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Role of urban vegetation in air phytoremediation: differences between scientific research and environmental management perspectives

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Air pollutant removal by urban vegetation is perceived to be a key ecosystem service for mitigating air pollution. However, the effectiveness of air phytoremediation in cities requires more synthesis to inform environmental management. A Bayesian meta-analysis approach was used to quantify the effectiveness of the removal of typical air pollutants—particle matter (PM), nitrogen oxide (NO_x), sulfur dioxide (SO_2) and ozone (O_3)—by synthesizing global field measurement studies. The results revealed that urban vegetation can mitigate the growth of air pollutant concentrations, with reduction rates of 16.5~26.7% for PM, 13.9~36.2% for NO_x, and 20.5~47.8% for SO_2. However, they failed to significantly mitigate ground-level O_3, corresponding to an increase of 5.1~25.9%. The variability in effect sizes was mainly influenced by the distance to nearest highway, ambient concentration, relative humidity, and green coverage. A questionnaire survey conducted in Shenzhen city (China) showed that most environmental managers supposed positive impacts of urban vegetation on all four air pollutants, which was at odds with our findings with respect to O_3. This study can inform the lessening of discrepancies between scientific research and environmental managers' perceptions on how to improve air phytoremediation for urban air pollution mitigation in China and elsewhere.

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INTRODUCTION

Urban air pollution is a global concern droved by excess industrial activity, heavy transportation, and intensive population mobility[1,2]. Primary air pollutants—including particle matter (PM), sulfur dioxide (SO_2), nitrogen oxides (NO_x), and ground-level ozone (O_3)—can have adverse impact on human health, including respiratory and cardiovascular diseases[3–6]. Developing environmental planning and practices that effectively reduce these air pollutants in urban areas has become a priority issue for scientists and policy-makers[7,8]. In recent years, air phytoremediation has been recognized as sustainable and cost-effective approach to mitigate urban air pollution in the urban environment, as solid air pollutants can either deposit on canopy surface, be absorbed through stomata, or dissolve in the wax of the leaves of trees, shrubs and herbaceous vegetation[9–11]. Previous studies have found that the PM concentration under the tree canopy is normally lower than in open urban areas[12–14]. Gaseous pollutants, such as NO_x, O_3, and SO_2 can be absorbed by leaf stomata through gas exchange, the effectiveness of which is influenced by the physiological condition of leaves, as well as the chemical and physical characteristics of air pollutants (e.g., stomatal conductance and diffuse velocity)[15–18].

Although many fumigate and field-survey experiments have confirmed that urban vegetation can reduce air pollutant concentrations[15,19], the overall effectiveness of GI (green infrastructure) remains unclear. This may undermine the integration of nature-based solutions (NbS) for public health into urban planning[20]. Previous studies using aerodynamic modeling suggested that green barriers composed by dense vegetation in deep streets canyons may slow down airflow, inducing higher concentrations of traffic exhausts under the tree canopy[21]. Field measurement studies have compared the concentrations of air pollutants between roads and adjacent greenspaces in Baltimore (USA), Helsinki (Finland) and Yanji (China), but found no significant differences in NO_x and SO_2 concentrations[13,22,23]. The results of the aerodynamic model and the measurement experiments suggest that the net effect of greenspaces on air pollutants reduction may not be significant due to the complexity of the urban atmospheric environment and the structure of greenspaces in different urban areas[24]. Additionally, biogenic volatile organic compounds (BVOC) released by plants under stress conditions can contribute to the photochemical production of O_3 in conjunction with NO_x, leading to elevated O_3 concentrations within the greenspaces compared to other areas[25]. A bibliometric analysis of 143 studies on air phytoremediation found that the majority of these studies focused on the purification effects of a single or only a few pollutants, and had methodological differences[26]. The lacks of standardization in study subjects and research methods make it difficult to arrive at a comprehensive understanding of air phytoremediation, which contributes to the development of an NbS approach based on plant-based air pollution purification[7,26,27]. To address this, more quantitative methods that can integrate evidence across studies are needed.

To bridge this research gap, we evaluated the overall effect of air phytoremediation based on an integrated approach. Based on numerous case studies, we applied a meta-analysis combined with robust statistical tools; we used a rigorous literature eligibility criteria to select high-quality field studies and quantified the uncertainties caused by geographical and environmental differences of studied sites. Then, we used a Bayesian mixed-effect model to synthesize the effects of pollutant reduction by urban vegetation based on the results; the statistical accuracy improved significantly with additional data acquisition, and the uncertainties of effects were quantified by posterior samples[28]. Since urban air

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phytoremediation is widely regarded as a cost-effective and nature-based approach to meeting clean air standards, decision-makers' perceptions of air pollution mitigation from urban vegetation directly influence the developments of policies[7,29]. Therefore, the investigation of their views on the effectivities of air phytoremediation is critical for identifying gaps between scientific knowledge and the assumptions of policy-makers.

The main objects of this study are to quantitatively synthesize the effects of air pollutant reduction by urban vegetation through meta-analysis, and then to analyze the relationships between these reduction effects and potential influencing factors. We focused on four major air pollutants: PM, NO_x, O_3, and SO_2. To highlight gaps between the policy-maker assumptions and scientific understanding with respect to air pollutant removal by urban vegetation, we selected one of the studied cities, Shenzhen, China, to conducted a questionnaire among local environmental managers. Finally, based on the above results, we provide suggestions to link scientific findings based on meta-analysis to the practicality of air pollution mitigation in Shenzhen, highlighting the important role of urban vegetation in NbS for public health.

RESULTS

The impacts of urban vegetation on air pollutants
The pooled effect size (natural log of response ratio, LRR) of the reduction effectiveness by urban vegetation of the four air pollutants were estimated using a Bayesian random-effect model. All point estimation (mean value) and interval estimation of parameters with 95% credible interval (CrI) were calculated based on the posterior samples drawn from the Bayesian model. When the 95% CrI was completely on one side of 0, it could be inferred that the vegetation had a significant effect on the concentration of air pollutants (i.e., the probability of increasing concentration or reducing concentration is higher than 95%). The pooled effect size indicated that urban vegetation significantly reduced the concentrations of PM, NO_x, and SO_2 by -21.3%, -25.9%, and -34.9%, respectively. However, urban vegetation was found to have a positive effect on O_3 concentration, causing it to be 15.0% higher over greenspaces than over non-greenspaces. The results of the meta-analysis also showed that the probability of reductions in the concentration of PM, SO_2, and NO_x by urban vegetation was higher than 95% (Fig. 1).
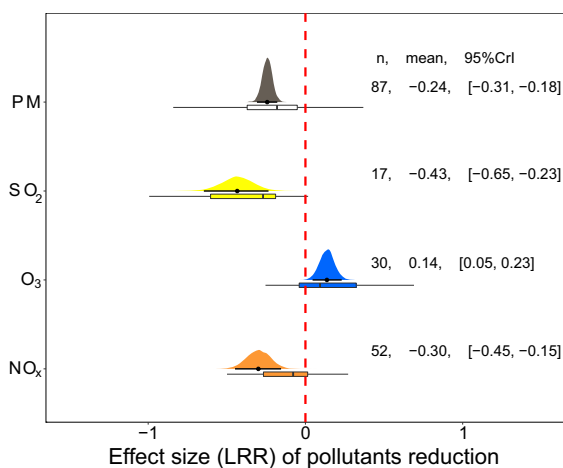

Fig. 1 The pooled effect size of four air pollutants. Effect size was represented by 95% Bayesian credible interval and mean value. The boxplot under the ridges show the distribution of observed effect sizes.

In general, we found that urban vegetation did not always successfully reduce the concentrations of air pollutants in adjacent areas. We did not find that urban vegetation can significantly reduce the concentration of ground-level O_3. In contrast, the concentration of O_3 increased by 5.1~25.9% in the urban greenspaces compared to control sites.

Factors influencing the air phytoremediation
The results of the subgroup meta-analysis indicate that the effectiveness of reducing air pollutants through urban vegetation is contingent upon the distribution pattern of the sampling points (Fig. 2a). Significances were found in the reduction of NO_x, SO_2, and PM. Specifically, urban vegetation showed a greater reduction effect on PM in the sub-point group (-30.2%) as compared to the separate point group (-13.9%). However, urban vegetation had a negative impact on O_3 concentration in the separate point group (32.3%), with no significant effect observed in the sub-point group (-1.0%). With respect to mitigating NO_x concentration, urban vegetation was effective in the separate point group (-54.2%), yet no significant trend was observed in the sub-point group (-7.7%).

The efficiencies of urban vegetation in reducing SO_2 and NO_x concentrations decreased during the winter or autumn seasons. Specifically, the reduction efficiency of NO_x during winter or autumn is significantly lower than that during the summer or spring. (Fig. 2b). Urban vegetation increases O_3 concentration by 11.6% during the summer or spring but no significant change in O_3 concentration was found during winter or autumn. The results also indicated that the reduction effect of PM was significant in both the summer and winter, but that the difference in terms of reduction effectiveness between the seasons was not significant.

