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Research article

A GIS-based approach to determining optimal location for decentralized inner city smart filters: Toward net zero cities

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ABSTRACT

Climate change has already begun to take visible effect globally in recent years. Given the climate change paradox and urbanization trends, cities' success would not only depend on smartness and sustainability, but also resilience to all forthcoming economic, environmental, or behavioral changes. Numerous technologies have surfaced and proved effective in CO_2 removal from the local environment. However, the optimal placement of these smart filters is a complex task and require logical and strategic decision-making. Determining the optimal location is one of the key factors for establishing a network of smart air filters. This study used a GIS-based suitability analysis for identifying optimal locations for smart filters based on pollution hotspots (population and spatial proximity to industry, commercial centers, roads, high-traffic areas, and intersections). The spatial analysis involves the determination and preparation of input layers, ranking layers, assigning weights to each criterion, and generation of a suitability map. The sites with a higher suitability score (7 or above) are optimum sites for air filters. The sites are spatially distributed over different regions. The findings revealed that GIS-based suitability analysis can be an effective technique for placing smart filters within an urban environment. These findings can help decision-makers to prioritize the location considering environmental constraints. The proposed solution aims to pave the way for fostering resilient, smart, and sustainable cities through a community sensing platform targeting hotspots within spatial variations.

1. Background

Urban air quality is gradually deteriorating and becoming toxic [1–3]. Urbanization and growing economic activities are widely perceived to cause these environmental problems [4–6]. This poses a significant concern for industry and transport sector to reduce their emissions and pollutants, as cities are expected to house two-thirds of the world's inhabitants [7,8]. This atmospheric pollution is also recognized as the major contributor to illnesses and death (i.e., 12 % of deaths globally) [9–11]. Air pollution is recognized as a serious threat to cities. According to Chen et al. [12], air pollution affects hundred thousand lives every year and leads to over 200 billion RMB in health expenditures. Cities experience a significant portion of the exposure that causes such health effects because of the increased concentration of people living there and the air pollution they produce. The air pollution trends have indicated that cities in the Middle East, South Asia, and Sub-Saharan Africa have observed an increase in air pollution. Whereas, 71 % of cities around the world witnessed increased concentrations of NO_2 [13]. In China, 81.1 % of urban centers exhibit concentrations of $PM_{2.5}$ more than 35

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μg/m^3 which is higher than the national average [14]. Moreover, air pollution also contributes to contemporary issues like global warming, urban heat islands, acid rain, and smog [15]. Thus, air pollution is a complex issue influencing humans on both local and global scales. Strategies to mitigate air pollution continue to be a global concern for researchers and policymakers [16,17].

There have been significant advancements in response to environmental concerns. Zero-carbon cities are one of the actions being taken to ensure zero-carbon emissions through smart technologies and system design [18]. The assessment of pollutant prevalence at a specific location can benefit exposure assessment and identification of populations at risk particularly vulnerable groups [19,20]. The deployment of Information and Communication Technologies (ICT), Internet of Things (IoT), and low-cost sensors to collect pollutant concentrations within urban areas is also one of the main pillars of smart and sustainable cities, that foster policy decisions accordingly [21–24]. The real-time monitoring and forecasting of air quality is an essential and challenging endeavor to make informed decisions [25,26]. Most studies focus on the deployment and application of air quality sensors and IoT for monitoring air quality in cities [27–30]. Besides, air quality sensors, new technologies have also surfaced and proved effective in removing gaseous pollutants from the local environment [31–33]. Although nature-based solutions like urban vegetation and green spaces are encouraged for improving air quality, urban environment restoration remains cumbersome owing to high land prices and space limitations [34,35]. Thus, it is critical to find alternative strategies to improve air quality. These smart solutions can be a way forward to remove hazardous pollutants from the air in congested urban centers.

Recent studies have identified the effectiveness of these technologies in capturing pollutants [36–39]. The air purifier installed in Xian, China has been estimated to purify the air in 10 sq. Km. of the study area [35]. The CityTree in Modena, Italy help a significant decline in particular matter concentration (i.e., 19–23 % for PM_{10}) [36]. Likewise, a pilot study in Hong Kong shows the effectiveness of roadside air filters in improving air quality [40]. Street lamps (air purifiers) developed by Huang et al. [41], can actively remove air pollutants from the street canyon. China is taking a leading role by demonstrating approximately 40 CCUS (Carbon Capture, Utilisation, and Storage) projects that can capture up to 3 million tonnes of CO_2 per year [42]. While there are enormous advantages to removing gaseous pollutants, the main concern is what the optimum location is to place air filters in an urban area [43,44]. The optimal placement of these sensors and smart filters is a complex task and requires logical and strategic decision-making. The main purpose of this study is to suggest a design framework for locating air filters in an urban environment considering pollution hotspots.

The Kingdom of Saudi Arabia (KSA), being one of the largest oil-producing nations in the world, has been seen as one of the major contributors to CO_2 emissions worldwide [45,46]. In contrast with the G20 range of 0.05–1.64, the Kingdom's death-attributable rate is 1.12 for every 1000 people per year [47]. After KSA's promising Vision 2030 in 2016, the Saudi Green Initiative (SGI) was inaugurated with the aim of achieving net zero carbon by 2060 [48].

