities, combining in-person coaching with online tools and resources.

The workshop aimed to achieve two main goals: (i) to familiarize students with environmental data analysis techniques, and (ii) to encourage the generation of use cases through qualitative feedback and local knowledge. Participants were required to have basic skills in either programming or environmental science to attend. Nine students from a computer science master's degree program, two women and seven men, participated in the workshop. The coding segment of the workshop was conducted in Python, a language taught in their study curriculum.

The lecture introduced air quality fundamentals, such as an overview of common pollutants, the air quality index (AQI), as well as common environmental monitoring methods, including stationary reference-grade monitoring and remote sensing techniques. It also provided context and background regarding the Whiteburn prototypes reported in Section 3.2, introducing the concepts of mobile air quality monitoring and opportunistic monitoring.

Next, the workshop included a mapping activity using "Google My Maps", an online tool that facilitates collaborative map annotation accessible via a public link. Initially, students were asked to add placemarks to locations of personal significance, such as places they visit frequently, their homes, workplaces, or the university campus. Then, they rated the air quality near these locations based on the Air Quality Index (AQI) standard [70], and adjusted the placemark color to match the AQI's "level of concern". Additionally, students created labels for the placemarks and added up to five descriptive tags for each location. While they had the freedom to choose the tags, example suggestions were provided to facilitate the process. The collaborative map created by the students is shown in Figure 3. Utilizing a digital map instead of a physical one, as done in the Sparwood workshop, aimed to establish a long-term collaboration with the students, allowing them to continue adding information to the map even after the in-person workshop. Throughout the activity, students were encouraged to discuss ideas, perceptions, and their progress collaboratively.

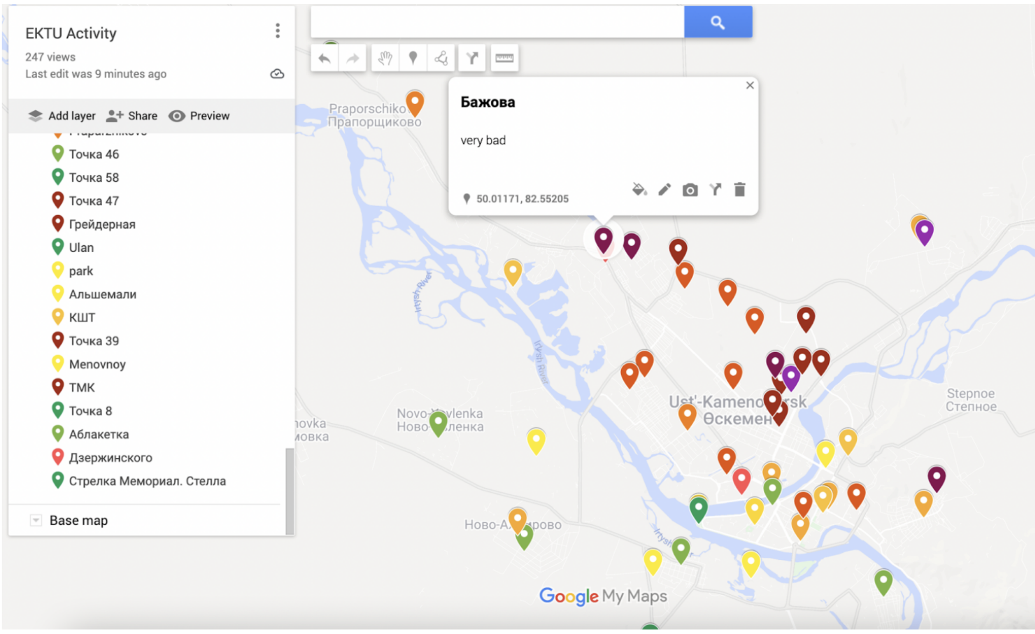

Figure 3. Google MyMaps Activity, with placemarks' colors according to the AQI standard.

Following the mapping activity, the students engaged in a Python coding session designed to provide them with fundamental environmental analysis tools. This activity was conducted using the Jupyter web-based computing platform [71]. The coding exercise utilized data gathered in Oskemen through the Whiteburn prototypes and one static sensor, along with data obtained from reference monitors.