The reduction effectiveness of urban vegetation varied depending on the types of GI (Fig. 2c). All types of greenspaces tend to significantly reduce PM concentration, with significant differences in the reduction effect between forest and small green patches (forest $= -18.1\%$, small patch $= -38.7\%$). In terms of the reduction effectiveness for NO_x, parks, and forests tended to significantly reduce NO_x concentration while roadside trees and small patches showed non-significant reduction effects. For O_3, parks and forests tend to significantly increase concentrations, while the trends of effect size for roadside trees and small patches were not significant. The study also found that only forests had a significant reduction effect for SO_2, while no significant trend was found for roadside trees and small patches.

The subgroup meta-analysis of leaf types revealed that coniferous plants have a greater ability to reduce the concentration of PM, SO_2, and NO_x compared to broad-leaf plants (Fig. 3a). This difference was significant in the reduction effect of NO_x, with coniferous plants reducing concentrations by 56.4%, while broad-leaf plants only reduced concentrations by 3.9%. It is noteworthy that for O_3, coniferous plants may increase concentrations more than broad-leaf plants. However, there was no significant difference in the effect sizes between the two types of plants.

A comparison of deciduous and evergreen species revealed that evergreen species had a greater ability to mitigate PM, SO_2, and NO_x concentrations compared to deciduous species, although the differences were not significant (Fig. 3b). However, evergreen species were found to have a significant effect on increasing O_3 concentrations, differing significantly from the effect of deciduous species (evergreen $= 18.5\%$, deciduous $= -4.9\%$).

Figure 4 illustrates the reduction effect of various families of plants. Through an analysis of the combination of air pollutants, direction of effect size, and family name of species, we identified a total of 52 patterns. The following is a summary of the combination patterns of the top 8 frequencies:
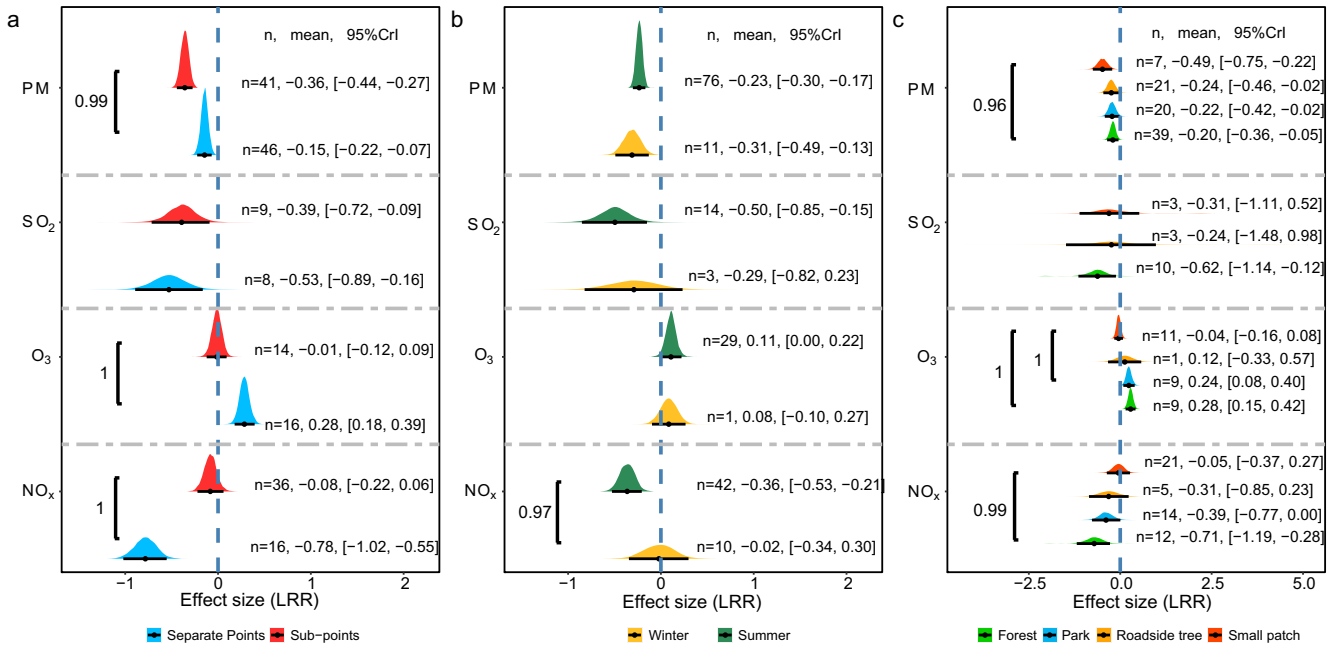
Fig. 2 The effect sizes and their 95% confidence intervals for the distribution pattern of sampling sites, seasons of the year, and types of greenspace. **a** Distribution pattern of sampling sites. **b** Seasons of the year. **c** Types of greenspace. Effect size was represented by 95% Bayesian credible interval and mean value. The posterior probability of difference between two samples greater than 0.95 were displayed.
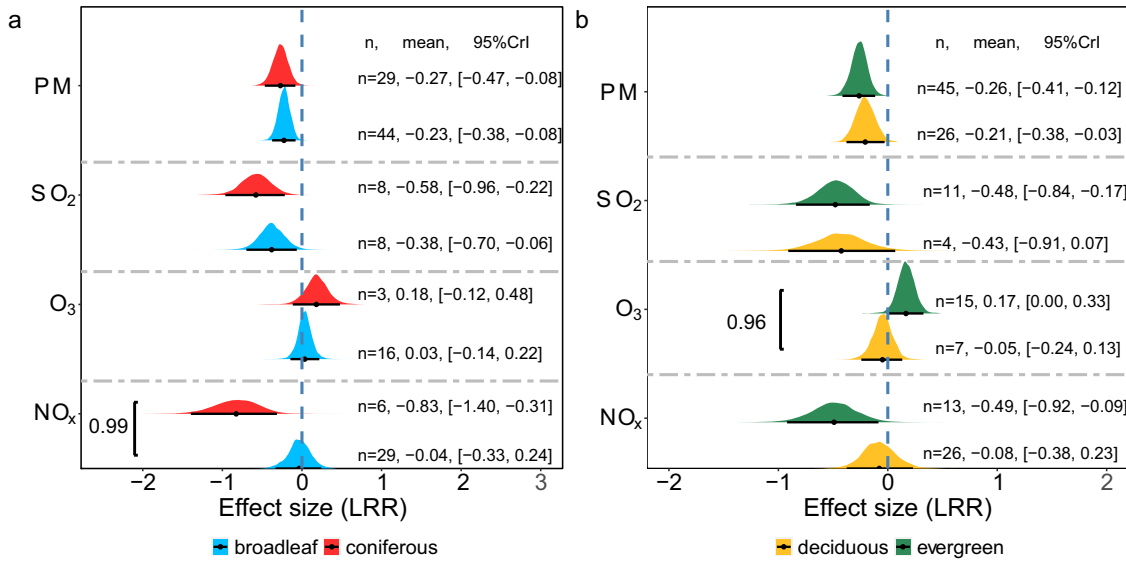

Fig. 3 The effect sizes and their 95% confidence intervals for leaf types and life forms. **a** Leaf types. **b** Life forms. Effect size was represented by 95% Bayesian credible interval and mean value. The posterior probability of difference between two samples greater than 0.95 was displayed.

- Pattern 1 (11.83%) represents the *Pinaceae* family, which has been found to reduce PM concentration.
- Pattern 2 (10.75%) represents other families, which have been observed to reduce NO_x concentration.
- Pattern 3 (7.53%) represents other families, which have been found to reduce PM concentration.
- Pattern 4 (5.91%) represents other families, which have been found to have no effect on reducing O_3 concentration.
- Pattern 5 (3.76%) represents the *Fagaceae* family, which has been found to reduce PM concentration.
- Pattern 6 (3.23%) represents the *Pinaceae* family, which has been found to reduce SO_2 concentration.

- Pattern 7 (3.23%) represents the *Fabaceae* family, which has been found to reduce PM concentration.
- Pattern 8 (3.23%) represents the *Moraceae* family, which has been found to reduce PM concentration.