To address the net zero objective and improve the overall air quality of urban areas in the Kingdom of Saudi Arabia, it is imperative to utilize the latest smart carbon capture technologies. This study aims to establish air filtering infrastructure to capture air pollutants. Moreover, the study aims to formulate a smart and sustainable concept utilizing a city-scale carbon and pollution filter framework. Consequently, the study intends to make the following contributions:

1. Identifying the main factors of emissions and pollutants hotspots in the city.
2. Laying out the common inner-city pollution and emission epicenters for locating the proposed tool in the urban context.
3. Outlining a systematic framework for optimal allocation of smart filters in an urban environment.

The focus uncovers the environmental impairments of a city's existing urban fabric (epicenters) to propose technological interventions for tackling air pollution and emissions. This is the first study in the context of Saudi Arabia that investigates the optimal location of air filters for improving air quality in urban areas. It could be of interest to local development authorities, urban managers, and policymakers. The paper exemplifies the baseline framework and governance guidelines that policymakers may adopt for mitigating air pollution. While nations advocate for achieving net zero and other long-term climate targets, cities have a vital role in this transition. The study will serve as a guide for determining the optimal location of air monitoring and smart filter stations.

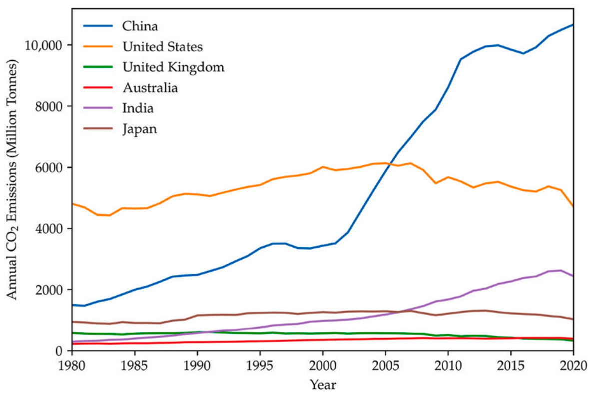

Fig. 1. CO2 emission between 1980 and 2020 [39].

2. Global commitment for climate resilience

According to the World Urbanization Prospects, 75 % of the global population is expected to migrate to cities by 2050 [49]. Cities will observe an increase in construction, urban sprawl, and the use of fossil-fuel automobiles for transportation to accommodate for the anticipated growth. Subsequently leading to rapid urban sprawl, air pollution, and added strain on the natural environment. The phenomenon of greenhouse gas (GHG) is also the result of urban spatial patterns. CO_2 constitutes the major share of GHGs, representing almost 72 % [48] which is mainly caused by human activities including transportation, heat, and burning of fossil fuels [50]. Fig. 1 shows the CO_2 emission from 1980 to 2020. It can be observed that there has been an increasing trend in CO_2 emission, especially in China and India. There are also health implications associated with increasing pollution and emissions in urbanized areas. At present, it is believed that around 99 % of world inhabitants have been exposed to substantial air pollution that exceeds WHO guideline limits [51]. The pollutants that are proven to be of concern to public health include particulate matter (PM2.5 and PM10), ozone (O_3), nitrogen dioxide (NO_2) sulfur dioxide (SO_2), and carbon monoxide (CO) [22,52–56]. According to Pidgeon [57], these pollutants are also responsible for poor health and air quality within inner cities.

In response to inevitable climate change and its impacts on humans, countries are making efforts to reduce their carbon footprint and move toward net-zero goals. For instance, Oslo, Norway was able to reduce its emissions by 16 % [58,59]. Globally, over 200 nations are actively engaged in addressing this issue and have established targets to achieve carbon neutrality [60]. During the recent COP28 conference, nations reached an agreement aimed at transitioning to decarbonized economies and societies. Net-zero carbon is defined as the balance of the amount of CO_2 *emitted* into the air by human activities with the amount of CO_2 *removed* from the atmosphere [61].

However, collecting and analyzing environmental big data is key to locating sources of pollution and making appropriate decisions accordingly. This is achieved through the deployment of sensors and Internet of Things (IoT) tools across the urban fabric [21]. Air quality is one of the common environmental parameters monitored by governments to ensure that city pollutants are within recommended limits. Air monitoring systems identify air pollution types and concentrations from toxic pollutants to particulate matter [62]. An urban monitoring management framework facilitates decision-making [21,63]. By deploying a network of sensor nodes, municipalities can monitor air quality and emissions across the built environment to make better urban management decisions. Thus, providing the opportunities of sensing beyond conventional problem-solving approaches. It should be developed to account for and mapping of the geographical distribution of pollution for a given city. While IoT sensors can be dispersed around a city to collect information around the clock, it is fundamentally important to know what exactly this data implies. This constitutes a foundational aspect of smart cities, playing a key role in pollution control and advancing public safety measures. Moreover, environmental monitoring could help to identify the pollution hotspots within an urban center.