The facilitators led the students through the steps of writing Python code to plot time series and generate maps for different parameters, such as temperature, humidity, and $PM_{2.5}$, by combining and modifying code snippets. In the final part of the workshop, the students were guided in plotting mobile data on an interactive map using the Python library folium [72]. This task was divided into two parts.

First, the focus was on data collected from a single location on the EKTU campus. The purpose was to introduce the students to mapping skills in Folium. They were given code snippets to set up a base map, determine the zoom level, and create code that plotted all the relevant data at the correct latitude and longitude coordinates. Afterward, they could save a web-page version of the map on their local computers to interact with it. In the second part, the students faced a coding challenge involving a larger dataset from mobile environmental monitoring. They had to modify the provided code to read and map this different environmental dataset, resulting in another interactive map.

The lecture, coding activity, and facilitator guide developed for this workshop have been made publicly available under an open-source license [73].

4. Results

4.1. Static Reference Monitor Analysis

The time series for $PM_{2.5}$, PM_{10}, and TSP for the year 2019 from the stationary monitor in downtown Sparwood are shown in Figure 4. We observed gaps in the time series of PM data, possibly resulting from power outages and other events. The stationary monitors indicate a typical peak in aerosol pollution around 9:00, and a smaller peak in the evening, likely attributed to traffic pollution. On weekends, these peaks are smaller. However, during the week, we observe additional peaks in PM, which can be attributed to various mining activities in the area. Furthermore, aerosol pollution appears to be higher in February compared to other months at all sites. This seasonal variation suggests that meteorology plays a crucial role in regulating pollutant concentrations in Sparwood.

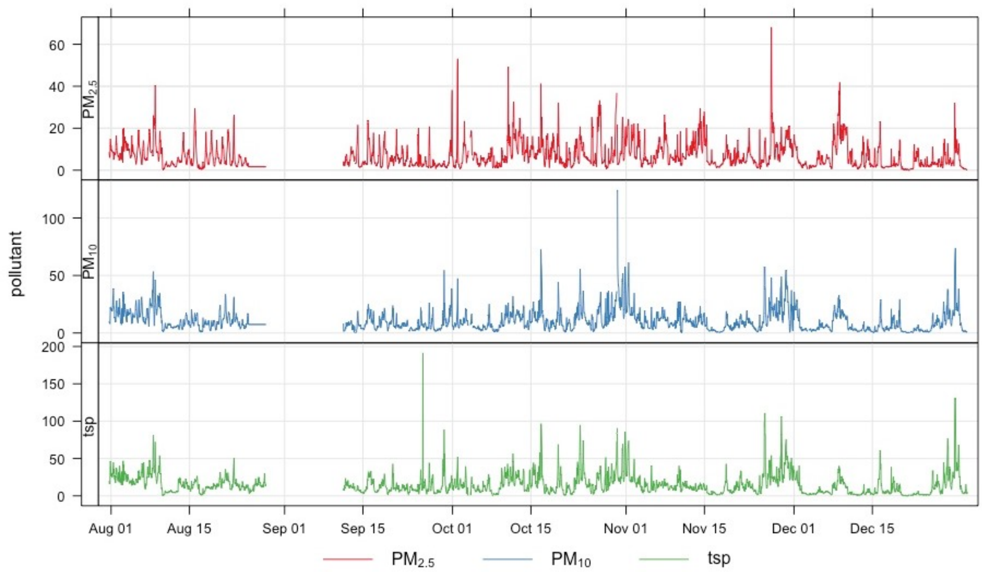

Figure 4. Hourly PM levels in downtown Sparwood.

Figure 5 displays pollution wind roses, in which PM levels are indicated by colors ranging from blue (low) to red (high) on wind roses displaying wind speed and direction. We positioned these wind roses on a map of the region, highlighting the location of each corresponding monitoring station in relation to the mine (shown in gray). To provide an idea of the area's scale, we overlaid the boundaries of the Canadian census dissemination areas encompassing Sparwood, identified by a nine-digit numerical code. For instance, at the Michel Creek Road Residence and Downtown Air monitoring site, high levels of both pollutants are detected at relatively high wind speeds from the northwest direction. Similarly, Sparwood Heights and the Whispering Woods Trailer show high PM concentrations when the wind arrives from the southeast. Overall, these plots reveal that all sites experience elevated pollutant concentrations when the wind blows from the mining site (displayed on the map in gray).

