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Research article

Mining association rules between lichens and air quality to support urban air quality monitoring in Nigeria

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ABSTRACT

Urban environments represent the most intense human-environment interaction. This interaction can result in negative outcomes like air pollution and its health implications. There is a significant data deficit in air quality monitoring across many developing nations, which prevents effective policies and measures from being taken to promote the accomplishment of sustainable development. Around the world, lichens have been used to track environmental changes due to their sensitivity to changes and concentration of atmospheric pollutants. This study investigated the relationships between lichen and air quality across some Nigerian cities. Lichen surveys were conducted in four cities. At various periods during the day, NO_2, SO_2, $PM_{2.5}$, and PM_{10} levels were measured. Association rule mining was carried out to investigate the relationship between lichen found and air quality categories. Results showed that the most prevalent lichen Genera are *Pyxine* in Abuja and Kano, *Diorygma* in Lagos, and *Dirinaria* in Port Harcourt. Out of the 40 rules found from the rule mining, 17 are important (lift values ≥ 1.1), capturing six of the fourteen lichen genera identified in the field. The findings indicated that there are important relationships between lichens and air quality indices, suggesting that some lichen species in Nigeria may serve as indicators of long-term air quality. To develop a network of urban environmental quality bioindicators across Nigerian cities, surveying and transplanting are advised. The use of lichen for air quality monitoring can provide information for sustainable management of air quality and environmental quality in Nigeria.

1. Introduction

The urban environment represents an area with one of the most intense interactions between humans and the environment, and showcases the social, economic, political, environmental and technological processes taking place within them [1]. These processes could bring about comfort and challenges when not managed adequately. Some of these challenges include air pollution and urban heat island effects [2]. Air pollution has been reported to have grave health impacts [3], some of which include pulmonary and cardiovascular problems, impaired host defence mechanisms, cancer, low birth weight, and infant mortality [4–6]. The situation in urban areas is especially dire because of the persistently high concentrations of air pollutants, the number of people exposed, as well as the possibility of delayed effects. As developing countries strive to become more industrialised, they are bound to generate more air

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pollutants. This could be attributed to the sacrifice of environmental quality for economic growth, preponderant use of outdated technologies (less expensive) as well as lax and poor enforcement of environmental laws.

According to the Global Burden of Disease Report in 2019 [7], lower respiratory infection is the fourth leading cause of death in Nigeria, outranked only by Neonatal disorders, Malaria and Diarrheal diseases. Thus, to achieve Sustainable Development Goal 11–making cities and human settlements inclusive, safe, resilient, and sustainable, and especially target 11.6 (Reduce by 2030, the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management), close attention must be paid to air quality. Given the negative health impacts of air pollution on human health, it is therefore pertinent that a concerted effort is made to monitor air pollution, especially in urban areas. According to WHO [8], policies reducing air pollution by any nation could significantly reduce the burden of diseases such as stroke, heart disease, lung cancer and chronic and acute respiratory diseases. The report estimated that ambient air pollution caused 4.2 million premature deaths globally across rural and urban areas. A disproportionately high percentage (91%) of these deaths were found to occur in low- and middle-income countries [8]. These burden estimates show that there is a need for a concerted effort at the regional, national, and international levels, as it is evident that the control of outdoor air pollution is beyond individuals due to the enormity of this problem.

Due to the challenges of cost and maintenance of monitoring equipment, bioindicators offer a cost-effective option for air quality monitoring when complemented by data mining, machine learning and citizen science. With many pollutants present within the urban environment, bioindicators such as lichens provide a good alternative for understanding the effects of the myriads of pollutants on the environment. Their forms, diversity, presence (or absence), and species are the outcome of the integration of these pollutants (known and unknown) over time [9]. Ecological indicators have found uses for many years as cost-effective tools for the assessment of environmental conditions, serve as early warning signals and in the diagnosis of causes of environmental problems [10]. Lichens are symbiotic organisms (fungus and algae or cyanobacteria) which have found wide usage as indicators of changes in the environment, as well as monitoring of air quality [9,11–14]. However, lichen communities and their application in air pollution studies are still very scanty in Nigeria. None of the works so far have covered the varying and large urbanisation gradients which are necessary to develop a reliable framework for using lichens as air quality indicators in the country. In addition, very little is currently known in the tropics (there are many works in Europe and North America), about the effects of air pollution, urban heat island effect and climate change on lichens traits especially in Nigeria. In a systematic review of transplant experiments in lichens and bryophytes, Mallen-Cooper and Cornwell [15] reported that 67% of the experiments (up to March 2020) focussed on the utilisation of lichens and bryophytes as indicators of air pollution. They identified Africa and Australia as geographical gaps in knowledge in this area.

Bioindicators are living organisms (animals, microbes, or plants) which are sensitive to pollutants in the environment and as such can be used to monitor the health of the ecosystem. Essentially, their population, morphology, physiology, and presence/absence can indicate the level of pollution in the environment. So, they serve as an indirect measure of the level of toxic or otherwise chemicals in the environment and monitoring them can indicate changes in the environment. To this end, we examined the relationship between observed lichen species and air quality across four major cities in Nigeria. This is aimed at supporting the utilisation of bioindicators (lichens) for air quality monitoring in West Africa and filling some of the data gaps in air quality data.

Lewis [16] utilised epiphytic lichens and bryophytes to characterise nitrogen pollution in the UK. The study led to the development of the Lichen Based Nitrogen Air Quality Index (NAQI) for the UK. The study utilised a simple, unweighted frequency-based scoring system, which correlates strongly with NH_3 concentrations in the air. A regression model was developed combining NH_3, NO_2 and bark pH to predict atmospheric N pollution–the combined effect of NH_3 and NO_2. From the resulting index, N-sensitive lichen species include *Graphis* sp, *Ochrolechia* sp, *Evernia* sp, *Sphaerophorus* sp, and *Parmelia* sp, while N-tolerant species include *Physcia* sp, *Lecidella* sp, *Candelariella* sp, *Arthonia* sp, *Amandinea* sp, *Xanthoria* sp, *Punctelia* sp.

