Characterization of particulate matter deposited on urban tree foliage: A landscape analysis approach

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HIGHLIGHTS

- Object-based method was applied to identify particles of leaf FESEM images.
- A computer-based landscape analysis was applied to leaf surface particles.
- Willow is efficient in dust retention in term of quantity and quality.
- Different PM size fractions show distinct spatial distribution characteristics.

GRAPHICAL ABSTRACT

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ABSTRACT

Plants can mitigate ambient particulate matter by cleaning the air, which is crucial to urban environments. A novel approach was presented to quantitatively characterize particulate matter deposited on urban tree foliage. This approach could accurately quantify the number, size, shape, and spatial distribution of particles with different diameters on leaves. Spatial distribution is represented by proximity, which measures the closeness of particles. We sampled three common broadleaf species and obtained images through field emission scanning electron microscopy. We conducted the object-based method to extract particles from images. We then used Fragstats to analyze the landscape characteristics of these particles in term of selected metrics. Results reveal that *Salix matsudana* is more efficient than *Ailanthus altissima* and *Fraxinus chinensis* in terms of the number and area of particles per unit area and the proportion of fine particulate matter. The shape complexity of the particles increases with their size. Among the three species, *S. matsudana* and *A. altissima* particles respectively yield the highest and lowest proximity. PM_{10} in *A. altissima* and PM_{10} in *F. chinensis* and *S. matsudana* show the highest proximity, which may influence subsequent particle retention. *S. matsudana* should be generally

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considered to collect additional small particles. Different species and particle sizes exhibit various proximities, which should be further examined to elucidate the underlying mechanism.

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1. Introduction

Particulate pollution is a worldwide environmental problem, and population-weighted ambient $PM_{2.5}$ concentrations have increased significantly (van Donkelaar et al., 2015). Particulate pollution can modulate global, regional (Buseck and Posfai, 1999; Wang et al., 2014), and local climates (Cao et al., 2016; Rosenfeld, 2000). This phenomenon is also concerned as a severe health risk (Kampa and Castanas, 2008; Nowak et al., 2014) that increases population mortality (Madaniyazi et al., 2015) and premature mortality (Xie et al., 2016). East Asia experiences severe urban particulate matter pollution (Boys et al., 2014), and urban areas, especially megacities, such as Beijing (Guo et al., 2014), are polluted by various sources (Bell et al., 2011). Optically scattering aerosols account for most of the total amount of aerosols in China (Zhang et al., 2012).

Vegetation can provide various ecosystem services, including air purification (Baumgardner et al., 2012; Beckett et al., 1998; Irga et al., 2015). Urban forests can be used as “biotechnology” to ameliorate urban air quality (Nowak, 2006) and it was estimated that, in the US, urban trees removed 214,900 tons PM_{10} based on data in 1994, providing an applicable way of improving air quality (Nowak et al., 2006). When modelling the functionality of the urban forest, taking the spatial heterogeneity into air pollution removed by urban forest is necessary (Escobedo and Nowak, 2009). A combination of the Weather Research and Forecasting (WRF) model and iTree can be useful in estimating regional pollutant removal by urban forests when field sampled data on trees in an area are not available (Cabaran et al., 2013). Based on the modelling of tree effects on $PM_{2.5}$ concentrations and human health in ten U.S. cities, the amount of $PM_{2.5}$ removed annually by urban trees varied between cities with annual values to human health varying from \$1.1 million to \$60.1 million (Nowak et al., 2013). In country level, the trees in U.S. removed 17.4 million tonnes of air pollutant in 2010 and the human health value was 6.8 billion U.S. dollars (Nowak et al., 2014). On air quality improvement, rural vegetation had greater effects while on human health urban vegetation had greater effects (Hirabayashi and Nowak, 2016).