However, the identification of pollution hotspots should be followed by mitigation measures. Over the recent years, novel technologies have surfaced for removing these pollutants from point sources or the ambient atmosphere [64,65]. Both direct air capture (DAC) and Carbon Capture (CC) can be utilized for this purpose. CCUS (Carbon Capture, Utilisation and Storage), plant facilities also enable air purification by absorbing CO2 from the air with a capture capacity of 500,000 metric tons and 800,000 metric tons/year respectively [66]. Harvey Bryan and Fahad Ben Salamah's [67] research suggests a prototype to integrate carbon capture within the building envelope. In 2018, Green City Solutions, a German company, developed an artificial tree as a resolution to pollution in urban centers (i.e., deployed in 25 cities) [68]. However, there remains a question of where to place these air filters in a given urban landscape [44]. The choice of optimal quantities and location of smart filtering tools requires a substantial understanding of pollution sources and factors (urban activities) contributing to the variability of ambient concentrations.

Thus, the aim of the research is to outline a framework for deploying data-driven decentralized carbon removal and purifying smart filters at the city scale. It acts as a guideline for the Kingdom towards achieving its net zero goals and essentially improving the outdoor air quality. It provides a mitigation plan for the removal of unavoidable emissions within city operations in pursuit of addressing the climate urgency in a facet to foster a smarter circular city. In an arid climate like Saudi Arabia, where maintaining green infrastructure (like trees) is a cumbersome task, smart carbon capture technologies can be a way forward to reduce air pollution.

Table 1
Urban hotspots for emissions.

Factors			References					
			Apte, Messier [70]	USEPA [78]	Pidgeon [57]	Rahman, Usama [23]	Lauriks, Longo [79]	Goyal, Gulia [56]
A	Transportation	Intersections	•	•		•	•	•
		Highways/Main Roads	•	•		•	•	•
B	Inner-city Industrial Activity		•	•		•	•	•
C	Commercial Activitiers		•	•		•		•
D	Dense Urbanization							•
F	Congestion		•		•			

3. Pollution hotspots in urban centers

It is evident from the discussion that air quality should be monitored periodically however, it is difficult to measure the pollutant hotspots using traditional stationary monitors in the urban context, as they often fall short in illustrating the spatial resolution [69,70]. The literature review suggested that in any given urban context pollution is mostly concentrated around specific locations. These studies exemplified the uneven trends of pollution hotspots with fluctuating concentrations across urban spatial scales [71,72]. These complex spatio-temporal concentrations are triggered by distinct land-use patterns. Thus, the no stagnant behavior and concentration or dissipation of air pollution and emissions are the urban forms [73], and spatial activities [56,57,70,74]. Apte et al. [70], arrived at twelve hotspots using a repeated sampling method via Google Street Vehicle for Oakland, CA. These pollutants were observed to be focused on major truck routes, vehicle repair facilities, and industrial sites [75]. In the urban context, congested traffic routes are identified as the major hotspot of air pollution [76,77]. The trends of atmospheric emissions in the United Kingdom indicated that pollutants were more concentrated around tourist attractions including the London Eye, Waterloo Overground, Tower Bridge, etc. [57]. Construction, building operations, and transportation account for most emissions in cities today. The main pollution hotspots extracted from the literature are indicated in Table 1.

The study in Cambridge uses contextual information such as traffic flows, demographics, and points of interest to identify the optimal location for placing air quality sensors [80]. Road network and points of interest data (factories, markets, shopping malls, hotels, education facilities, etc.) were incorporated in Bejing, China to determine the location of air quality monitoring stations [74, 81]. A similar study by Rahman et al. [23], uses road networks, industrial areas, commercial areas, and other factors as contextual information for inferring the location of air quality monitoring stations. Thus, air quality is considered a localized issue associated with primary pollution hotspots. These hotspot areas can be marked and prioritized for air quality monitoring and management.

4. Methodology

Urban spatial patterns play a critical role in identifying the nodes at which high rates of air pollutants and CO_2 emissions are accumulated within cities. To estimate the potential location for installing air filters in the given urban context, we propose a three-stage framework. The first stage corresponds to benchmarking emission and pollution factors among international and national cities. The benchmarking stage provides a list of potential emission hotspots in urban areas. The second stage corresponds to the selection and collection of hotspots for the study areas. In the third stage, a GIS-based suitability model is developed that incorporates pollution hotspots and their weights to allocate the optimum location for air filters. The proposed framework is implemented for the city of Al-