Our meta-regression found that the effect size for NO_x reduction was negatively correlated with greenspace coverage, air temperature, background concentration, wind speed, and distance to traffic roads, but positively correlated with relative humidity (Fig. 5a–f). A significant trend was found with respect to the slope between effect sizes and background concentration, relative humidity, and distance to traffic roads. The effect
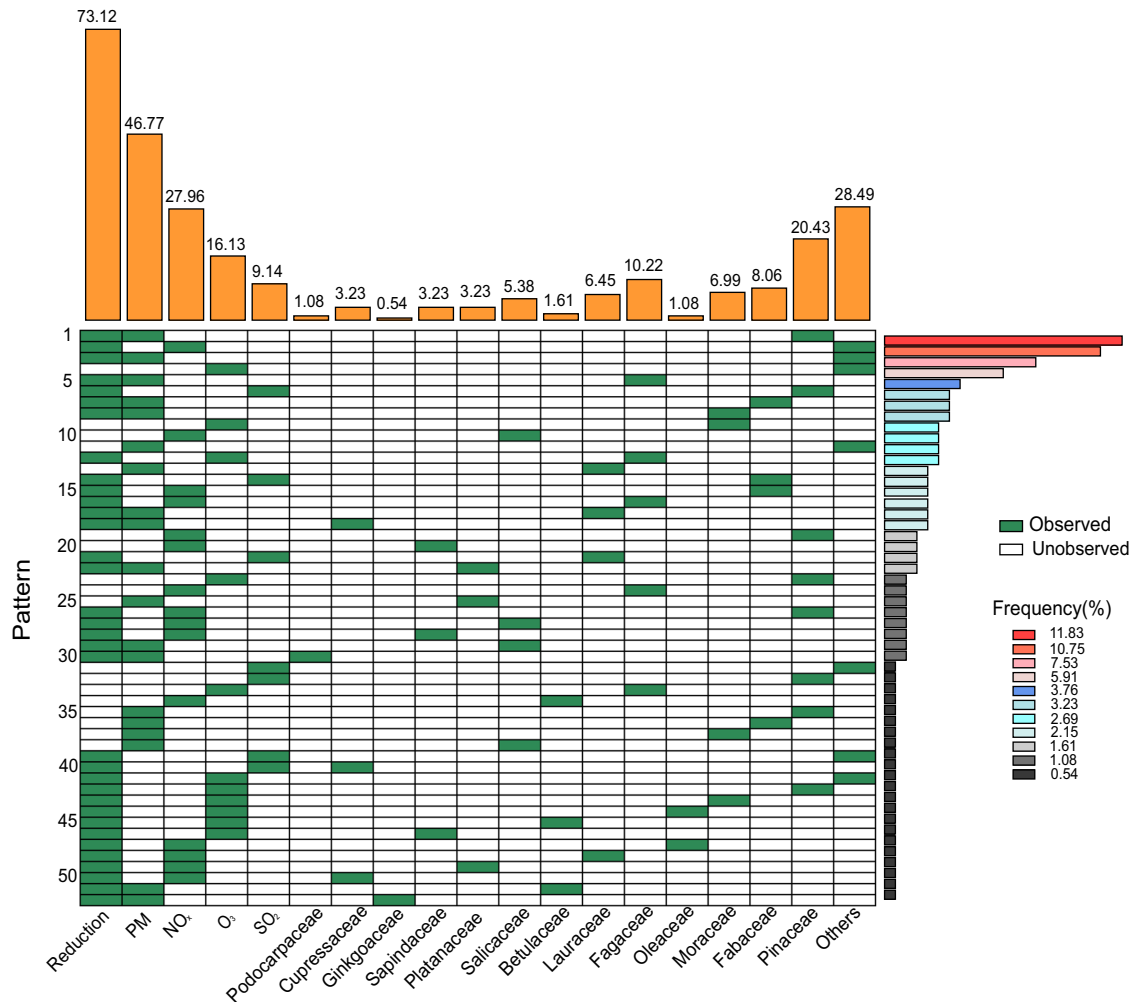
Fig. 4 Summary of the frequency of patterns. Combinations of different variables characterizing air pollutants, reduction effect and vegetation family names in different cases. The central main graph displays the pattern code on the vertical axis and the variable name on the horizontal axis. The green squares indicate that the variable has a value of 1, while the white squares indicate that the variable has a value of 0. For example, a green square for the reduction variable indicates the presence of a reduced concentration (valued as 1), while a white square indicates the absence of a reduction effect (valued as 0). The bars on the right side of the graph are arranged in descending order of the frequency of pattern occurrence. The top bar depicts the frequency of occurrence for each variable. The frequency is displayed in percentage).

size for O_3 was positively correlated with distance to traffic roads, relative humidity, greenspace coverage, and air temperature, but negatively correlated with background concentration and wind speed (Fig. 5g–l). The posterior probabilities indicated that only the slopes of distance to traffic roads, greenspace coverage, and air temperature were significant. The effect size for SO_2 was negatively correlated with greenspace coverage, wind speed, and air temperature, but positively correlated with relative humidity, background concentration, and distance to traffic roads (Fig. 5m–r). A significant trend was found for the slope between effect sizes and relative humidity for SO_2. The effect size for PM was negatively correlated with distance to traffic road, greenspace coverage, relative humidity, and background concentration of PM, but positively correlated with air temperature and wind speed (Fig. 5s–x). A significant trend was found for the slope between effect sizes and background concentrations. In conclusion, all 6 categories identified in the meta-regression analysis were found to be correlated with the effect size of air pollutant reduction. However, it is noteworthy that the direction and degree of significance with respect to the four pollutants varied.

Environmental managers' perceptions on air phytoremediation

Through a citywide survey of Shenzhen, feedback from 458 questionnaires was received, although the responses of 137 participations were excluded from the final summary due to their undefined certificates of employment with Shenzhen Municipal Bureau Ecology and Environment (SMBEE). Therefore, 321 effective questionnaires were collected for the final analysis. The feedback showed that there were large differences in the scientific understanding (as indicated by our meta-analysis) of air phytoremediation and the perceptions of most environmental managers (Fig. 6a). More than half of respondents accepted that urban vegetation has a dust retention function that reduces $PM_{2.5}$ (Fig. 6a). Additionally, 46.73% and 42.06% of respondents believed that urban vegetation mitigates the concentrations of SO_2 and NO_x, respectively. However, most managers also believed that urban vegetation has a positive effect on mitigating ground-level O_3 (Fig. 6a), which may indicate their neglect of the contributions of BVOC in ground-level O_3 formation.