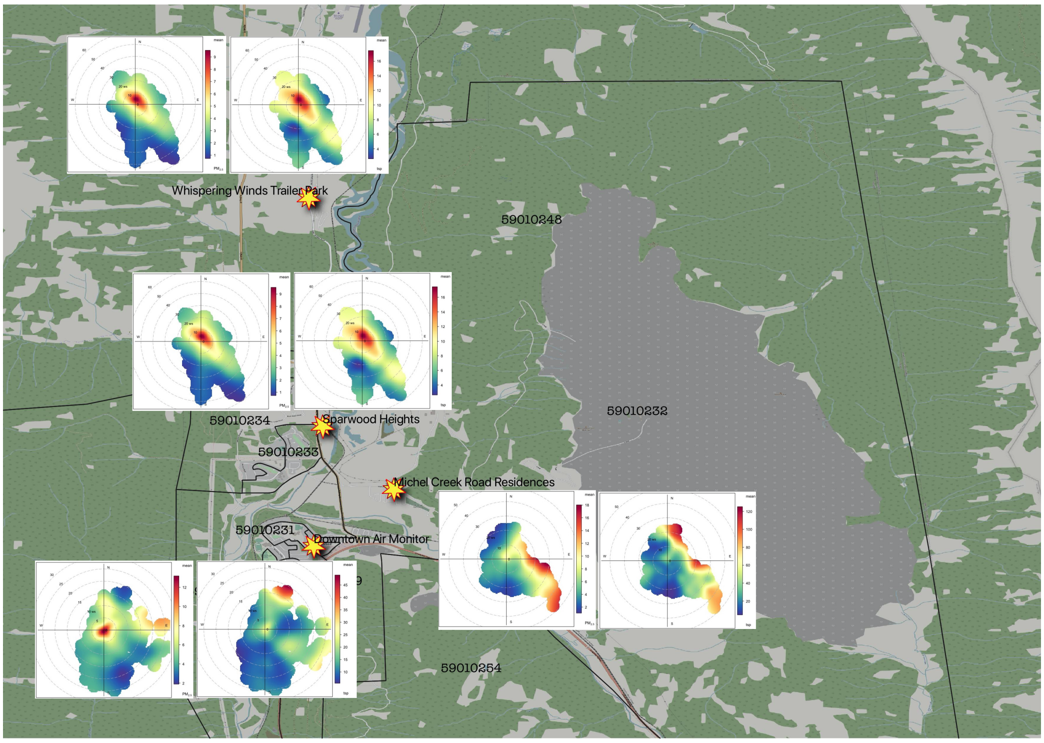

Figure 5. Map displaying pollution wind roses of $PM_{2.5}$ and TSP versus wind speed and wind direction from each stationary monitor for the year 2019. The underlying dissemination area boundaries are also displayed.

Differences in the patterns of the wind roses in Figure 5 for $PM_{2.5}$ in comparison to TSP are also discernible. For example, for the downtown air monitor, we see the bulk of $PM_{2.5}$ pollution comes from the nearby surroundings at low wind speeds, likely due to traffic pollution close by. However, the bulk of TSP appears to impact the monitor when wind speeds are high and the wind is coming from the northeast, i.e., from the mine.

Hourly averages for the downtown air monitor are the following:

- Hourly average $PM_{2.5}$: 6.9 $\mu g/m^3$ (min: 0.1, max: 68.2);
- Hourly average PM_{10}: 10.5 $\mu g/m^3$ (min: 0.1, max: 124.3);
- Hourly average TSP: 15.2 $\mu g/m^3$ (min: 0.1, max: 191.4).