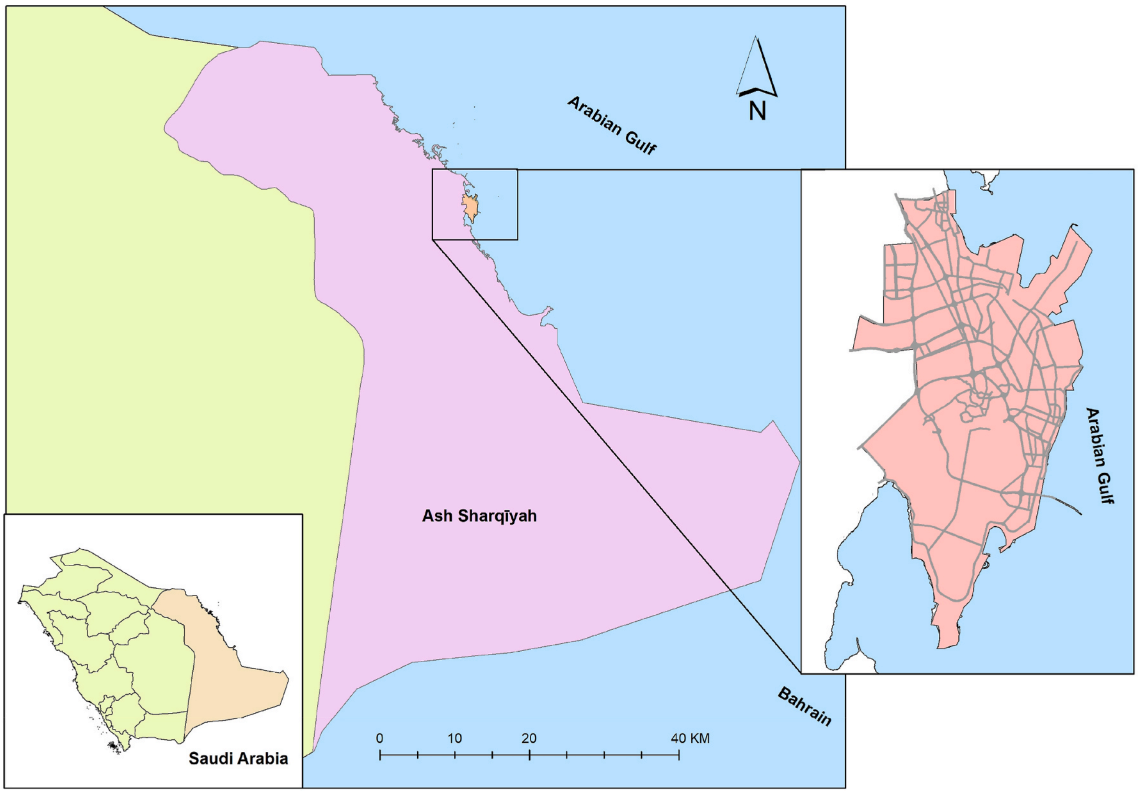

Fig. 2. Location map of study area.

Khobar which is located along the coast of the Arabian Gulf in the Eastern Province of the Kingdom of Saudi Arabia (see Fig. 2).

Al-Khobar serves as the commercial hub of the Eastern Province, featuring contemporary malls, offices, and modern infrastructure. According to the census, the city has a population of 658,550 [82]. Like other cities in Saudi Arabia, Al-Khobar also experiences a very