The perception gap was found by comparing the results of the meta-analysis with those of the questionnaire (Fig. 6b). Based on
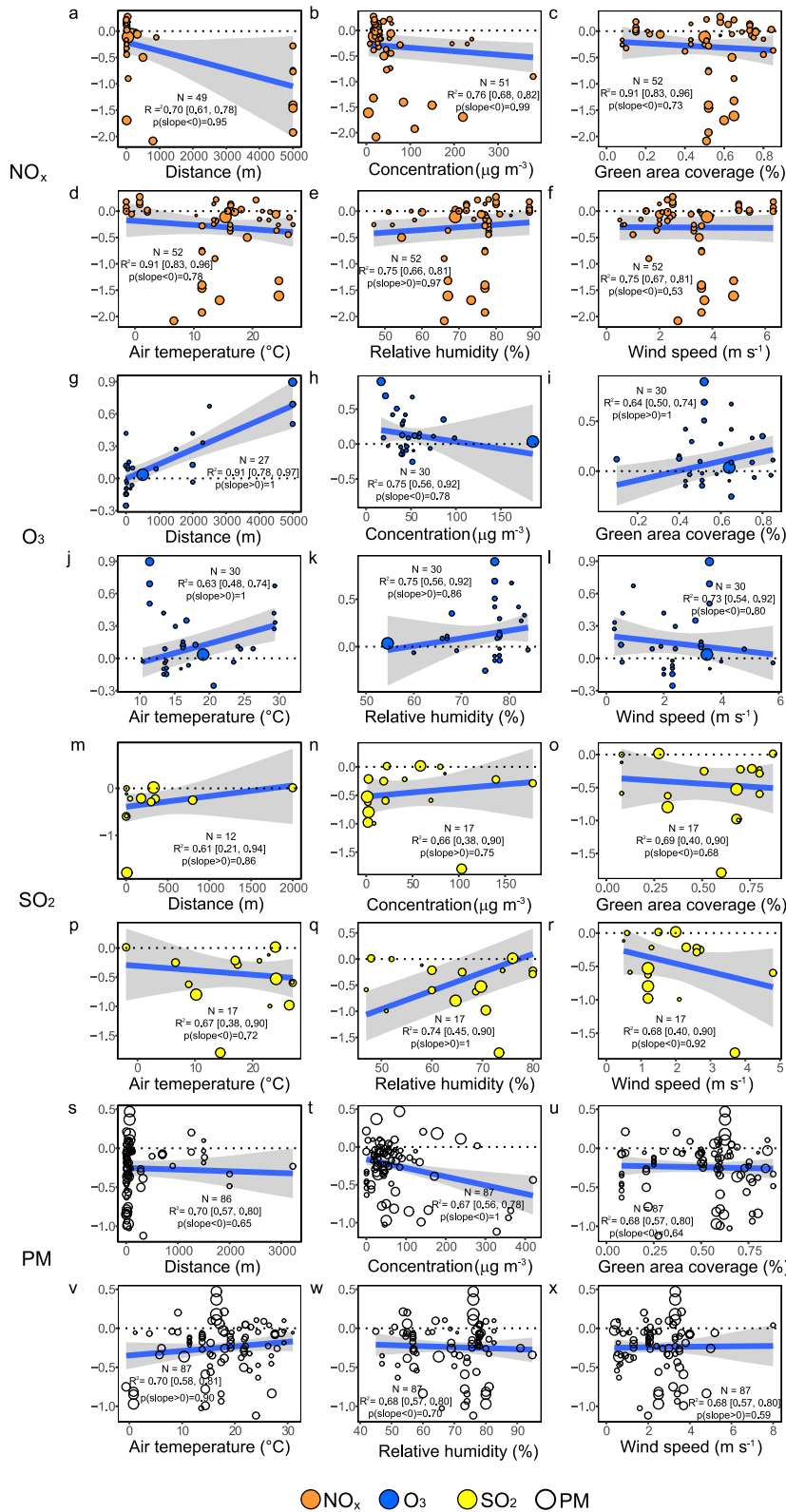
Fig. 5 The relationships between the effect sizes of the four types of air pollutants and environmental and meteorological factors. **a**, **g**, **m**, **s** distance to traffic sources. **b**, **h**, **n**, **t** air pollutants' background concentration. **c**, **i**, **o**, **u** greenspace coverage of sampling site. **d**, **j**, **p**, **v** air temperature, **e**, **k**, **q**, **w** relative humidity. **f**, **i**, **r**, **x** wind speed. The circles represent the calculated effect size of each extracted measurement and the size of the circle is proportional to the standard error of the effect size. The shaded area around the fitted line represents the 95% confidence interval. The text describes the number of observations (N), Bayesian R^2, 95% confidence interval of R^2, and the posterior probability of the slope <0 or >0. **a–f** refer to NO_x, **g–l** for O_3, **m–r** for SO_2, and **s–x** for PM).
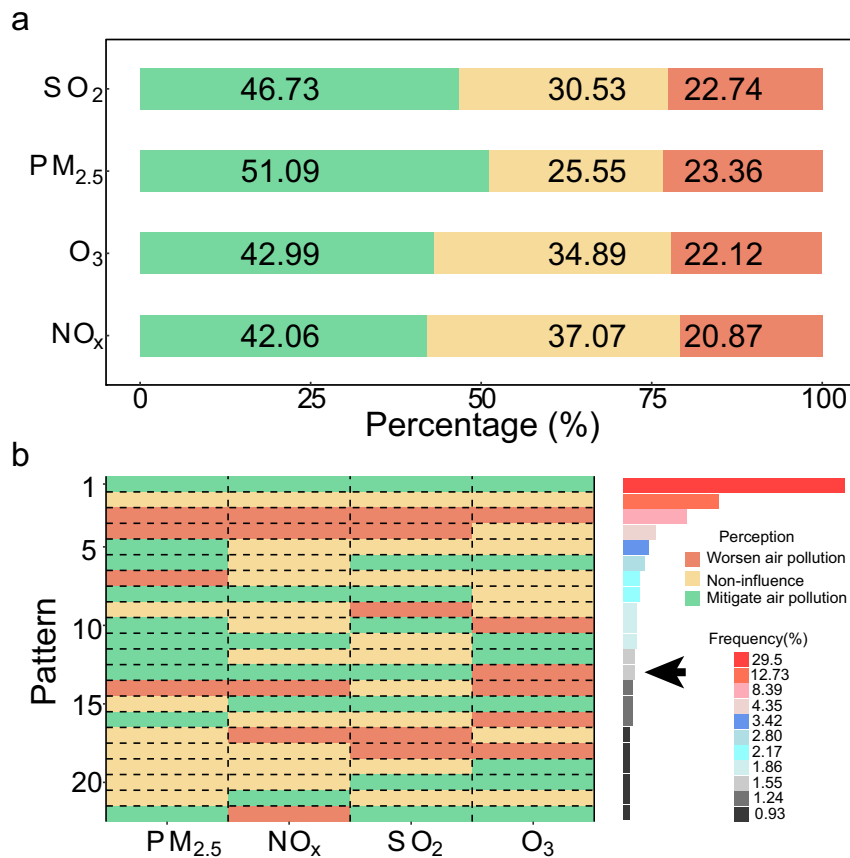
Fig. 6 The perspectives of urban environmental managers on air phytoremediation in Shenzhen. a Summary of the urban environmental manager's perception on air phytoremediation in Shenzhen. b Summary of the frequency of combination of urban environmental manager's perspectives. The main graph displays the pattern code on the vertical axis and the pollutant name on the horizontal axis. The green squares indicate that the perception 'mitigate air pollution', orange squares indicate that the perception 'non-influence', red squares indicate that the perception 'worsen air pollution'. The bars on the right side of the graph are arranged in descending order of the frequency of combination occurrence (displayed in percentage). The combination that is consistent with the results of meta-analysis indicated by an arrow. For concision, only combinations with frequency in the top 50% are displayed).

the frequency of the combination of response results, 29.50% (Pattern NO. 1) of respondents believed that urban vegetation has a mitigating effect on the concentration of all four pollutants, while only 1.55% of respondents held the views consistent with the meta-analysis results (Pattern NO. 13). Therefore, there was an obvious discrepancy between the opinions of environmental managers and the consensus of relevant scientific studies. Based on these findings, we can conclude that the effects of urban vegetation on air pollutants removal—are positive for PM, NO_x and SO_2, but negative for O_3, which were not fully recognized by most environmental managers.

DISCUSSION
This meta-analysis revealed differences in the impacts of urban vegetation on air pollutant removal, showing that it significantly reduces the concentrations of NO_x, SO_2, and PM in surrounding greenspaces, but—perhaps unexpectedly—increases the concentration of O_3 (Fig. 1). These results show that O_3 concentrations over greenspaces were significantly higher than those over open areas, and were consistent with the results of previous studies based on field measurement[30–32].

The cases included in the meta-analysis are all based on measurements of pollutant concentrations. These cases represent the net effect of pollutant deposition and production in urban

greenspaces. Therefore, the results of this study may not be consistent with studies focusing on model-based estimation or field measurements of deposition. In fact, the use of different methods in the same area may yield significantly different results. For example, a model-based study estimated that trees and forests in the conterminous United States could remove 14,330,000 tons of O_3 from the atmosphere every year based on a deposition model[33]. However, a study that combined a LUR (land use regression) model with field measurements found higher O_3 concentrations in parks compared to those in surrounding areas in Los Angeles[25]. The increase in O_3 concentrations in urban greenspaces may be related to the photochemical pathway of O_3 production[34,35]. A number of studies have found that plants release BVOC under stressful conditions in interaction with NO_x, which together precipitate O_3 production[34,36]. This effect can cause urban greenspaces in some areas to have elevated surrounding O_3 concentrations. Therefore, the results of this study reflect a net effect of urban greenspaces, between O_3 pollution mitigation and BVOC-mediated O_3 production. This does not conflict with previous model-based or measured deposition studies. We also note that our results differ from those of earlier studies based on field concentration measurements, as they found significantly lower O_3 concentrations within the canopy than outside the canopy in adjacent areas based on gas concentration measurement experiments[13,37].

Table 1. Summary table for factors that influence the effect size of air pollutant reduction by urban vegetation.

Types of influence factors		PM	SO$_2$	O$_3$	NO$_x$
Environmental factors	Distance to sources	↓	↑	↑*	↓*
	Background concentration	↓*	↑	↓	↓*
Meteorological conditions	Air temperature	↑	↓	↑*	↓
	Relative humidity	↓	↑*	↑	↑*
	Wind speed	↑	↓	↓	↓
Vegetation factors	Green area coverage	↓	↓	↑*	↓
	Types of green area	F > S	Non sig.	F > S, P > S	S > F
	Season of year	Non sig.	Non sig.	Non sig.	W > S
	Leaf types	Non sig.	Non sig.	Non sig.	B > C
	Life forms	Non sig.	Non sig.	E > D	Non sig.

For continuous variables, the trend of influence factors is marked by arrows; the down arrow (↓) indicates that the factor is negatively correlated with the effect size; the up arrow (↑) indicates that the factor is positively correlated with the effect size; the significance level p (slope > 0) >0.95 or p (slope < 0) >0.95) is indicated by asterisks. For category variables, significant differences of effect size are marked by an unequal sign.
F forest, *S* small patch green area, *P* park, *W* Winter or Autumn, *S* Spring or Summer, *C* coniferous species, *B* broad-leaf species, *D* deciduous species, *E* evergreen species, *Non sig.* no significant differences.

We suggest that this variability occurs due to NO$_2$ production by the oxidation reaction of soil-source NO and O$_3$, which depletes the O$_3$ beneath the canopy, indirectly causing lower O$_3$ concentrations[38]. In addition, most of the studied cases involved with O$_3$ had effect size significantly larger than zero (Supplementary Fig. 7), as based on Bayesian mixed-effect model. This suggests that more studies support the observation in increasing O$_3$ concentrations caused by urban greenspaces.