Díaz-Álvarez and de la Barrera [17] examined nitrogen deposition via extensive sampling of *Anaptychia* sp., the mosses *Grimmia* sp. and *Fabronia* sp., and the bromeliad *Tillandsia recurvata* (L) across the Mexico Valley. While the bromeliad and the mosses selected had a linear and positive response to NO_x this was not the case for the selected Lichen. Despite the lichen selected being abundant, it was found that it is not a reliable indicator of NO_x pollution in the study area.

Across Europe and North America, a generalisation could be made from studies on lichen found in urban areas. Lichens with a preference for high nutrients concentration are usually dominant within the urban landscape e.g. Munzi, Correia [18]; Vieira, Matos [19]; Geiser, Jovan [20]; Davies, Bates [21]; Seed, Wolseley [14]. From across the different works carried out across most of Europe, North America and some in South America and Asia, there are common Lichens found across heavily polluted areas and less polluted areas. For example, the works of Chetia, Gogoi [22]; Yatawara and Dayananda (2019); Manninen (2018); Sujetovienė (2010); Gadsdon, Dagley, Wolseley, and Power (2010), showed some similarities across different parts of the world concerning lichen genera found across heavily and less polluted areas.

Data mining or knowledge discovery is the process of extracting useful information from datasets or databases. According to Frawley, Piatetsky-Shapiro [23], this has the potential to identify unknown and useful information from data. Thus, allowing the extraction of new patterns, meanings, and understanding from the data. Association Rule Mining (ARM) is a data mining technique which seeks to extract rules that can characterise frequent patterns among items in a database. Frequent patterns or sets form the basis for the generation of the association rules, thus the prediction of items is based on the occurrence of the others. Its application started with retail or basket data - the database of customer transactions was explored for association and rules that can define customer behaviour [24]. Its application has grown significantly wide within the increasing availability of large databases. Recently Tandan, Acharya [25] applied ARM to identify COVID-19 symptoms patterns and rules. The study showed that symptom rules differ by age and by sex, so also the investigation identified severe rules which resulted in deaths. Li, Li [26] examined the association between air quality and industrialisation progress in China using ARM. They reported that a high industrialisation level, high urban population, a high non-agricultural output value, high non-agricultural employment proportion, and a high proportion of value-added manufacturing is associated with heavy air pollution in China. Using data from the Swedish Traffic Accident dataset from 2011 to 2017, Fagerlind, Harvey [27] utilised an a priori algorithm in an ARM to identify the association between Individual-Based Injury Patterns (IBIP). They were able to identify 77 IBIP and the associated road user type. Thus, supporting the development of road safety countermeasures for different road user types. Xia and Ruan [28] developed a decision-support framework for urban space function replacement using ARM. They examine parking lots and their association with other points of interest (POI) across the city of Hangzhou. Mining of the function association patterns allows for the recommendation of function replacement for parking spaces across the cities to support urban renewal. Using data from the Internet of Things (IoT) -based sensors for air quality monitoring Tuysuzoglu and Birant [29] described how a smart city framework for triggering the initiation of air quality management system can be implemented using weighted ARM (WARM). The application is based on the frequently relations or association between air pollution features and their characteristics. They compared the traditional ARM and the WARM using data from 21 monitoring stations in Turkey and reported that WARM offers an improvement over the traditional ARM.

2. Materials and methods

2.1. Study area

The study was carried out across four major cities (Abuja, Kano, Lagos, and Port Harcourt). These locations belong to various ecological zones which provides the opportunity to examine the diversity of lichens that could be found across this environment (Fig. 1). For example, Abuja has predominately Western African Mesic Woodland and Grassland while Kano is dominated by the Sudano-Sahelian Shrub Savanna ecosystem.

Port Harcourt (PH) and Lagos have a mixture of the Atlantic Ocean Mangrove and the Antostema - Alstoneia Swamp Forest Ecosystems. However, the dynamics of human activities and industries vary significantly to create unique urban environments across these two cities as well as Abuja and Kano. These attributes are also evident from their footprints (Table 1), with population density ranging from 3000–13,500 persons/km^2.

2.2. Lichen sampling and air quality data collection

The study adopted a correlational design and to ensure wide coverage, land use and land cover guided the purposive sampling for the lichen survey. Distinct land use and land covers across the cities were surveyed (industrial, residential, commercial/business, transportation, and educational). Lichen samples were collected, and samples were sent to experts for identification. Furthermore, a GPS-enabled camera was utilised during the lichen survey to ensure that the location of the samples was adequately captured.