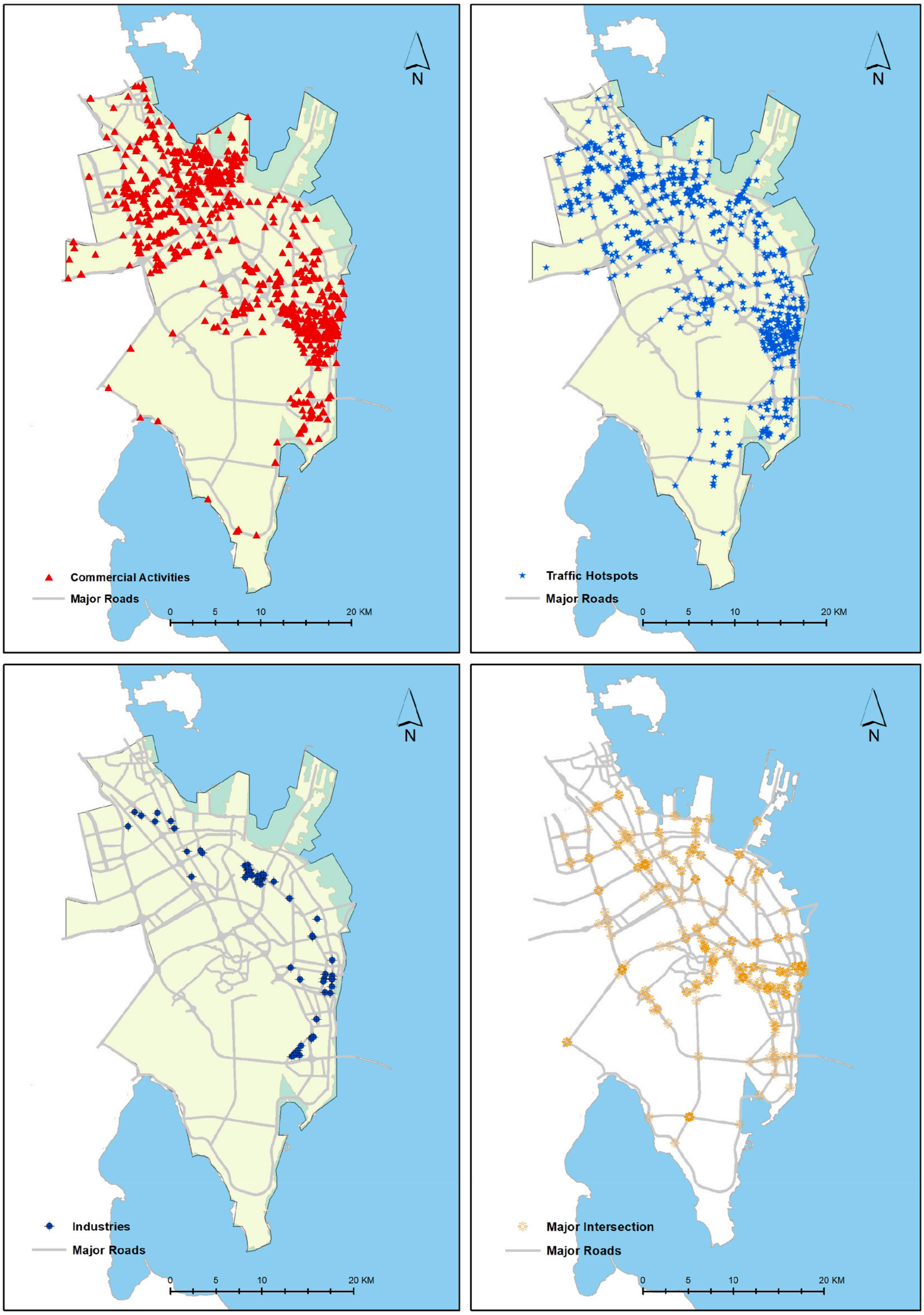

Fig. 3. Location of Commercial, Traffic, Intersection, and Industries centroids.

hot and dry summer with an annual average temperature of 33 °C. The urban heat island effect can be observed due to increasing industrial and human activities.

5. Application and analysis

5.1. Data sources

The factors deduced from the first stage serve as an initial point to select hotspots/POIs for any given urban environment. The input contextual factors/POIs used in the study to recommend the optimal location mainly include major roads, intersections, high-traffic areas, commercial centers, industrial areas, and populated areas (see Fig. 3). The vector layers corresponding to major roads, and intersections were extracted from the open street maps (OSM). Intersections are the places where two major roads (i.e., primary and secondary) intersect each other. High-traffic areas were marked using the live traffic layer from Google Maps during morning, afternoon, and evening peaks. In addition, our knowledge about the study areas also helps us identify the congested routes that are predominantly commercial blocks and high-density areas. The data about the industry was extracted from OSM and Google Maps. Similarly, land use maps, OSM, and Google Maps were used to create the data about commercial activities. The commercial activities include supermarkets, department stores, restaurants, petrol pumps, malls, banks, café, etc. The vector layer from Worldpop (https://www.worldpop.org/datacatalog/) was utilized to make inferences about population density.

5.2. Suitability analysis

In this study, GIS-based suitability analysis with six criteria (i.e., population density, industrial areas, commercial areas, major roads, high traffic areas, and intersections) is used to identify the optimal location for placement of air filters. The benchmarking emission and pollution factors indicated that these criteria are predominantly associated with high levels of air pollution in an urban environment. The GIS suitability analysis approach identifies areas where the mentioned criteria or at least one of them have a greater influence. ArcGIS 10.8 was used to perform the spatial analysis.

GIS-based suitability analysis consists of the following steps: determination of input layers, ranking layers, assigning weights to each criterion, and generation of a suitability map (see Fig. 5). In the spatial computation of optimal locations, all the input layers were converted to raster using raster analysis. The environment for raster analysis was set to produce output layers with a pixel size of 10 m. This pixel size was adopted to capture the maximum spatial details. The layers (roads, intersections, industrial areas, commercial areas, and high-traffic areas) were converted to raster layers using Euclidean distance from each geographic feature. In the second step, each layer was ranked into seven categories, where a high score indicates a higher suitability for the installation of air filters. The distance intervals used to categorize these geographic features were based on studies that establish the link between pollutant concentration around its emission source [83–85].

The distance ranges were used to rank each indicator including roads, intersections, industrial areas, commercial areas, and high-traffic areas into seven ranks (See Table 2). Thus, the area adjacent to the specific facility was given a rank of 7 (high rank) because high pollutant concentration is expected around the emission source (see Fig. 4). The population density layer was ranked using quantile classification where the number of observation are distributed evenly in each class.

Each ranked layer was then assigned weights. The weights were assigned based on the percentage of contribution of each spatial feature toward air pollution. According to reports, transport accounts for 25 % of air pollution whereas industrial activities correspond to 15 % of pollution [86,87]. Alsahli and Al-Harbi [85], assigned weights of 40, 30, 20, and 10 % respectively for population, roads, industry, and high-traffic areas. According to Al-Sinan et al. [48], in Saudi Arabia, 22 % of CO_2 emissions are due to road transport. These percentages were adopted and used to assign the weights to each criterion. The weights for population density, industrial areas, commercial areas, major roads, high-traffic areas, and intersections were assigned 30 %, 20 %, 20 %, 10 %, 10 %, and 10 % respectively. Subsequently, the suitability map was computed by spatially overlaying ranked layers with their corresponding weights. The following equation was used for this purpose:

$$PV_{Sij} = \frac{\left[\left(PV_{PDij} * 0.30\right) + \left(PV_{Iij} * 0.20\right) + \left(PV_{Cij} * 0.20\right) + \left(PV_{Rij} * 0.10\right) + \left(PV_{HTij} * 0.10\right) + \left(PV_{INij} * 0.10\right)\right] *}{7} 10 \quad (1)$$

Where PV_{Sij} represents the pixel value of the suitability map at the ith row and jth column. PD represents population density, I is used

Table 2
Rank distances for input raster layers.