Interestingly, we also found significant differences in the effect sizes of air pollutants reduction under different patterns of sampling points (Fig. 2a). For the result of the reduction effect of NO$_x$ by vegetation, we found that NO$_x$-related pollution can be mitigated by urban greenspace. However, the reduction effect is not significant when the distribution of sampling points was based on a sub-point pattern, which can be explained by the environmental characteristics of these sampling points. In these studies, most sampling points were set in the green belt adjacent to highways and the configuration of greenbelts is generally composed of dense shrubs or small trees. Based on the result of some aerodynamic experiments, these dense greenbelts may obstruct wind flow and increase the concentration of NO$_x$ below tree canopies[39,40]. On the other hand, some studies suggested that NO emission from soil may lead to increased concentration of NO$_2$ under tree canopies due to the denitrification effect of soil bacteria and because NO in the air is rapidly oxidized by O$_3$ to produce NO$_2$[23,37]. In general, these two factors could be partly explained by the fact that urban vegetation could not reduce the concentration of NO$_x$ in studies with a sub-point distribution pattern.

It is worth noting that our meta-analysis found that the O$_3$ concentration may decrease over greenspace when the study was designed based on a sub-point distribution pattern. The low O$_3$ concentration below the tree canopies could be explained by two factors. Firstly, most sub-point pattern studies measured the O$_3$ concentration under dense tree canopies, which may lead to decreased solar radiation and temperature; photochemical formation of O$_3$ is suppressed under these conditions[13]. Secondly, the photochemical formation of O$_3$ is also influenced by the concentration of NO$_x$. At low concentrations, NO$_x$ is a precursor to O$_3$ formation, however, at higher concentrations, NO$_x$ catalyzes O$_3$ destruction, which leads to decreased O$_3$ concentration[34,35]. Interestingly, we found that most studies based on sub-point pattern were conducted adjacent to roads. Therefore, the lower O$_3$ concentration in these studies could be due to the massive NO$_x$ from traffic exhaust, leading to the destruction of O$_3$.

The PM reduction effect size based on separate point pattern is significantly higher than the PM reduction effect size based on sub-point pattern. This result could be explained by the heterogeneity of meteorological conditions, and pollutant concentration may introduce more variation in the measurement results[41,42], leading to a higher estimated effect size compared to the result of studies based on a sub-point distribution pattern.

Using subgroup meta-analysis and meta-regression analysis (Figs. 1–5), we found that there were three types of influencing factors impacting air phytoremediation: (1) Environmental factors: such as distance to the pollutant sources, background concentrations of air pollutants, and characteristics of air pollutants. (2) Meteorological conditions: air temperature, relative humidity, and wind speed. (3) Vegetation factors: greenspace coverage, types of greenspace, season of year, leaf types, life forms (Table 1).

The effectiveness air phytoremediation is influenced by a variety of environmental factors (Table 1, Fig. 5), which mainly affect the dispersion and deposition of air pollutants. Dispersion of air pollutants at the local scale relies on the fluid dynamics of air flows around obstacles, which often displays a dilution effect of concentration of air pollutants[43]. For NO$_x$ and PM, which are primarily emitted from traffic-related sources, our meta-regression found a negative correlation between the effect size of concentration and the distance from nearest road (Fig. 5a, s). This negative correlation indicated that the concentration of pollutants is lower in greenspaces far from traffic-related sources, which can be explained by the dilution effect[44].

Interestingly, in contrast to NO$_x$ and PM, positive correlations between traffic sources distance and the effect sizes of O$_3$ and SO$_2$ were found (Fig. 5g, m). The positive correlation of O$_3$ could be explained by the following reason. As mentioned earlier, BVOC emitted from vegetation may induce the formation of O$_3$ by photochemical reaction. The sample sites far away from the traffic sources included in the meta-regression were primarily located in greenspace with large coverage and dense canopies, such as urban parks and suburban forests. Higher concentrations of BVOC in these area were observed by some studies, which may have induced more O$_3$ from photochemical reaction[31,36,45]. For SO$_2$, we also observed a non-significant correlation between distance to traffic sources and effect size. We believe that the reason for this non-significant correlation could be explained by the limitation of study cases. Among our 17 study cases, only two were conducted in greenspace near SO$_2$ emission sources (thermal power plants and steel plants), while most cases were conducted near roads.

Therefore, the vegetation in these greenspaces were likely only lightly affected by SO_2 sources, leading to a non-significant trend.

Foliar deposition of air pollutants is a major process for air pollutant purification by urban vegetation[43,46]. This is because most vegetation has large surface area-per-unit volume compared to smooth manufactured surfaces such as those found on buildings and roads[47]. In the process of foliar deposition, the concentration of air pollutants is an important factor in determining the total amount of deposition. Our meta-regression observed that the reduction effectiveness of urban vegetation for NO_x, O_3, and PM increased with increasing background concentration of these air pollutants (Fig. 5b, h, t), which indicate that foliar deposition may contribute to the purification of air pollutants by vegetation.

The subgroup meta-analysis revealed that the types of greenspace have major impacts on reduction effectiveness (Fig. 2c, Table 1). Extensive GI such as suburban forests and urban parks have a better reduction effect on NO_x and SO_2, which is consistent with previous studies[48–50]. One reason for this is that large greenspaces generally boast larger foliar area and long dispersion distances, thus increasing the purification effect[51]. However, we found that the reduction effect of PM in forests was significantly lower than the reduction effect of PM in small green patches. This could be explained by the aerodynamic effects of vegetation canopy. The studies of forest greenspaces included in the meta-analysis were of mature secondary forests with dense canopy structure. Previous aerodynamic studies and measurement studies indicated that dense canopy may obstruct the velocity of local wind flow, resulting in higher PM concentration under tree canopy, which is not beneficial for net PM purification[39,52].

Compared with roadside trees and small green patches, urban parks, and suburban forests significantly increased O_3 concentrations, and the effect size of O_3 concentration was positively correlated with greenspace coverage (Fig. 2c, Fig. 5i). This result was consistent with previous studies conducted in suburban areas[32,53,54]. However, caution should nonetheless be taken: the observation numbers of effect size for roadside trees ($n = 1$) was small, and although the Bayesian model yielded convergent results, there may still be a problem of insufficient representation, and more observations should be used to confirm results. Our meta-regression found that negative correlations can be observed between the effect sizes of pollutant (NO_x, SO_2, PM) concentrations and greenspace coverage (Fig. 5c, o, u), which indicates that increasing the area of urban nature may have positive impacts on air pollutant reduction.

Our analysis of the effects of leaf types and life forms on air phytoremediation showed that coniferous and evergreen species exhibit a greater reduction effect on PM, SO_2, and NO_x concentration compared to broad-leaf and deciduous species (Fig. 2). Coniferous species are primarily found in the *Pinaceae* and *Cupressaceae* families. These species have narrow leaves and a larger surface area-per-unit area[55]. As a result, the area for absorption and deposition into the leaves is larger, resulting in a higher mitigation capacity[43]. Furthermore, evergreen species have more absorption and deposition time due to leaves presenting in the canopy throughout all seasons compared to deciduous species[10,43]. However, it should be noted that coniferous and evergreens species have been found to increase O_3 concentration in our result, which may be attributable to the fact that these species tend to have dense canopies and a higher emission rate of BVOC, leading to more O_3 generated by photochemical pathways accumulating under the canopy (Supplementary Table 2). Our analysis of species taxonomy reveals that the *Pinaceae* family has the highest frequency of occurrence (Fig. 4), with the exception of plants with unidentified species names. Studies has demonstrated that the *Pinaceae* family has a purification effect on PM and SO_2[10,56]. However, there are also studies that suggested that the *Pinaceae* family may increase the

concentration of O_3[32]. This suggests that although *Pinaceae* plants are beneficial for afforestation, they must be carefully considered in greenspaces planning to ensure a balance between ecosystem services and disservices.

The impacts of meteorological factors (air temperature, relative humidity, wind speed) on the air phytoremediation effectiveness of four air pollutants are complex. We found that there was a significant positive correlation between the effect sizes of O_3 concentration and air temperature (Fig. 5j), indicating higher O_3 concentration was found over greenspaces compared to non-green areas. A possible explanation for this positive correlation is that the amount of BVOC emitted from vegetation increases when temperature and solar radiation increase, which may lead to an increased concentration of O_3 produced by photochemical reactions[35]. For NO_x and SO_2, meta-regression revealed that relative humidity was significantly positively correlated with effect size of concentration (Fig. 5k, q), indicating the reduction effectiveness of these two air pollutants decreased under high humidity. One reason for this phenomenon may be related to the water solubility of NO_x and SO_2. Under high humidity conditions, this may reduce the atmospheric concentration of gaseous NO_x and SO_2 and cause them to be deposited as hydrated ions[57]. Moreover, most cases were conducted during the highly humid conditions of summer and the background concentrations of NO_x and SO_2 were correspondingly low. Therefore, these two reasons may contribute to the reduction of foliar deposition, leading to a positive correlation between relative humidity and effect size. We did not observe a significant correlation between wind speed and the concentration effect size for the four air pollutants. This non-significant correlation may be explained by the experiment protocol of these studies. To avoid the influence of high winds, most studies were conducted in low wind speed conditions.