In Oskemen, the station with the highest average concentrations for all pollutants is at the College of Transportation and Life Safety in the city center. The annual average PM_1, $PM_{2.5}$, and PM_{10} concentrations are 40.6, 70.9, and 94.9 $\mu g/m^3$, respectively. $PM_{2.5}$ and PM_{10} levels are 14 and 6 times higher than WHO guideline values, respectively, and on average 10 and 8 times higher than Sparwood average values, respectively. Strong spatial variation of PM concentrations is observed as readings across stations can vary by a factor of 5 to 10. Extremely high maximums are observed at all stations, with PM_1, $PM_{2.5}$, and PM_{10} hitting over 200, 500, and 1000 $\mu g/m^3$, respectively, very often. Higher PM concentration levels are found in the winter, which reaches levels ten times higher than summer readings in some cases, likely due to biomass and coal burning to meet domestic heating needs. There is an evident diurnal trend in PM levels for all stations, where PM levels reach the daily low in the afternoon around 14:00 to 15:00 and observe daily high at night around 21:00 to 22:00.

Hourly averages for the city center air monitor are the following, the time series are displayed in Figure 6:

- Hourly average PM_1: 40.6 µg/m^3 (min: 0.1, max: 315.2)
- Hourly average $PM_{2.5}$: 70.9 µg/m^3 (min: 1.5, max: 1086.4)
- Hourly average PM_{10}: 94.9 µg/m^3 (min: 1.6, max: 1800.2)

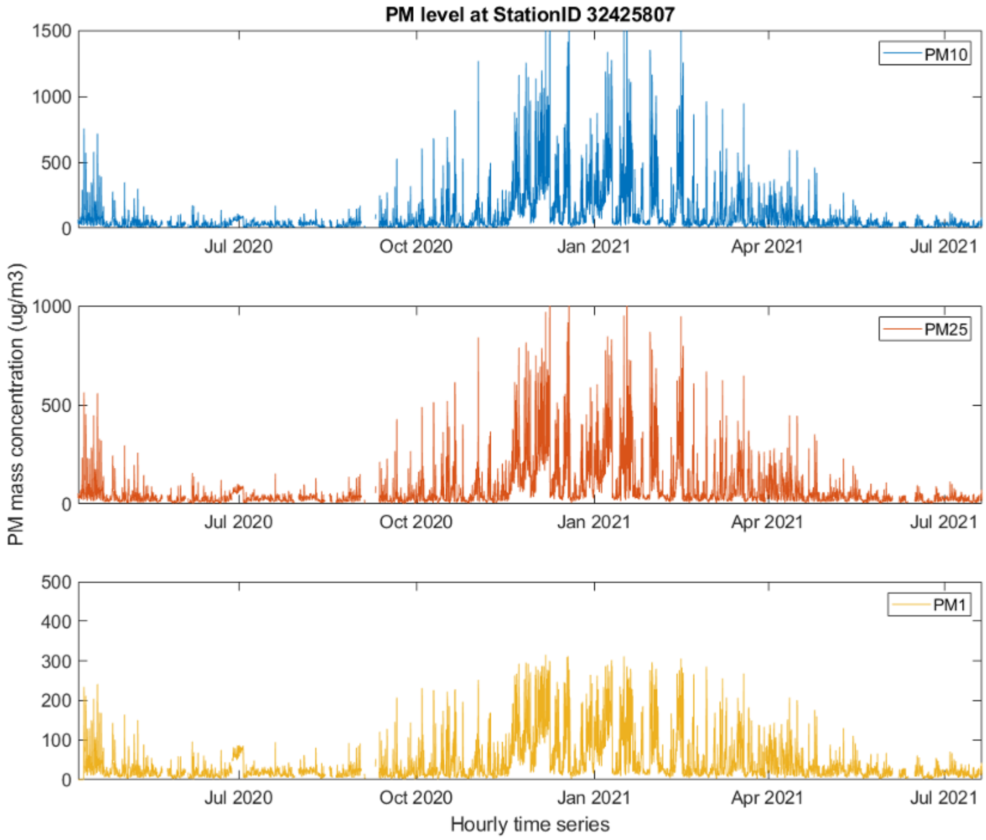

Figure 6. Hourly PM levels at Oskemen city center station.