Distance (meters)	Rank
0–25	7
26–49	6
50–99	5
100–150	4
151–300	3
301–500	2
>500	1

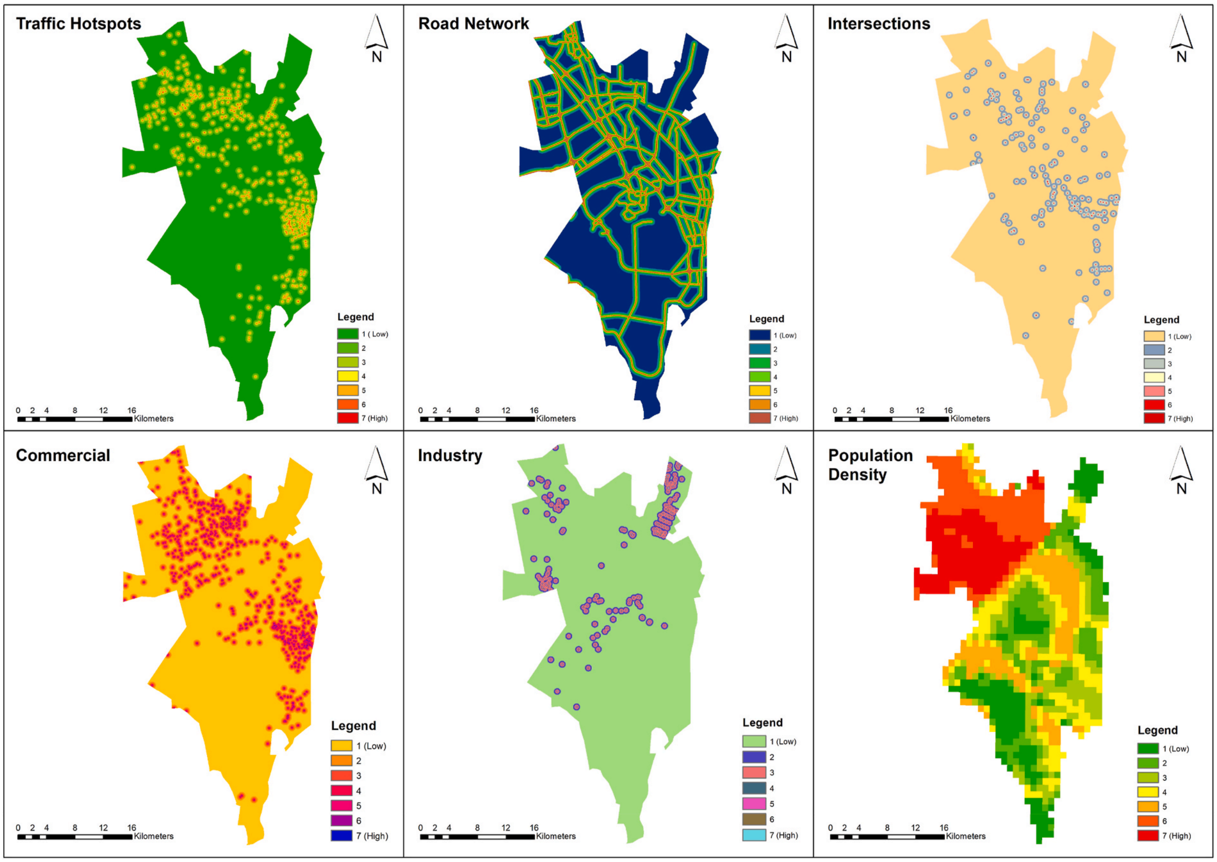

Fig. 4. Euclidean Distance based ranking of Indicators.

for industrial areas, C represents the commercial areas layer, R is used to represent the major roads layer, HT represents the layer of the high-traffic area, and IN shows the intersection layer. The resulting suitability map layer has a scale of 10 as presented in the equation. The areas with high suitability scores are closer to the emission source and thus these are the optimal sites in the urban environment for placing air filters. These locations could potentially encounter elevated levels of pollutants, stemming from one, two, or multiple sources such as traffic, commercial activities, and industrial operations. Thus, the author adopted the logic of choosing those areas with three or more factors in proximity.

Determining the optimal location for carbon removal air filters within a built environment context is the focus of this study. These allocations are based on population density, spatial proximity to industrial, commercial, major roads, high-traffic, and intersection areas. GIS-based suitability analysis is performed to identify the location having maximum influence. The study region is ranked on a scale from 1 to 10 as shown in Fig. 6. GIS suitability analysis evaluates the potential locations within the study region by considering input criteria. The process assigns lower scores to areas that do not meet the specified criteria. The areas with high scores (i.e., 7 or above) are relatively closer to emission sources, either to industries, commercial, roads, high-traffic areas, or intersection areas. Whereas areas having lower suitability scores (i.e., equal to or less than 6) constitute 76 % of the study region and are relatively far away from the emission sources. The potential sites for carbon removal air filters are spatially distributed over different neighborhoods including Al Thuqbah, Al-Khobar Al Shamalia, Tayabhoh, An Nada, Al Manar, Al Faisaliyah, and Al Rawadah. The spatial dispersion of higher suitability scores offers numerous choices for decision-makers in establishing a network of air filters for carbon removal and achieving the goal of net-zero cities.