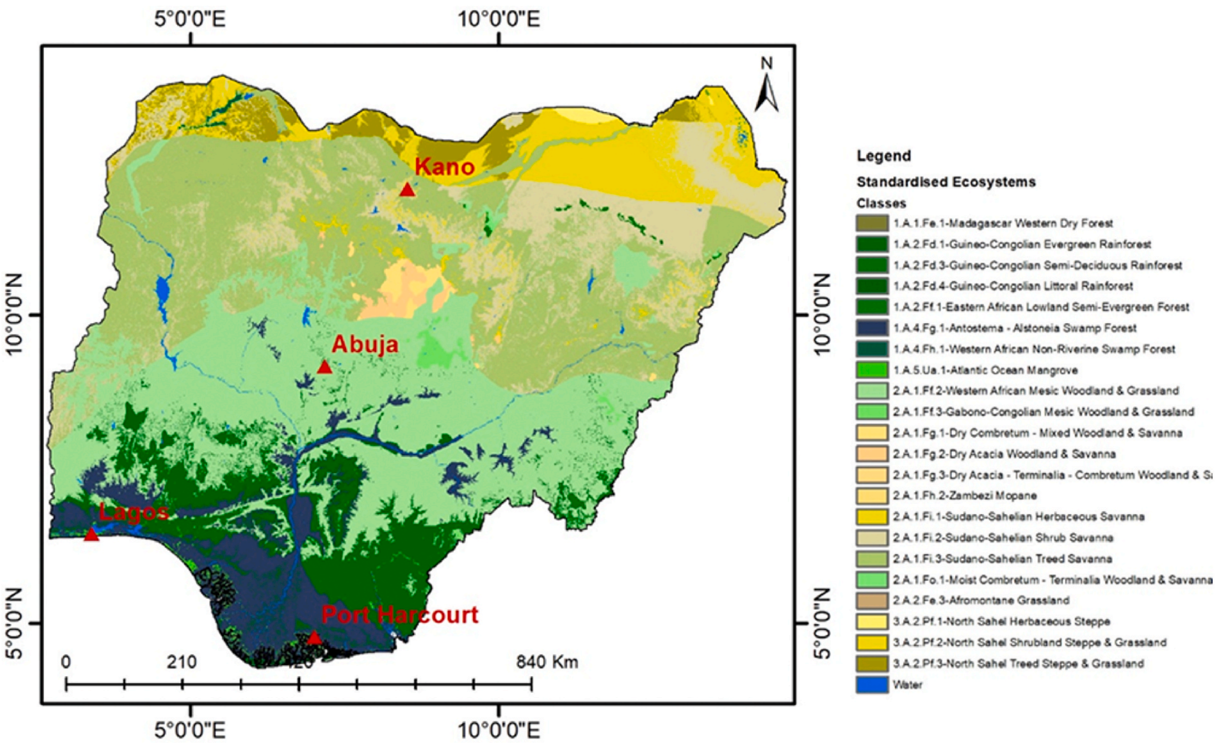

Fig. 1. African standardised ecosystem map of Nigeria and the study locations. *Source*: Extracted and adapted from Sayre, Comer [30].

Table 1
Urban footprint of selected cities.

World Rank	Urban Area	Population Estimate	Land Area (km^2)	Population Density (person/km^2)
21	Lagos	14,630,000	1943	7500
112	Kano	2,695,000	907	3000
138	Abuja	3,980,000	324	12,300
247	Port Harcourt	2,130,000	158	13,500

Source: Cox [31].

Air quality measurements were carried out during the lichen survey and repeated to capture another time of the day. Thus, if the first measurement was carried out during the morning hours the second measurement was carried out during the afternoon hours. Measured pollutants are NO_2, SO_2, $PM_{2.5}$ and PM_{10}. We assumed that the average of these two measurements should give a general indication of the air quality at the site. Handheld GPS was also used to capture the location of air quality measurements. The AeroQual series 500 was used for the quality measurement. Each measurement captured a 15-min average of the concentration of these pollutants in the atmosphere at shoulder height. The measurements were taken around each of the lichen sampling locations.

2.3. Data engineering

The georeferenced air quality measurement data were projected to the Universal Transverse Mercator 1984 Zone 32 N within a Geographical Information System (GIS) Software. A 300 m buffer was created around each of the measurements and the Zonal Statistics was used to compute the average of the measurement points falling within the Zones created by the dissolved buffers. This allows for the computation of the average, which combined the different hours of the day and nearby measurements.

The identified lichens were linked to their respective extraction locations using their geotagged pictures. The geotagged pictures were overlaid on the buffer zones created earlier. Air quality parameters for the location at which each lichen was found were extracted based on the overlay analysis. This created a dataset, which has lichen name, their location data, and the average of the air quality parameters.

The measurements were then classified based on the WHO-recommended 2021 Air Quality Guideline (AQG) levels [32]. Thus, values up to the AQG level are classified as good and others as Poor, Very Poor and Extremely Poor (Table 2).

2.4. Association rule mining

The combined data created a database structure (Fig. 2) comprising the required dataset for the ARM analysis. The a priori algorithm was used for the ARM. This method utilises prior knowledge of the frequency of the itemset within the database. The approach involves the partitioning of the database into parts and contrasting them with other sets. The resulting scores are used to classify the parts as frequent or otherwise. These are then continuously aggregated creating larger elements set until the specified frequency threshold or support is achieved. This implementation was carried out using R language [33] within the Rstudio [34] environment. The *arules* package [35] and the *arulesViz* package [36] were deployed in the analysis and rule visualisation respectively. To measure the strength of association, three indices were used - support, confidence, and lift.

Support is the frequency of the *antecedents* and/or the *consequent* occurring together in the dataset. Thus, it is the percentage value of the joined rule (head and body; *antecedent* and *consequent*) occurring among all the groups considered or the entire dataset. It expresses the frequency of a collection of items (head and body) occurring together as a percentage of all transactions thereby showing the frequency of a rule's body and head occurring among all the groups considered. Rules with high support (highly supported) are more meaningful than others with low support. For our analysis, this was set as 2.5%.

Confidence is the percentage value showing the frequency of the *antecedent* and *consequent* occurrence among all the with the rule *consequent*/body. This is a measure of the reliability of the rule. Thus, when there is a strong association between the *antecedent* and the *consequent* a high confidence value is recorded. This initial threshold for confidence was set at 1%

Lift is the ratio of the confidence of a rule and the expected confidence of the rule. The expected confidence is calculated as the product of the support for the rule's *antecedent* and *consequent* divided by the support for the *consequent*. This measures the importance of the rule as it examines the reliability of the rules considering the frequency of the *consequent*. The general principle is that a lift above 1 signifies a strong association between the antecedent and the *consequent*. For this analysis, an initial threshold of 1.1 was set for lift.

ARM as a data mining technique is beneficial for this study in allowing the discovery of new understanding, patterns and meaning from the dataset. The extracted rules thus allow for the characterisation of the frequent patterns for the prediction of the occurrence of

Table 2
Classification of Air quality measurements.