4.2. Pollution Hotspots Analysis

Hotspots of $PM_{2.5}$ derived from data collected by Whiteburn prototypes are displayed in Figure 7. The size of the clusters is proportional to the number of days over which $PM_{2.5}$ measurements greater than 100 µg/m^3 were observed. The color of the clusters varies by the number of $PM_{2.5}$ measurements greater than 100 µg/m^3 observed in the same location. For example, hotspot cluster #1 (Figure 7, top) represents a cluster of 62 measurements of $PM_{2.5}$ concentrations greater than 100 µg/m^3 made over 5 days in the same 100 m radius during the period of mobile monitoring. The detection of high $PM_{2.5}$ values in the same area over multiple days indicates that such a hotspot is likely not due to noise in the instrument but is caused by a local source, which warrants further investigation.

In Sparwood, hotspot #1 in Figure 7 (top) corresponds to measurements made in a parking lot near Sparwood's train station. A large stockpile of coal is located close to the parking lot next to the station, which is one likely source contributing to this hotspot. The loading and unloading of coal on the train is another potential contributing source. Hotspot #2 is close to the blasting site in the mine. Hotspot #3 is located close to a lagoon where coal being processed is stored.

Figure 7 (bottom) shows the mobile monitoring route in Oskemen. The size and color of clusters denote the concentrations of the hotspots, ranging from less than 20 to over 200 µg/m^3. The average and median $PM_{2.5}$ concentrations were 129.4 and 107.4 µg/m^3, respectively, during the monitoring period. The extreme value hit 672.4 $\mu g/m^3$. The biggest hotspot (hotspot #1) occurred at a major intersection next to the train yard and the heavy industrial district. The lowest $PM_{2.5}$ concentrations were observed towards the south of the city and close to green spaces.