6. Discussion

The smart city notion notably revolutionized the way we live today. From CCTVs to drones, digital technologies, and artificial intelligence have become the core of many governments nowadays. In conjunction, the rise of big data in recent years has driven the world by storm and opened a larger spectrum of opportunities. Undoubtedly smart tools are not always the ideal solution for all city challenges. However, it shall be integrated to function as a platform for yielding a greater environmental outcome. The development of the latest carbon capture technologies like CCUS has paved the way for moving toward net-zero cities. The study hence proposed a network for carbon removal air filters that shall form a layer for the smart city model, transforming global ecosystems through local interventions. However, there has been little application of carbon removal filters within a built environment context. Establishing an

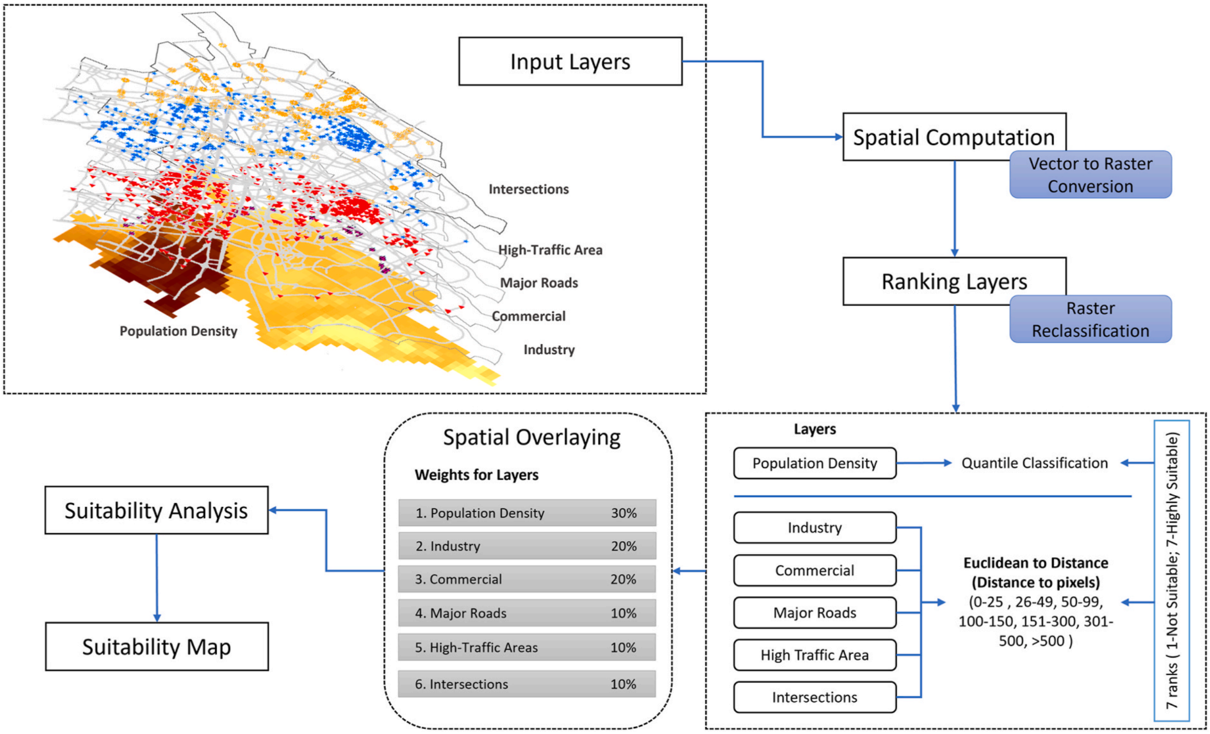

Fig. 5. Methodology: GIS-bases suitability analysis.

effective network of carbon removal requires optimal placement of air filters. It is therefore paramount to establish governance for reducing and removing emissions from city operations through integral or multifaceted approaches.

There are common urban factors that contribute to the quality of air and emissions within a city. This study first identified the potential air pollution hotspots in an urban area as a preliminary site selection measure. The optimal allocation of smart air filters is built on these emission sources. Similar pollution hotspots were also utilized by Refs. [23,74] for location recommendation of air quality sensors.

The proposed framework facilitates the first task of site readiness evaluation by studying the following:

- Transport-related sites especially frequent high-congestion, intersections,
- Densely urbanized areas through population density
- Industrial development across cities
- Attraction points across the city (i.e., social gatherings, public squares, malls, etc.)

Location optimization is a well-recognized problem in the literature [43,88] and has practical implications in various fields including health care [89], risk assessment [90], and logistics [91]. GIS-based suitability analysis serves as a useful spatial analysis to define the optimal location locations for air filters [85,92]. The technique does not require emission inventory data and considers multiple attributes that majorly cause air pollution in urban areas. The flexibility of suitability analysis makes it a universal tool that can be applied in any given urban setting. The approach used in this study can be generalized for another urban area, where the criterion is intended for optimal site selection for establishing the network of carbon removal air filters. Additionally, the criteria and weights can be adapted to fit the local environment.

These sensors could be embedded in the parasitic intervention for monitoring purposes. Thus, the integration between technology, tactical urbanism, as well as architecture is the collective case this paper proposes for making cities smarter and more sustainable. Using smart air filters, the governing entity can target the specific sites at which elevated levels of pollutants are present in the air. The large-scale deployment of smart air filters would help to improve air quality not only at the local scale but also at the regional scale, contributing to the broader goal of creating net-zero cities. However, this study does not reflect on the efficiency or capacity of air filters. Besides the perspective of policymakers and people towards the acceptability of air filters is not included. Nevertheless, incorporating vehicular flow data along with road networks can provide precise assessments of pollution caused by traffic.