Class	$PM_{2.5}$ (µg/m^3)	PM_{10} (µg/m^3)	NO_2 (µg/m^3)	SO_2 (µg/m^3)
Good	$\leq$15	$\leq$45	$\leq$25	$\leq$40
Poor	16–25	46–55	26–35	41–50
Very Poor	26–35	56–65	36–45	51–60
Extremely Poor	>35	>65	>45	>60

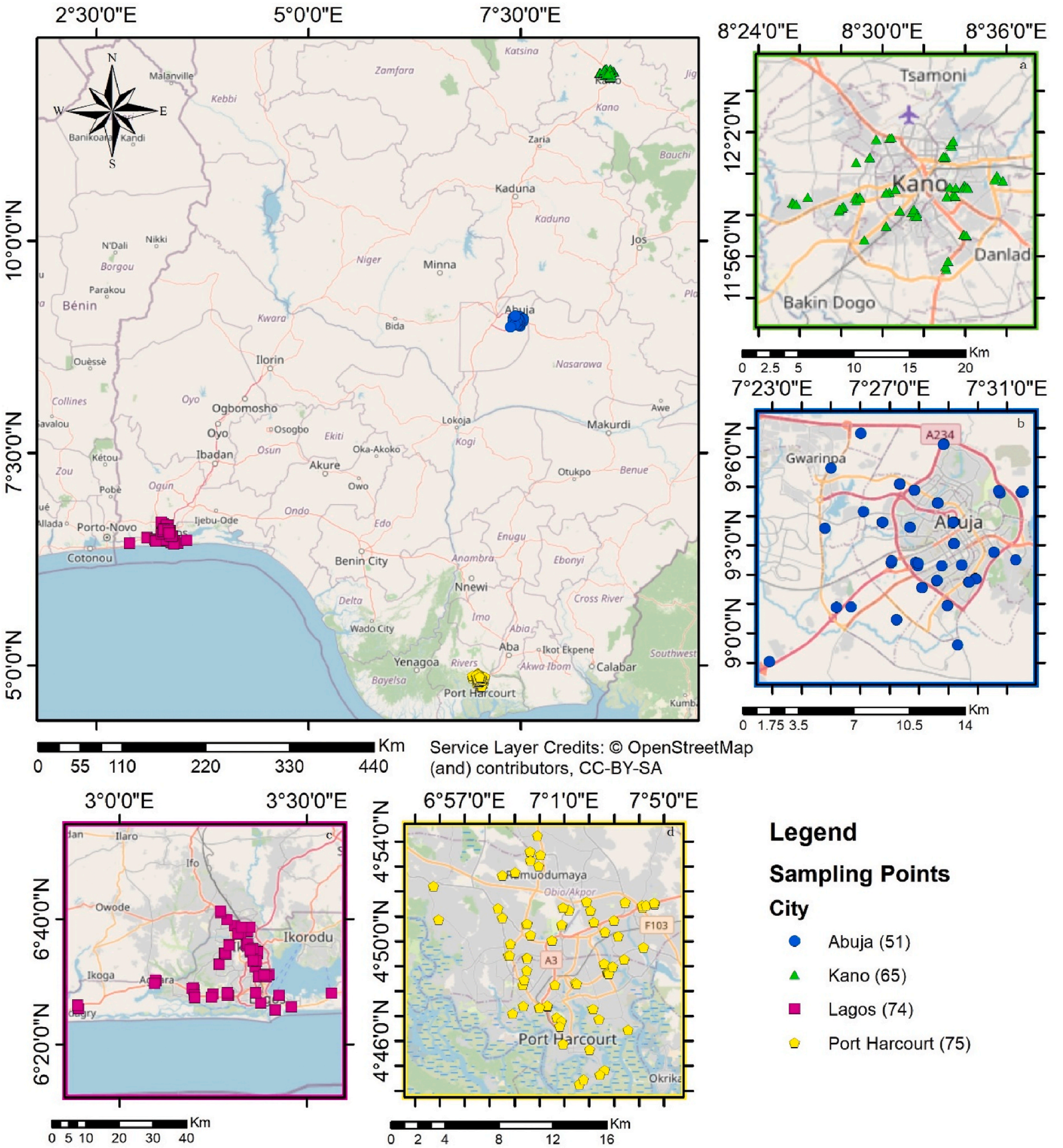

Fig. 2. Air quality Sampling points across the four cities (a) Kano (b) Abuja (c) Lagos (d) Port Harcourt.

other items in the dataset. This is important for the identification of the association between Lichen species and Air quality parameters. Most especially as the dataset as in the case of this study where lichen species are examined for association with air quality classes.

3. Results

3.1. Pollutant concentrations and air quality classification

The locations of the air quality sampling are presented in Fig. 2 and a total of 265 points were sampled across Morning hours (06:00 to 11:59), Afternoon (12:00–15:59) and Evening (16:00–20:00). The summary of these measurements is presented in Table 3.

For Abuja, the highest values for $PM_{2.5}$ were recorded during the afternoon period, across the three periods, the afternoon also has

Table 3
Summary statistics of the air quality measurements across the cities over different periods.