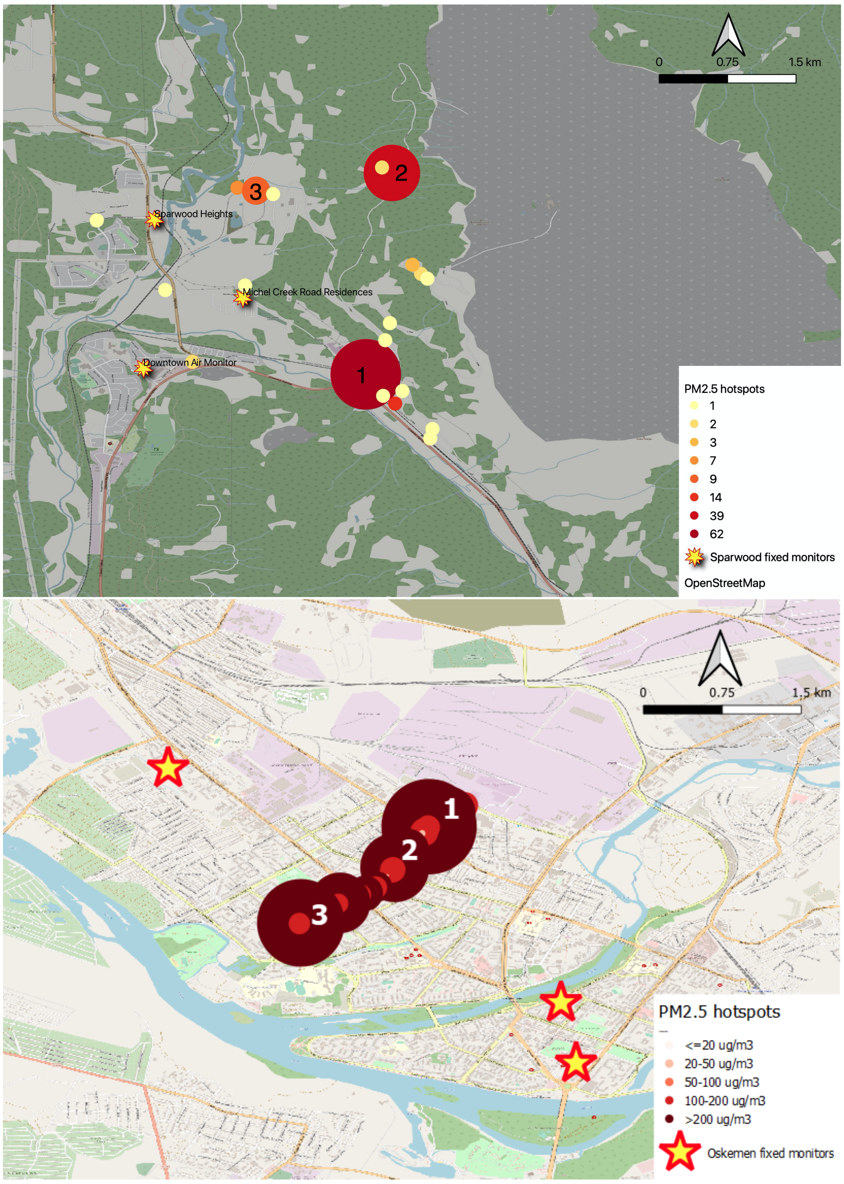

Figure 7. $PM_{2.5}$ hotspots detected using mobile monitoring in Sparwood between December 2019 and March 2020 (**top**) and in Oskemen in December 2021 (**bottom**).

The Oskemen mobile deployment was halted just a few weeks after the start due to political unrest in the country during early 2022. In March 2022, the deployment was cancelled as a consequence of the Russian invasion of Ukraine and the resulting international sanctions that affected Russia and Kazakhstan incidentally, as a member of the Eurasian Economic Union.

4.3. Observations from Community Engagement Workshops

During the workshop in Sparwood, participants collectively identified six pollution sources (Figure 2, left). They highlighted that the main source of pollution was dust carried by heavy-duty vehicles traveling between the mining site and the town, rather than the mining activities themselves. Residents mentioned observing dust coming off vehicles on major roads (sources #1 and #5), during commutes to and from the mine processing plant (#4), while idling in parking lots (#6), and near temporary workers' lodgings (#2). Only two sources were directly linked to mine activities: dust from the mine blast site at location #3 and dust from the coal stockpile site carried by strong winds at location #4. After annotating the map, participants collaboratively discussed and commented on the identified sources. One participant pointed out that the current mitigation practice of washing workers' vehicles when they leave the mine is ineffective, as it can only be performed when the ambient temperature is above minus seven Celsius. This limitation means that vehicles cannot be washed for several days a year, as Sparwood experiences freezing temperatures from October to April. Another participant suggested that the train transporting refined coal out of the processing plant and heading westbound could be a pollution source due to potential leakage.

Two participants engaged the environmental scientist present during the workshop with questions regarding dust composition. They asked whether it is possible to identify pollution sources by analyzing the chemical composition of the dust found in different parts of the town, as compared to chemical signatures of known pollutant byproducts of the mining activity.

Following this discussion, a map with the data from the mobile air quality sensors (described in Section 3.2) was overlaid to the locations pinpointed by the workshop participants (Figure 2, right). Each point on the map represents one PM_{10} reading collected by either of the two Whiteburn prototypes, and the size of the dots corresponds to the PM_{10} value, with larger dots indicating higher concentrations (hotspots). The participants observed that three hotspots coincide with the pollution source locations identified by Sparwood residents, while one pollution source (#1) fell outside the area of data collection. Interestingly, two sources indicated by residents (#4 and #6) did not show high levels of PM_{10}. Conversely, two hotspots (C and E) are in locations that were not identified as possible pollution sources by the participants.

This result was aligned with participants' expectations, as the data plotted on the map was the outcome of a short-term data collection experiment. The participants acknowledged that the PM_{10} map was likely changing as the data collection extends throughout the summer; a season known in Sparwood for a higher intensity of dust events.

Finally, the researchers encouraged the audience to propose new applications for air pollution data. Some participants suggested conducting a comparative study, benchmarking air quality in Sparwood against towns with similar geography and socio-economic characteristics, but without a mine. The aim was to quantify the impact of mining operations as a distinguishing factor in the air quality of the two towns. Additionally, two participants asked the researchers to investigate potential correlations between PM_{10} data and the prevalence of pulmonary diseases.