By comparing the results of the meta-analysis with those of questionnaire in Shenzhen, we found that environmental managers didn't realize that urban vegetation may induce the formation of O_3 (Fig. 6). This perception gap can be explained by the following reasons. Compared to the environmental monitoring of $PM_{2.5}$, SO_2, and NO_x, the relevant environmental protection department in China started to monitor ground-level O_3 only in recent years, leading to an insufficient understanding of the drivers of O_3 pollution[58]. At the same time, there have been few studies related to O_3 caused by vegetation BVOC, compared to those focused on the dust retention effect and stomatal absorption of gaseous pollutants[59,60].

We believe that understanding the interactions between urban vegetation and air pollution should be enhanced in environmental management. Gaps between science and management perception may influence sustainable urban planning and weaken the air purification benefits provided by GI. Across the world, departments in urban management have begun to prioritize vegetation growth rate and the decorativeness of landscapes[7]. However, ecological criteria such as the ability to absorb air pollutants, the emission rate of BVOC, and canopy size remain lacking as guides to urban planning. For example, species of urban trees were dominated by *Populus tomentosa*, *Sophora janonica*, *Salix babylonica* and *Pinaceae* family due to the demand for rapid greening in many Chinese cities (Supplementary Table 2). Although these trees have rapid growth rates and drought resistance, many studies have found that the BVOC emission rate of *Populus* trees and *Sophora* trees were high[7,45]. A study conducted in Beijing found that the urban core of Beijing is a hotspot of BVOC emissions due to the high greenspace ratio and emissions intensity, indirectly causing ground-level O_3 pollution[45]. In addition, traditional garden landscaping focused on esthetics often exacerbate negative environmental effects such as the obstruction of airflow caused by dense vegetation. A study conducted in Shenzhen's urban forest parks revealed that the O_3 concentration in the forests was significantly higher than that in

nearby commercial and residential areas with lower greenspace coverage[30]. This may be explained by the decreased velocity of airflow in the forest due to the obstruction effect of dense vegetation canopy, leading to the accumulations of BVOC and O_3.

It is necessary to improve our understanding of the relationships between urban greening and air pollution control to improve policy and planning[27,61]. Every coin has two sides, and we found both positive and negative impacts of urban vegetation on air pollution—and this should be considered when it comes to adopting NbS in cities for air quality. The results of our study can serve as a foundation for urban environment management, providing useful information for environmental managers to optimize air pollution mitigation by through a NbS. Based on our analytical results, policy and planning suggestions are as follows:

1. Although urban vegetation plays an important role in atmospheric NO_x, SO_2, and PM removal in urban areas, its potential contribution to ground-level O_3 pollution should not be ignored. Optimization of tree species selection should be considered in urban planning and greening. Avoid selecting plants with a high BVOC emission rate in urban greenery (Supplementary Table 2) appears to be a feasible way to mitigate BVOC emissions and reduce potential O_3 production through photochemical reaction with proper ratios between VOCs and NO_x[7,8,36]. Optimally, in urban areas, controlling both the emission sources of BVOC and transport NO_x can more effectively minimize O_3 production[34], since O_3 pollution gradually becomes the main air pollutant in megacities with high greenspace coverage, including in Shenzhen[31,54,62].

2. In cities, roadside vegetation may induce the increase of air pollutants due to high planting density[21,63]. In order to achieve air pollution mitigation through a NbS approaches, spatial configuration and the aerodynamic effect of greenspaces (e.g., canopy structure, planting density, planting distance, shape of street canyon) should be considered in urban planning. For example, dense green lanes and street trees should be avoided in narrow streets, because vegetation canopy may trap traffic emissions[21]. On the other hand, the leaf types and leaf surface functional traits of the plant also require attention. For example, cuticle thickness, chemical composition of the cuticle, stomata density, and trichomes density can affect the adsorption capacities of pollutants such as PM[11]. Therefore, when selecting plants for air phytoremediation, management approaches should consider the functional traits of the plants and the structure of the plant canopy to optimize the spatial structure of the forest and the configuration of air phytoremediation species in order to achieve better air quality[48].

3. The case study in Shenzhen showed that there are gaps between scientific understanding and the perception of environmental managers with respect to urban vegetation and O_3 pollution. This gap also occurs in other cities in China and across the world[8]. Therefore, environmental managers need to enhance their understanding of the latest scientific findings and strengthen cooperation with relevant scientific research departments through various avenues. For example, relevant environmental managers can collaborate with research institutions to share the latest management practices and research findings during government-university project cooperation[64], aiming to reduce the perceived disparities between managers and researchers. Furthermore, researchers can actively disseminate the latest academic findings through public lectures and social media, in order to advance public and professional understanding.

Undeniably, there this study faced several limitations. Firstly, the publication bias was assessed using contour-enhanced funnel plots and an asymmetric test (Egger's test, Supplementary Fig. 3, Supplementary Fig. 4). We didn't observe significant asymmetry in the funnel plots for SO_2 and O_3 (Supplementary Fig. 3). However, significant asymmetry was detected for PM and NO_x effect sizes (Supplementary Fig. 4). We used trim and fill method to analyze the sensitivity of results, potentially influenced by 'missing' studies. The differences between the adjusted pooled effect size and the original effect size were non-significant. We also re-assessed the asymmetry of the funnel plot for the mix-effect model and did not find significant asymmetry (Supplementary Fig. 4). This suggests that the asymmetry of the original funnel plot could be explained by differences between study heterogeneity and potential influencing factors[65].

Secondly, in our meta-analysis, the pooled effect size of the reduction effects for three air pollutants by urban vegetation was estimated based on the Bayesian method. However, the precision and reliability of estimation by the Bayesian model decrease if prior information is insufficient[66]. We applied the leave-one-out validation method to assess the sensitivity of the pooled effect size estimated by the model (Supplementary Fig. 5). The mean value of the pooled effect size did not substantially change by omitting a single study. However, the width of the 95% credible interval increased when some studies were omitted. We believe this decrease in predicted precision may be due to a lack of measurement data. By adding more data, the reliability and robustness of our Bayesian model would likely increase and the precision of the 95% confidence interval would also improve.

Last but not least, the questionnaire focused on environmental managers' perceptions of air phytoremediation was only conducted in one of the case study cities, and the feedback merely reflected the management options available in Shenzhen. In the future, such investigations should be carried out in more studied cities to obtain more representative feedback that can reveal general perceptional gaps between scientific findings and management perceptions.

Aforementioned limitations should not cause large bias in the findings. The applied meta-analysis focuses on integrating the results from numerous field research and can reveal relevant factors influencing air phytoremediation by urban vegetation. The findings also can provide scientific insights into urban air pollution mitigation using NbS approaches. Additionally, this study compared the results from meta-analysis with the perspectives of urban environmental managers, revealing potentially crucial discrepancies between science and practice. From the perspectives of environmental management, scientific finding can be better integrated into practical management for better human well-being improvement.

METHODS
Research questions
The studies used for the meta-analysis included in situ experiments of the monitoring of air pollutant concentrations and their differences between greenspaces and open areas[13]. We selected case studies focusing on PM, NO_x, O_3, and SO_2, given their high concentrations in urban areas with adverse impacts on human health[3,4,6]. We only selected those studies conducted by field measurement methods because of their rigor and to ensure a similar scientific hypothesis was proposed across studies; if urban vegetation has a positive impact on air pollution mitigation, the concentrations of specific air pollutants above the greenspaces should be lower than those above the non-green areas. Accordingly, the difference in concentrations of air pollutants over greenspaces and those over non-green areas can be converted to an effect size, which can be used to represent the

reduction efficiency of air pollutants by urban vegetation. In addition, we also investigated the influence of potential mediating factors (e.g., distance to the traffic road, background concentration, meteorological conditions, green coverage, species taxonomy, leaf types, and life forms) on this reduction efficiency by using a Bayesian approach.

Overall, the research questions in this study were: (i) Does urban vegetation effectively reduce four typical air pollutants, and what are the differences among them? (ii) How is the effectiveness of air phytoremediation influenced by environmental, meteorological, and vegetation factors? (iii) How is the effectiveness of air phytoremediation acknowledged by environmental managers?

Meta-analysis

We performed the meta-analysis following the Preferred Reporting Items for Systematic Reviews and meta-Analyses (PRISMA)[67]. We conducted a systematic literature search in the Web of Science (Thompson-ISI, Philadelphia, PA, USA, http://apps.webofknowledge.com) and China National Knowledge Infrastructure (http://www.cnki.net) databases from March to May 2022. The time period of published studies was set from 1 January 1999 to 31 December 2021. We use the advanced search mode supplied by the Web of Science to acquire search records. First, three general search queries were evaluated using combinations of field tags (TS = Topic) and Boolean operators (AND, OR), then, the [AND] operation was used to combine the

search queries to obtain precise search results (Table 2). Query #4 returned 9189 records after the advanced search.

The following criteria were used to determine which studies were included in the meta-analysis.