CITY	TOD	Count	$PM_{2.5}$				PM_{10}				NO_2				SO_2			
			Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum
ABJ	Afternoon	24	27.79	24.5	12.00	96.00	67.19	37.5	16.00	310.00	82.21	59	0.00	360.00	466.67	550	0.00	1100.00
	Evening	5	16.20	14	13.00	22.00	27.40	28	24.00	31.00	97.20	86	46.00	162.00	680.00	700	300.00	900.00
	Morning	22	22.68	20	12.00	53.00	33.86	28.5	0.00	66.00	87.82	70	0.00	236.00	572.73	500	0.00	1600.00
KAN	Afternoon	31	30.06	20	8.00	83.00	95.55	64	17.00	251.00	2.42	0	0.00	19.00	290.32	300	0.00	900.00
	Evening	13	86.00	30	0.00	371.00	267.92	130	65.00	775.00	5.69	0	0.00	59.00	853.85	700	100.00	2500.00
	Morning	21	41.86	31	17.00	200.00	78.14	69	23.00	161.00	30.33	18	0.00	84.00	761.90	800	200.00	1600.00
LAG	Afternoon	29	16.62	13	5.00	72.00	43.10	33	11.00	142.00	50.35	29	0.00	400.00	988.55	500	0.00	8600.00
	Evening	14	13.14	13	4.00	32.00	52.21	29	13.00	188.00	45.00	42	0.00	102.00	550.00	400	0.00	1400.00
	Morning	31	23.06	17	7.00	109.00	72.45	39	16.00	577.00	84.45	85	0.00	235.00	603.23	600	0.00	1600.00
PHC	Afternoon	23	41.65	32	18.00	122.00	106.39	83	26.00	366.00	18.48	9	0.00	91.00	773.91	700	0.00	2900.00
	Evening	3	33.33	33	30.00	37.00	42.33	42	38.00	47.00	35.33	47	1.00	58.00	200.00	200	100.00	300.00
	Morning	49	59.80	53	16.00	157.00	127.96	137	25.00	282.00	53.18	51	0.00	167.00	736.73	700	0.00	2400.00

ABJ – Abuja, KAN – Kano, LAG – Lagos, PHC- Port Harcourt City.

the highest mean concentration of $PM_{2.5}$. In Kano, the highest $PM_{2.5}$ concentration occurred in the evening period while the lowest value was also recorded during this period. However, this period recorded the highest mean $PM_{2.5}$ concentration for the city of Kano. Across the three periods in the city of Kano, the mean concentration of $PM_{2.5}$ is in the order of Afternoon < Morning < Evening. For, Lagos, the highest $PM_{2.5}$ was recorded in the Morning hours followed by afternoon and then evening. Minimum $PM_{2.5}$ values across the period range between 4 $\mu g/m^3$ and 7 $\mu g/m^3$. While the mean concentration has an order of Morning > Afternoon > Evening. In PH, the morning hours have the highest (just like Kano and Lagos) as well as the lowest $PM_{2.5}$ concentration. In the evening the $PM_{2.5}$ concentration ranges between 30 $\mu g/m^3$ and 37 $\mu g/m^3$ resulting in this period having the lowest average PM2.5 concentration.

For PM_{10}, the highest average concentration was recorded for the evening period in Kano (267.92 $\mu g/m^3$) while the lowest average (27.40 $\mu g/m^3$) was recorded in Abuja during the evening hours. The lowest observed concentration was recorded in Abuja during the morning hours. Across the cities, Abuja (Morning and Evening), Lagos (Afternoon), and PHC (Evening) showed average PM_{10} concentrations below the WHO AQG level.

The highest average NO_2 concentration was recorded in Abuja (Evening hours) while the highest maximum concentration was recorded in Lagos during the afternoon hours. Across Kano, the average values were comparatively lower during the afternoon and evening hours than in other cities. Afternoon hours in PHC recorded an average value below the AQG level.

SO_2 concentration was found to be generally high across the four cities. The average values were considerably high across all periods of the day. The highest maximum recorded was during the afternoon in Lagos (8600 $\mu g/m^3$) and the lowest average stood at 200 $\mu g/m^3$ recorded during the evening hours in PHC. Comparing the averages for the times of the day across each city, the afternoon period was found to be relatively better in Abuja and Kano (lowest average), and the evening hours were relatively better across the remaining cities.

3.2. *Frequency of lichen*

Across the four cities, fourteen genera were found with varying diversity among the city (Table 4). In Abuja, the most common genus was *Pyxine* (31%) followed by *Candelaria* and *Parmotrema* with 20% and 16% frequency respectively. Across Kano, only two genera were found and *Pyxine* was the most common (93%). In the city of Lagos, six genera were found, and two genera were dominant *Diorygma* (46%) and *Physcia* (44%). For Port Harcourt, diversity is limited to eight genera with *Dirinaria* (25%), *Physcia* (24%), and *Diorygma* (22%) as the three most found genera. The results indicated that based on the sampled areas diversity is in the order Abuja > PH > Lagos > Kano.

3.3. *Frequency of elements*

For the lichen, *Physcia*, *Diorygma* and *Pyxine* were the most common elements. Among the $PM_{2.5,}$ the class Poor occurred more than half of the time while for PM_{10}, the class Good was the most frequent. For $NO_{2,}$ most of the places sampled fell into the class – Extremely Poor while the same class was the most frequent for SO_2.

From this analysis, the ten most frequent items are highlighted in Table 5, and this is made up of 3, 3, 2, 1 and 1 members from the lichen type, $PM_{2.5}$, PM_{10}, NO_2, and SO_2 classes respectively.

3.4. *General overview of rules*

Using the threshold stated in the method for ARM analysis, 230 rules were found. From these rules, 75, 95, 51, and 9 have lengths of

Table 4
Frequency of Lichen found across the four cities in Nigeria.

Genera	Counts			
	Abuja	Kano	Lagos	PH
Arthonia	7	0	0	0
Bacidia	2	0	4	0
Candelaria	48	0	0	0
Chrysothrix	2	0	13	5
Cryptothecia	0	0	0	2
Diorygma	0	0	101	15
Dirinaria	13	0	0	17
Graphis	0	0	3	9
Hyperphyscia	4	0	0	0
Lecanora	35	0	2	2
Parmotrema	37	0	0	0
Physcia	15	3	97	16
Pyrenula	0	0	0	1
Pyxine	73	43	0	0
Total Frequency	236	46	220	67

For the ARM analysis, we excluded *Cryptothecia*, *Hyperphyscia* and *Pyrenula* i.e., those with less than 5 occurrences. This resulted in a dataset with 562 instances of air quality data joined with identified lichen attributes.