5. Discussion

Stationary reference monitors provided a baseline for PM concentrations with continuous measurements at the same location. Seasonal variation in PM levels suggests that meteorology plays a significant role in regulating pollutant concentrations. In Sparwood, the static monitors located away from the minefield showed that $PM_{2.5}$ and TSP levels are highest when the wind speed is low, indicating that instantaneous air pollution from mining emissions may not reach these locations. On the other hand, static monitors near the minefield recorded the highest particulate matter pollution when strong winds blew from the minefield's direction, indicating direct air quality impacts from mining activities. The impacts of mine blasts on PM at the four reference monitoring sites have also been considered. The results showed that blasting led to high levels of $PM_{2.5}$ at three sites and TSP at two sites, while PM_{10} levels remained unaffected. Blasting usually expels large crustal matter (TSP) into the atmosphere, which could explain the observed increase in $PM_{2.5}$, possibly due to increased vehicular traffic resulting from the blasting schedule.

To gain a more detailed understanding, further information on the schedule of various mining processes is necessary.

Stationary reference monitors did not capture the spatial variation in local air quality effectively. Currently, satellite datasets can provide estimates of pollution at a 1 km resolution on clear days. Most satellite products also provide a snapshot of air quality, usually once or twice a day. LCSs can provide granular spatial and temporal insights into pollution. As our study areas were fairly limited, ground-based LCSs have been deemed appropriate instruments of choice for this experiment. Indeed, the data from the LCSs (Section 3.2) provided valuable insights. In Sparwood, they confirmed that areas near the mining field had higher particulate matter pollution concentrations (39 and 62 $\mu g/m^3$, respectively), while pollution levels close to the town center were relatively low (less than 15 $\mu g/m^3$). The LCS data revealed several hotspots of pollution in Sparwood, including areas near a blasting zone, a coal stockpile near the train station, and a zone near a lagoon on the mining site. In Oskemen, the biggest PM hotspot was located at the edge of a large industrial complex for metallurgy, and smaller hotspots were present at major road intersections with heavy traffic.

The locations of the identified hotspots in Sparwood and Oskemen are aligned with areas that residents from the community engagement workshops had also pointed out as problematic regarding air pollution. However, it is worth noting that the hotspots identified were limited to the sampling routes used by the vehicles carrying the monitors. During the workshop, residents identified additional potential hotspots that were not covered by the current mobile monitoring deployment. For instance, in Sparwood, they pointed out likely hotspots scattered around residential neighborhoods, attributing them to dirty vehicles commuting to and from the mine. This qualitative data complemented the insights from the measurements and allows for planning better monitoring routes for the mobile LCS campaigns, e.g., by deploying Whiteburn prototypes on vehicles of residents near the hotspots identified during the workshop.

However, residents' perceptions of air quality issues may be limited by what they can see. For example, residents mentioning dirty vehicles as the primary pollution source could be biased by the high visibility and frequency of such events. On the other hand, a train transporting heavy coal loads might leak a significantly higher quantity of minerals than workers' trucks, but its effect may be less noticeable because it runs only once a day and away from major roadways. In addition, residents might have focused on complaints about dirty vehicles because the solution is straightforward: washing the vehicles. Other pollution sources such as mine blasts may be more challenging to mitigate but could have a more positive environmental impact in the long run. Indeed, the purposes of citizen engagement activities and the LCSs presented in this paper are to provide community members with the knowledge and tools to expand their understanding of environmental issues beyond their human senses. By doing so, they can analyze and combine data with their local knowledge, allowing for a more comprehensive and informed approach to addressing air quality concerns.

During the workshops, community members showed significant interest in learning more about air quality and environmental science. They were eager to understand how data could support their efforts to improve air quality in Sparwood and expressed a willingness to take action to reduce air pollution. A few participants even inquired about the possibility of having a sensor deployed on their own properties. Additionally, they requested regular consultations and exercises similar to those conducted in this paper to stay involved. In Oskemen, the students were highly engaged during the workshop and completed the assigned tasks as expected. Some students even went beyond the allotted time, continuing to work on the Python code [73], adding more functionalities, and fixing any small bugs they encountered in the code. This attitude was found in participants of all ages across the two coal-centric cities, representing a profound sense of community, but also deep concerns about the impact of air pollution on public health.