1. The studies should be conducted based on field measurement methods. Literature reviews, modeling studies, and indoor experiments were excluded.
2. The studies concerning air pollutant concentrations should be included, and those based on sap-flow measurement, dry/wet deposition measurement, and stomatal conductance measurement were excluded.
3. The sampling design of the study should compare the concentrations of air pollutants across different land cover types. For example, the experiment sites were set in large greenspaces (e.g., city parks, residential green areas), and the control sites should be set in open areas with low vegetation coverage (e.g., traffic roads, industrial areas).
4. The studies should contain sufficient sampling points to represent the local concentration of air pollutants; studies with <3 sampling points were excluded.
5. The studies should report the basic characteristics of pollutant concentrations, including mean value, sample size, and standard deviation (standard error), or these values should be calculated from texts, tables, and statistical graphs.

Two authors (Cheng Gong and Chaofan Xian) independently screened the titles and abstracts of studies returned by search query #4 (Table 2). Based on above eligibility criteria, we obtained 56 relevant studies (Fig. 7) with 186 pairs of concentrations for four types of air pollutants, comprising 87 pairs for PM, 52 pairs for NO_x, 30 pairs for ground-level O_3, 17 pairs for SO_2 (Fig. 8a). The concentration data for this study were from 42 cities in 17 countries, with China ($n = 81$) and Finland ($n = 24$) occupying 54.8% of the total dataset (Fig. 8b). The trend in the number of relevant studies published has been going upward; however, the number of studies has decreased in recent years, which is consistent with the finding reported by another recent study[26] (Fig. 8c).

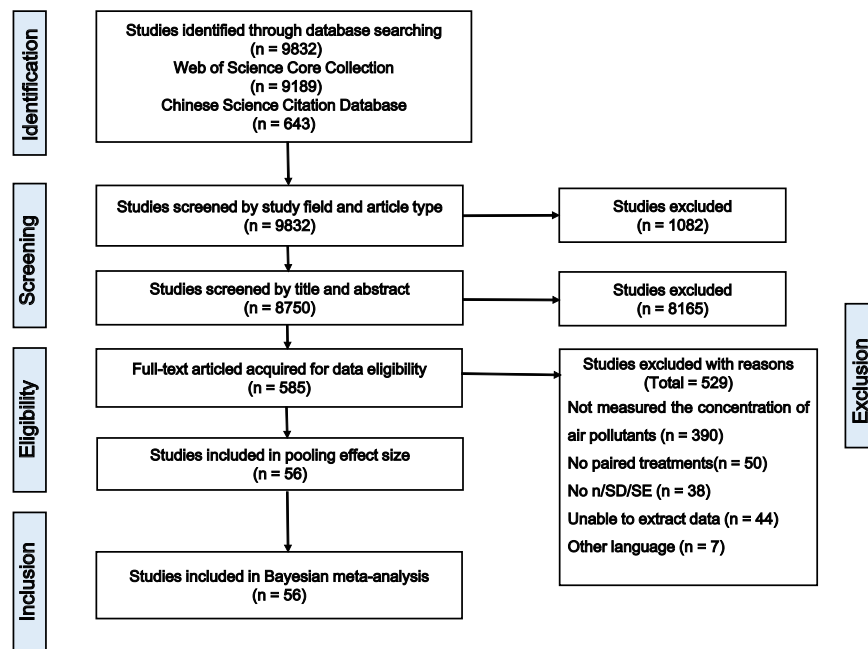| Table 2.	Search query and results.	
Search term	Search query	Hits of records
Query #1	#1: TS = (air pollut*)	1,006,460
Query #2	#2: TS = (urban* OR city)	1,374,054
Query #3	#3: (vegeta* OR tree* OR green infrastructure* OR greenspace*)	2,401,366
Query #4	#1 AND #2 AND #3	9189

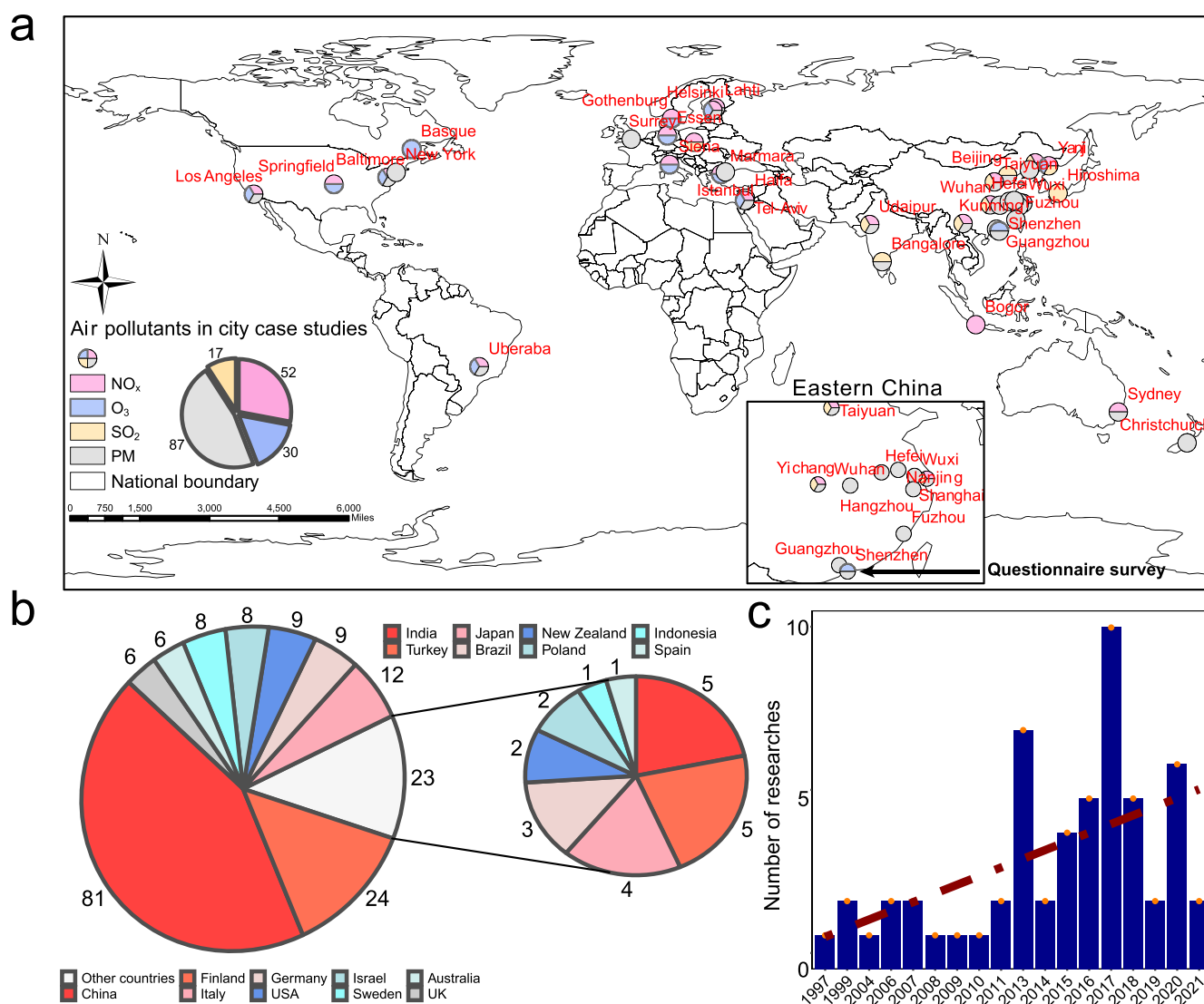**Fig. 7** Flow chart for the selection of eligible studies in the meta-analysis.

Fig. 8 The international distribution of case studies. a The distribution of case studies; the number of effect sizes for each air pollutants are showed in pie chart. The city (Shenzhen, China) in which we conducted a questionnaire of environmental managers is indicated. **b** Numbers of effect sizes per country. **c** The trend by study publication year, with the dashed line and curve indicating the linear fit).

The information for conducting the meta-analysis is shown as follows:

Means, standard deviations (standard errors), and sample sizes. For the studies that only reported quantiles and median values of the pollutant concentrations, we estimated the means and standard deviation of these samples based on the method proposed by Luo et al.[68] and Wan et al.[69]. Then we used software WebPlotDigitizer 4.5 (https://automeris.io/WebPlotDigitizer/) to extract data from statistical graphs.

Space distribution pattern of sampling points. To understand the role of sampling method, we classified the distribution pattern of sampling points into 'sub-point' and 'separated point' categories. For 'sub-point' sampling method, each sampling point consisted of a pair of sub-sampling units; one located in the green area (experiment site) and another placed in an open area (control site) without vegetation cover (Fig. 9a, b). As to the 'separate point' sampling method, no sub-sampling points were deployed and all sampling points were located separately in the study area (Fig. 9c).

These separate sampling points were partly located inside the green areas, and others were located in the non-green areas, such as highways and urban squares.