Table 5
Frequency of elements in the transactional dataset for the ARM.

Lichen Types	Frq	$PM_{2.5}$ Class	Frq	PM_{10} Class	Frq	NO_2 Class	Frq	SO_2 Class	Frq
Arthonia	0.01	Good	**0.26**	Good	**0.59**	Good	0.12	Good	0.01
Bacidia	0.01	Poor	**0.51**	Poor	0.07	Poor	0.03	Poor	0.00
Candelaria	0.09	VPoor	0.16	VPoor	**0.20**	VPoor	0.08	VPoor	0.00
Chrysothrix	0.04	EPoor	**0.07**	EPoor	0.14	**EPoor**	**0.77**	**EPoor**	**0.99**
Diorygma	**0.21**								
Dirinaria	0.05								
Graphis	0.02								
Lecanora	0.07								
Parmotrema	0.07								
Physcia	**0.23**								
Pyxine	**0.21**								

Frq = Frequency, Vpoor = Very Poor, Epoor = Extremely Poor.

2, 3, 4, and 5 respectively. Examining the quality of the rules, results showed that the minimum support recorded is 0.027 and the maximum is 0.772 with a mean of 0.093. The top 10 rules found among these 230 are all related to the air quality parameters (Table 6). These top rules showed that there is more support for association across the various air quality parameters than between lichen and air quality parameters. For example, there is strong support for the rules which indicated that across the four cities extremely poor NO_2 conditions occurred with extremely poor SO_2 conditions (Rules 1, 4 and 7). In these top 10 lists, there is also strong support for poor $PM_{2.5}$ conditions to be associated with extremely poor SO_2 and NO_2 as shown in rules 5, 6, 7, 9, and 10 (Table 6). Furthermore, the result indicated that a good condition of PM_{10} under poor to extremely poor conditions of $PM_{2.5}$, SO_2 and NO_2 across the cities. The indication, therefore, is that poor and often worse air quality conditions for one of these three parameters ($PM_{2.5}$, NO_2 and SO_2) is likely to be associated with poor to worse for any of the other two.

3.5. Lichen itemset and left-hand side of rules

3.5.1. General association rules for the identified lichens

Examining the itemset with each of the lichen types there are a total of 150 sets showing association with the lichens (Table 7). Itemset having *Physcia* 26% of the time had the best itemset with a support of 23%. Itemset with *Pyxine* and *Diorygma* occurred 21% each, however, the best item for each had the support of 20% and 3% respectively. *Candelaria* itemsets were found at 10% (out of 150) with the best-having support of 8%. Fifteen *Parmotrema*-related itemsets were found and the best set has the support of about 7%. *Lecanora* itemsets occurred in 11 out of the 150 itemsets and the best support was found for itemset showing an association between this Lichen and extremely poor SO_2 conditions (7% support). *Dirinaria* itemsets occurred 7 times and the best-supported itemset show association between this Lichen and extremely poor SO_2 class. *Chrysothrix*-associated itemset occurred once and this itemset showed support of about 4% (an association with extreme concentration of SO_2). Among the best-supported itemsets for the lichen's association with extremely poor SO_2 class showed up the most (Table 6). This indicates that there is a robust association between the lichens identified and poor SO_2 conditions.

3.5.2. Lefthand side rules for the lichen

Forty rules were identified with the lichen types appearing on the LHS of the rules (Appendix 1), with support ranging between 2.7% and 23.3%. The confidence showed the proportion of the itemset with a particular lichen (X) in which any of the air quality parameters also appears (item Y). Across the rules identified, confidence ranged between 0.138 (*Diorygma* – Poor PM_{10} Class) and 1 (*Physcia* – Extremely poor SO_2 Class). Lift expresses how likely an item within a set is likely to occur together with other items in that itemset. Therefore, itemsets with a lift greater than 1 have a very high likelihood that elements in the set will occur together. Examining the lift values, the highest lift (4.48) was recorded for the association between *Pyxine* (Table 8) and extremely poor $PM_{2.5}$ Class while the lowest (0.36) was recorded for the rule associating *Diorygma* with poor $PM_{2.5}$ class (Appendix 1). Narrowing down to

Table 6
Top 10 rules within the targeted support and confidence threshold.

Rule	Items	Support	Count
1	NO_2 = ExPoor, SO_2 = ExPoor	0.772	434
2	PM_{10} = Good, SO_2 = ExPoor	0.594	334
3	PM_{10} = Good, NO_2 = ExPoor	0.552	310
4	PM_{10} = Good, NO_2 = ExPoor, SO_2 = ExPoor	0.552	310
5	$PM_{2.5}$ = Poor, SO_2 = ExPoor	0.505	284
6	$PM_{2.5}$ = Poor, NO_2 = ExPoor	0.427	240
7	$PM_{2.5}$ = Poor, NO_2 = ExPoor, SO_2 = ExPoor	0.427	240
8	$PM_{2.5}$ = Poor, PM_{10} = Good	0.286	161
9	$PM_{2.5}$ = Poor, PM_{10} = Good, SO_2 = ExPoor	0.286	161
10	$PM_{2.5}$ = Poor, PM_{10} = Good, NO_2 = ExPoor	0.281	158

Table 7
Summary of items associated with the lichen types.