These findings demonstrate the power of integrating various data sources and analysis methods to generate meaningful insights on air quality. The validation of quantitative insight from static monitors and LCSs with personal, local experiences and knowledge was empowering for the communities involved.

Limitations

However, our study was affected by a number of limitations that must be addressed in future research:

- The mobile monitoring measurements were conducted during specific timeframes: November 2019 to March 2020 in Sparwood and December 2021 in Oskemen. However, the experiment had to be suspended in late March 2020 due to COVID-19 lockdown restrictions. While the data collected during these periods provided valuable insights, it is essential to acknowledge that PM concentration levels tend to be lower in winter compared to the warmer and drier summer months. Consequently, the dataset may not fully represent the air quality in Sparwood during other seasons. Additionally, data collection efforts in Oskemen were impacted by regional unrest, leading to complications and interruptions. As a result, the dataset in Oskemen is smaller than initially planned, and there was limited opportunity for international knowledge exchange.
- The low-cost sensors we utilized were not locally calibrated. These sensors operate based on light scattering to detect particles, but they may underestimate PM concentrations when coal dust dominates, as coal particles do not scatter much light. To address this limitation in future experiments, we can incorporate black carbon aethalometers, which can estimate the percentage of coal dust in the aerosol mix of coal-centric cities. Although current aethalometer models are relatively expensive, the ongoing development of low-cost aethalometer technology offers promising opportunities for enhanced sensing when combined with our mobile monitoring approach. For this study, we assumed that a significant portion of the dust in Sparwood and Oskemen originated from other crustal sources, which is likely the case. We also believe that our OPCs were capable of detecting most hotspots in the area, allowing us to draw meaningful conclusions about air quality in these regions. It might be possible that an extreme value of pollution is due to noise in the low-cost sensor. Therefore, in applying hotspot detection methodology, we specifically look for persistent extreme values in pollution in the same location over time. In this manner, we were able to identify persistent hotspots of pollution in the study area.
- Due to limited information about various mining processes in Sparwood, we focused solely on investigating the impact of blasting on PM levels at the reference monitoring sites.
- The community engagement workshops in both Sparwood and Oskemen were limited to a single day and had a small number of participants. It is essential to have more extensive and representative engagement with the community to capture diverse perceptions of air pollution in these towns.

6. Conclusions

This study aimed to explore diverse data collection methods, community engagement activities, and crucial environmental factors in coal-dependent cities. Our analysis revealed that the different data collection and analysis approaches complemented each other, enhancing the understanding of particulate matter pollution in Sparwood and Oskemen.

This hybrid approach proved especially valuable in data-scarce environments, where purely quantitative results might not yield robust conclusions. Additionally, the presented approach has been successful in fostering community engagement, raising environmental awareness, and providing a unique platform for dialogue on environmental issues among different stakeholders.

Future work aims at conducting more mobile sensing experiments and increasing the LCS reliability by developing a calibration procedure that accounts for the high black carbon levels commonly present in aerosols in coal-dependent cities, extending the calibration protocol for the LCS Whiteburn prototype developed in [74]. The Whiteburn prototypes will be improved to perform calibration and hotspot analysis algorithms directly onto the device, leveraging machine learning approaches. New methods to collect qualitative feedback about pollution sources using digital tools and data-driven community engagement activities will also be explored. In this respect, all the materials from the citizen engagement workshops have been made publicly available on GitHub [73]. We hope that research groups worldwide will build on this work to develop new citizen engagement and educational activities, making a positive impact in the often data-scarce coal-centric cities.

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Abbreviations

The following abbreviations are used in this manuscript:

AQ	Air Quality
EPA	Environmental Protection Agency
LCS	Low-Cost Sensor
PM	Particulate Matter
TSP	Total Suspended Particulate
AQI	Air Quality Index

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