Distance to the nearest road. The emission of pollutants from traffic-related sources is the main source of atmospheric pollution[50]. Therefore, we extracted information about the distances between the greenspaces and the nearest intercity highways, intra-urban arterials, or intra-urban secondary roads to assess their impacts on pollutant dispersion. This information was taken from each study's methods section or the map of sampling point distribution. Earlier studies without sampling distribution maps were not included in this analysis.

Types and coverage of greenspaces. The air pollution reduction effect of vegetation may be influenced by the types of greenspaces[70,71]. Therefore, we classified greenspaces into four groups: (a) Forest, with the sampling point located in a large forest area in the suburban zones; (b) Park, with the sampling point located in a large urban park or residential green area; (c) Roadside trees, with
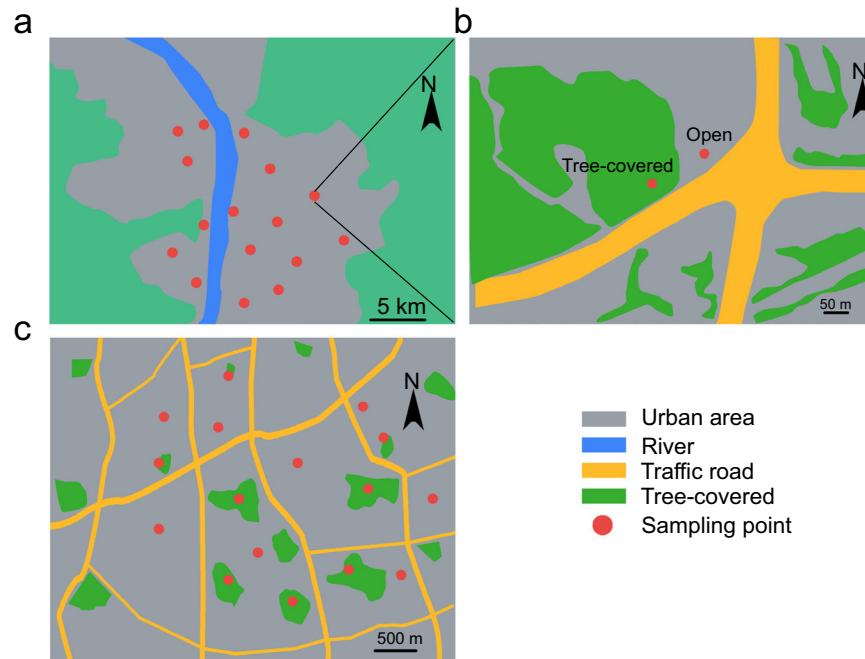
Fig. 9 The distribution patterns of sampling points. a, **b** sub-sampling points pattern, **c** separate sampling points pattern.

studies conducted under tree canopy adjacent to roads; (d) Small green patch, with studies conducted in fragmented and small green patches. The green coverage of each greenspaces was taken from each study's methods section or the map of sampling point distribution.

Meteorological conditions. Gas exchange between vegetation canopy and the atmosphere can be influenced by meteorological condition[16]. Therefore, air temperature, relative humidity, and wind speed during the sampling period were extracted from each study. If these meteorological data were not provided in the study, we obtained them from the meteorological stations nearest to the study area[72].

Background concentration of air pollutants. The data on background concentration for the four pollutants in each study were taken from the studies where available and remote sensing dataset[73,74] for the studies without relevant data. For earlier studies in which it was difficult to obtain background concentrations from the original study and remote sensing products, we used the mean concentrations of pollutants reported in the study to represent it.

Seasons of the year. According to the seasons of the experiments, we divided studies into two categories: one conducted during the spring or summer, and another conducted during the autumn or winter. These two types of studies were coded as the Summer group and the Winter group, respectively.

Dominant species. To investigate the relationship between air phytoremediation and species taxonomy, the species and family names of the dominant species in greenspaces were collected. The species and family names follow the International Plant Names Index[75].

Leaf types. Leaf types of vegetation in greenspaces were classified according to their species name and the photographs of the sample plots. They were divided into two categories: coniferous and broad-leaf.

Life forms. Using the species names and descriptions from the studies, we classified the dominant vegetation in greenspaces as either deciduous or evergreen.

We chose to use the natural log of response ratio (LRR) as the measure of effect size[76] and defined air pollutants' concentration, samples size, and standard deviation in the experiment site (i.e., greenspaces) as M_E, N_E, and S_E, respectively. Similarly, M_C, N_C, and S_C denote air pollutants' concentration, samples size, and standard deviation in the control site (i.e., traffic road). The LRR effect size and its variance were calculated by:

$$LRR = \ln\left(\frac{M_E}{M_C}\right) \tag{1}$$

$$Var_{LRR} = \frac{S_E^2}{N_E M_E^2} + \frac{S_C^2}{N_C M_C^2} \tag{2}$$

A negative value of LRR indicates that the concentration of air pollutants in the experiment site was lower than the air pollutants' concentration in the control site. The percent change from the control sites can be calculated: D (%) = (e^{LRR}−1) ×100%. To assess possible publication bias, we ran Egger's Test of the intercept to quantify the funnel plot asymmetry[77]. A significant intercept value (e.g., $p < 0.05$) indicated that there was a substantial asymmetry in the Funnel plot, which may be explained by publication bias. We applied the 'trim and fill' method to assess whether the sensitivity of the results was influenced by 'missing' study cases[78], but no significant differences were found between adjusted effect sizes and original effect sizes (Supplementary Fig. 3 and Supplementary Fig. 4).

Variations in sampling protocols, measurement methods, meteorological conditions, and site characteristics between studies may lead to significant heterogeneity among studies. To deal with this issue, we conducted a Bayesian meta-analysis of the pooled effect (μ). The Bayesian method, which differs from the frequentist method, not only estimates the parameters of models but also gives the samples of posterior distribution of interested parameters[66]. The samples of posterior distribution allowed us to calculate the probability that the interested parameter was smaller or larger than some specified values. Additionally, we

used a Bayesian random-effect model to account for the dependence of multiple observations within one study (Supplementary Methods). To investigate the heterogeneity and influence factors of air pollutants mitigation effect under different experimental conditions, we conducted a subgroup meta-analysis based on category variables by using a Bayesian mixed-effect model, and the category variables were coded as fixed-effect factors. Then, we conducted a Bayesian meta-regression analysis to explore the relationship between effect size and environmental, meteorological, and vegetation factors. The effect size was calculated using the software OpenMEE, which is an open-source software designed for performing meta-analysis, specifically catering to research in the fields of environmental science, ecology, and evolutionary biology[79]. All the Bayesian models were built using the R package 'brms'[80] under the R 3.6.3 environment[81]. The statistical graphs were produced using R packages 'ggplot2'[82], 'ggridges'[83], and zComposition[84].

Questionnaire survey and comparative analysis

The urban environmental management department plays a crucial role in shaping the planning, construction, and maintenance of urban greenspaces in Shenzhen (as do analogous agencies in other cities in China)[85]. The perspectives of department managers regarding air phytoremediation are likely to directly influence the formulation and implementation of related environmental policies and greening practices. Therefore, a brief questionnaire survey was conducted to assess gather the perspectives of urban environmental managers on the air phytoremediation in one of the cities (Shenzhen) included in the meta-analysis, which serves as a key demonstration city for sustainable urban planning in China[85–87]. The question asked in the survey was: 'What's the effect of urban vegetation on air pollutants?'. The question was designed to engage participants by presenting a situation in which they had to choose only one option for determining their perception of the air pollutants influenced by urban vegetation (Supplementary Fig. 1). The questionnaire was previously used in a citywide survey of environmental management conducted by the Shenzhen Municipal Bureau Ecology and Environment (SMBEE) in August 2020.

In order to explore the differences between scientific research and environmental management in terms of the results of air phytoremediation (for PM, SO_2, NO_2, and O_3), we compared the results of the aforementioned meta-analysis with the responses to the questionnaire. We analyzed the proportion of respondents in the questionnaire who have a positive or negative perception of air phytoremediation. For example, those who believe that urban vegetation has a positive effect on mitigating all four air pollutants, those who believe that plants can mitigate PM concentration but have a negative effect on SO_2, NO_2, and O_3, those who believe that urban vegetation can mitigate PM and SO_2 concentration but have a negative effect on NO_2 and O_3. Finally, the most representative perception can be compared with the result of the meta-analysis.

DATA AVAILABILITY

The datasets aggregated and/or analyzed during the current study are available at this data repository: https://github.com/rogerclarkgc/code_for_role_of_air_phy/tree/master/data.

CODE AVAILABILITY

The R code of the current study are available at this code repository: https://github.com/rogerclarkgc/code_for_role_of_air_phy.

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C.G., C.X., and Z.O. designed the research; C.G., C.X., and J.L. participated in data collection. C.G. performed the data analyses. C.G. and C.X. performed data visualizations. C.G. wrote the original manuscript. C.X., T.W., and Z.O. commented on the draft and provided significant edits. All authors approved the manuscript for submission.

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