Lichen Types	Frequency	Itemset	Support
Candelaria	15	Genera = *Candelaria*, SO_2 = ExPoor	0.085
Chrysothrix	1	Genera = *Chrysothrix*, SO_2 = ExPoor	0.036
Diorygma	31	Genera = *Diorygma*, PM_{10} = ExPoor	0.028
		Genera = *Diorygma*, $PM_{2.5}$ = VPoor	0.028
Dirinaria	7	Genera = *Dirinaria*, SO_2 = ExPoor	0.053
Lecanora	11	Genera = *Lecanora*, SO_2 = ExPoor	0.069
Parmotrema	15	Genera = *Parmotrema*, $PM_{2.5}$ = Poor	0.066
		Genera = *Parmotrema*, PM_{10} = Good	0.066
		Genera = *Parmotrema*, NO_2 = ExPoor	0.066
Physcia	39	Genera = *Physcia*, SO_2 = ExPoor	0.233
Pyxine	31	Genera = *Pyxine*, SO_2 = ExPoor	0.196

those rules with a lift above 1.1, 17 rules were found (Table 8). Out of the eight lichens highlighted in Table 7, six of the lichens have rules with lift $\geq$1.1.

Pyxine showed a high likelihood of association with Poor $PM_{2.5}$ (Extremely Poor), NO_2 (Good), and PM_{10} (Very – Extremely Poor). *Diorygma* displayed not only a high likelihood association with good $PM_{2.5}$ and PM_{10} conditions but also extremely poor NO_2 conditions. Poor and extremely poor $PM_{2.5}$ and NO_2 respectively were found to be associated with *Parmotrema* occurrence. So also, is the association with good PM_{10} conditions for this Lichen. *Candelaria* showed a high likelihood of association with poor $PM_{2.5}$ and extremely poor NO_2 conditions. For *Lecanora* occurred in high likelihood with poor $PM_{2.5}$ while *Physcia* occurred in high likelihood with good $PM_{2.5}$ and very poor to extremely poor PM_{10}. A lift of 1.19 was recorded for the best rule identified for *Dirinaria* showing that there is a high likelihood of this species occurring in association with very poor $PM_{2.5}$ conditions. The result showed that the PM concentration showed up more often than other air quality parameters in association with the lichen species occurrence.

4. Discussion

4.1. The pattern of air quality

Across the cities, there is a clear indication of poor air quality across the different periods of the day. Average PM and NO_2 concentrations showed variations across periods of the day and in the cities. However, the average SO_2 concentration was consistently high across all periods and cities. This reflects the reality of urban air quality in Sub-Saharan Africa (SSA) attributable to rapid urbanisation, (leading to increasing motorisation–often older vehicles with less efficient technologies), industrialisation, open burning of municipal waste/poor waste management system [37], extensive use of fossil fuels in transport, power generation and domestic sectors, as well as poor enforcement and monitoring framework [38]. The extent of the observed air pollution underscores the health impact of ambient quality in SSA. Recently, WHO [8] reported that 91% of premature deaths due to ambient air quality occur in both cities and rural areas of low and middle-income countries. The observed poor air quality in the urban areas is in line with various studies across the country e.g., Schwela [38], Lawal and Asimiea [39], Aliyu, Botai [40], Aliyu and Botai [41], Obanya, Amaeze [42], Daful, Adewuyi [43].

Table 8
Rules with lift values over 1.1

No.	Rules	Support	Confidence	Coverage	Lift	Count
13	Genera = *Pyxine* => $PM_{2.5}$ = ExPoor	0.07	0.32	0.21	4.48	37
18	Genera = Pyxine => NO_2 = Good	0.07	0.34	0.21	2.78	39
31	Genera = *Diorygma* => $PM_{2.5}$ = Good	0.14	0.68	0.21	2.62	79
5	Genera = *Parmotrema* => $PM_{2.5}$ = Poor	0.07	1.00	0.07	1.98	37
14	Genera = *Candelaria* => $PM_{2.5}$ = Poor	0.07	0.85	0.09	1.69	41
6	Genera = *Parmotrema* => PM_{10} = Good	0.07	1.00	0.07	1.68	37
25	Genera = *Pyxine* => PM_{10} = VPoor	0.06	0.30	0.21	1.53	35
9	Genera = *Lecanora* => $PM_{2.5}$ = Poor	0.05	0.74	0.07	1.47	29
36	Genera = *Physcia* => $PM_{2.5}$ = Good	0.09	0.37	0.23	1.41	48
21	Genera = *Physcia* => PM_{10} = ExPoor	0.04	0.19	0.23	1.39	25
7	Genera = *Parmotrema* => NO_2 = ExPoor	0.07	1.00	0.07	1.29	37
26	Genera = *Physcia* => PM_{10} = VPoor	0.06	0.24	0.23	1.24	32
16	Genera = *Candelaria* => NO_2 = ExPoor	0.08	0.94	0.09	1.21	45
2	Genera = *Dirinaria* => $PM_{2.5}$ = Poor	0.03	0.60	0.05	1.19	18
33	Genera = *Diorygma* => PM_{10} = Good	0.14	0.68	0.21	1.15	79
19	Genera = *Pyxine* => PM_{10} = ExPoor	0.03	0.16	0.21	1.13	18
34	Genera = *Diorygma* => NO_2 = ExPoor	0.18	0.85	0.21	1.11	99

4.1.1. Lichen presence and urban environment

The presence of *Arthonia*, *Chrysothrix*, *Cryptothecia*, *Dirinaria*, *Pyrenula*, *Graphis* and *Pyxine* across the urban environment was in agreement with the findings of Yatawara and Dayananda [44]. They reported the presence of these genera across rural, semi-urban and urban areas of Kegalle Urban Council in Sri Lanka. However, they reported the presence of *Pamotrema* in semi-urban and rural areas, *Physcia* was present in both semi-urban and urban areas, and *Lecanora* only in rural ecosystems all of which we found across the urban environment in Nigeria. Across the four cities, the presence of *Physcia* > *Pyxine* = *Diorygma*. This is contrary to the findings of Yatawara and Dayananda [44] in which *Pyxine* was reported as the most dominant genus in the urban ecosystem. However, across the drier cities (Abuja and Kano) *Pyxine* is the most dominant while the genera *Diorygma, Physcia*, and *Dirinaria* are dominant across the coastal cities of Lagos and Port Harcourt. The low diversity observed could be attributed to the impact of human activities across the urban landscape. There is evidence indicating that an increase in urbanisation, population density, and vehicular movement intensity has a strong influence on lichens species, due to the changes in environmental quality resulting from these [45]. *Physcia*, *Pamotrema*, and *Cryptothecia* were reported in rural areas, *Dirinaria*, *Physcia*, *Pyxine*, and *Pamotrema* in Surburban while *Pamotrema* and *Graphis* were found across the urban area by Lucheta, Mossmann Koch [45] in their study of Sinos River Basin in southern Brazil. In the study by Pinho, Augusto [46] they provided evidence which corroborates the conclusions that local environmental factors are more important for lichen diversity and species across different ecosystems. Thereby, reiterating the relevance of lichen in revealing the local environmental conditions.