7. Conclusion

The experience of previous decades has shown that urban sprawl is inevitable. Cities are anticipated to host more population

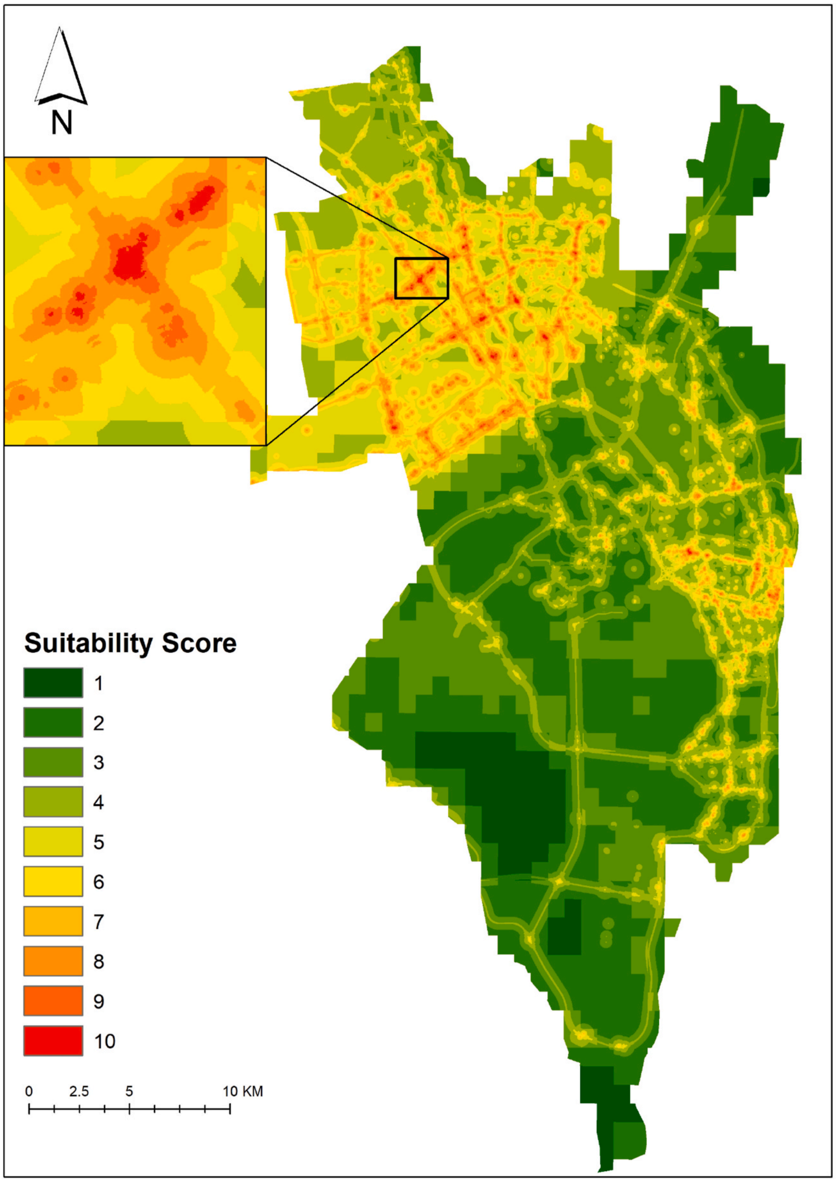

Fig. 6. Suitaiblity map for optimal location of air filter.

growth and must expand to accommodate shelters and infrastructure demand. This expansion often leads to higher emissions, exposing urban dwellers to elevated levels of air pollution. Additionally, as city inhabitants commute, operate buildings, or even gather at social events, air quality fluctuates. Decarbonization and intelligence are thus definitive choices for the future development of cities. KSA has pledged to reduce 30 % of its emissions by the year 2030 and this can only be achieved by removing CO2 from the air [48]. This ambitious goal can only be achieved through innovative technologies.

This study proposed a network of carbon removal air filters based on pollution hotspots in the context of the built environment. These carbon removal air filters could help realize cities' decarbonization plans with data-driven planning. In an arid climate like Saudi Arabia, where maintaining green infrastructure (like trees) is a cumbersome task, smart carbon capture technologies can be a way forward to alleviate air pollution.

It has been concluded that decarbonizing and filtering the air from pollutants in our cities and the built environment in KSA is vital for tackling the threats posed by climate change. The objective of net zero cannot only be achieved by reducing emissions but also by employing carbon removal technology. A city must, therefore, leverage emission avoidance, reduction, and removal to address this climate urgency.

Since the cost associated with carbon technology is quite high thus, further research shall explore the advancement and intervention to make large-scale implementation feasible. Future research needs to concentrate on technical materials and specifications of smart filters that are more efficient. Research is also required to comprehend the public perception regarding these technologies to ensure social acceptability and active engagement. Additionally, supportive policies are required that encourage the widespread development of air filters within the existing built environment.

Data availability statement

Data will be provided upon request.

CRediT authorship contribution statement

Habib M. Alshuwaikhat: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Muhammad Aamir Basheer:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Investigation, Funding acquisition, Formal analysis, Data curation. **Lujain T. AlAtiq:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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