4.1.2. Highly supported association and important rules

The highly supported rules indicated that high concentrations of NO_2 and SO_2 are often associated, while a high concentration of $PM_{2.5}$ is often associated with a high concentration of NO_2 and SO_2. This indicates that when one of the three parameters is poor there is very high support for the conclusion that others are also poor. This finding highlights the well-documented association between human activities such as transportation, combustion of various kinds (generating sets, cooking fuels, burning of refuse, etc.) and poor air quality due to the generation of PM, Sulphur, and Nitrogen oxides in the urban environments. This implies that with the measurement of one of these parameters we can imply the concentration of the other.

The screening of the Lichen-Air Quality association rules based on the lift values revealed that seven genera have robust and important rules for the association between lichen and air quality across the selected urban environment. The association rules found for the genera *Pyxine*, *Physcia* and *Lecanora* identified them as tolerant to heavy pollution (PM, SO_2 and NO_2), thus relevant as bio-indicators of poor air quality. This was in agreement with the findings of Conti and Cecchetti [9], Lewis [16], Davies, Bates [21], Yatawara and Dayananda [44], Wolseley and Aguirre-Hudson [47], Gadsdon, Dagley [48], Sujetovienė [49], Manninen [50], Asta, Erhardt [51] which identified them as tolerant to heavy pollution found across heavily disturbed sites e.g., urban centres and roadsides. The genera *Candelaria*, *Diorygma* and *Parmotrema* were also found to be N-tolerant and PM-tolerant, thus indicative of poor air quality. The genus *Dirinaria* was found to be PM-Tolerant. The tolerance of *Dirinaria* to PM pollution was in line with the findings of Chetia, Gogoi [22] in East India. *Candelaria*, *Diorygma* and *Parmotrema* were reported to be N-sensitive by Seed, Wolseley [14] from their survey of the UK. This is contrary to the findings from the current study which indicated that *Diorygma* and *Parmotrema* were found within the heavily NO_2-polluted area while *Dirinaria* was found within poor PM pollution areas of the city. *Candelaria*, *Dirinaria*, and *Parmotrema* were mainly found in Abuja - a city increasingly becoming polluted due to increasing urban population pressure. However, Davies, Bates [21] reported that pronounced NO_2 pollution is identified with a greater presence of *Physcia*, *Candelaria*, and *Lecanora* in London, pointing to their tolerance of ambient N concentration. This was also confirmed for *Physcia* and *Candelaria* in Colombia by Correa-Ochoa, Vélez-Monsalve [52] This contradiction could be attributed to the complexity of the effect of nutrients (N and S) on lichen - nutritious and directly toxic depending on the form and quantity in which they present in the environment [53].

Diorygma was also reported by Seed, Wolseley [14] as N-Sensitive, however, the association found in our study pointed to its presence in heavily polluted areas in the city. However, since the presence of lichens across the current study focussed on lichens on the tree trunk, there is a possibility that the presence of these sensitive Genera in heavily polluted areas is an indication that they were relics of past pollution regime [54].

There is strong support for association rules linking poor PM conditions to poor NO_2 and/or poor SO_2 conditions. And the identification of the high lift rule relating specific lichen to poor PM, NO_2 and SO_2 corroborated the findings of Davies, Bates [21]. They reported that Lichen species found around high PM concentration areas are also associated with high NO_x and SO_2 concentrations.

5. Conclusions

In urban areas across Nigeria, it was shown that the poor condition of any of the air quality parameters is often likely to indicate the poor condition of the others. Across most parts of the cities investigated, air quality is generally poor even across different times of the day. Thus, when recorded PM is poor, the state of SO_2 and NO_2 is likely to be poor as well and vice versa. Lichen-air quality association rules were identified, particularly for poor air quality conditions as observed across the four major cities in Nigeria. Association rules offer a rapid assessment framework that can be used to understand the lichen air quality relationship. These associations can be easily updated as new data is added to the database. The use of lichen especially in low- and middle-income countries where monitoring is sparse when supported by citizen science platforms offers a platform for monitoring air quality in a resource-poor environment. This can provide information for sustainable management of air quality and urban environmental quality in these regions.

The data utilised for this study is limited to four major cities in Nigeria and our sampling was purposive, thus the rules discovered may potentially change if a larger dataset was utilised. However, the rules appeared robust base on the agreement with existing literature. Furthermore, the changes to the confidence, support and lift may change the outcomes of the analyses – leading to more or fewer rules. The selection of the threshold for the current study was implemented to ensure that a smaller set of robust rules were identified. We plan to continue data collection through the engagement of citizen scientists to broaden the coverage of the dataset and the potential rules. Based on the data collated, the association rules found, were more those for poor air quality than otherwise.

Author contribution statement

Olanrewaju Lawal: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Chimezie Jason Ogugbue and Tijjani Sabiu Imam: Analyzed and interpreted the data; Contributed materials, analysis tools or data.

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Data availability statement

Data associated with this study has been deposited at Mendeley Data and Digital Commons Data.

Declaration of interest's statement

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.heliyon.2023.e13073.

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