In the street environment urban plants can affect air quality by means of affecting deposition and dispersion of the pollutants, and consequently the design and choice of vegetation barriers matters (Abhijith et al., 2017; Janhäll, 2015). In addition, the wind direction greatly influences pollutant concentrations of the environment adjacent to the road, depending on the relative location of road and the vegetation according to the wind direction, and the air pollutant concentrations decline to background values between 115 and 570 m or 160–570 m according to different normalization methods (Karner et al., 2010). The combination of barrier and mature trees brought about consistently lower pollutant concentrations (Baldauf et al., 2008). Furthermore, wide vegetation barriers with dense leaf and vegetation-solid barrier combinations are two types of design that effectively reduce downwind particle concentration (Tong et al., 2016).

To identify effective particle retention species, we should quantify particles on plant leaves by using various techniques. For instance, microscopic observation is commonly used to determine the amount of particles on leaves (Sgrigna et al., 2016; Song et al.,

2015). Compared with water wash method, microscopy can quantify particles with original diameters (Yan et al., 2016a). Compared with the wind tunnel method, microscopy can identify particle deposition in actual environments, where particles yield various diameters. Microscopy can also obtain species-specific information regarding particle retention effect; conversely, the model method (Tiway et al., 2009) can estimate the large-scale removal of particulate matter by vegetation, and some models can consider spatial variation (Hirabayashi et al., 2012). Compared with the spectrum method (Yan et al., 2015), microscopy can reveal the size distribution and shape information of particles and may indicate the source of particles (StoffynEgeli et al., 1997).

Microscopy has been performed to quantify the number and shape of particles retained on tree leaves (Deljanin et al., 2014; Manisha et al., 2016). Using an automatic mapping approach (Yan et al., 2016b), we can quantitatively characterize the spatial distribution of particles on leaves. This parameter can potentially indicate the particle deposition process on leaf surfaces and provide new insights into particle retention and its characteristics. However, the spatial distribution pattern of leaf particles has yet to be quantified. Landscape metrics showing landscape patterns are calculated by using the landscape analysis software Fragstats. These metrics include three levels: landscape, class, and patch. Landscape level metrics can quantify the overall condition of the particles (i.e. number density, leaf area percentage covered by particles); class level metrics can quantify characteristics of particles from different fractions including spatial patterns that can quantify the spatial

Fig. 1. Flow chart for data process.

distribution of leaf particles; patch level metrics can quantify characteristics of individual particles (area and shape). Using a landscape framework, we can quantify and summarize the size, shape, and spatial pattern of leaf particles. However, this method has been rarely used in studies. Therefore, this study aimed to (1) apply the landscape concept and method for the quantification of leaf particle characteristics; (2) determine the differences among three common broadleaf species in terms of the number of particles, leaf area covered by these particles, and particle weight; and (3) compare the characteristics of particles with different diameter intervals in terms of their number, area, and spatial distribution in common broadleaf species.

2. Methods

The data process from sampling to landscape analysis is summarized in the flow chart (Fig. 1). The boxes represent the material or the data to be processed. The text beside the arrows denotes the equipment or software used and the processes conducted.

2.1. Sampling

We collected the samples from sites near the fifth ring road in

the Olympic Forest Park in Beijing on May 22, 2015, five days after the latest precipitation on May 17, 2015. We used high-reach scissors to cut leaves from three common broadleaf species: ailanthus (*Ailanthus altissima* (Mill.) Swingle, AA), ash (*Fraxinus chinensis* Roxb., FC), and willow (*Salix matsudana*, SM). Leaves facing the road were chosen to better represent the particulate matter on the leaf of which the road dust may be an important source. The distance from sample trees of AA, FC and SM to the nearest road was 16, 14 and 13 m respectively. To avoid differences, the sampled trees were all at the same site near each other (Fig. 2). The three trees we chose had similar distance to the road, sunlight, wind condition and individual size. The prevailing wind direction was Northwest in spring in Beijing (Sun et al., 2015) and the sampled trees were located south of the road.

We chose one healthy tree for each species and randomly cut leaves facing the road at 3 m height. We chose the three species because they are common in Beijing and have distinct leaf characteristics. The leaves of AA have microgrooves but do not have hair; the leaves of FC have coarse texture but do not have hair; and the leaves of SM have sparse hair and dense stoma. Leaves were carefully put into paper envelopes to avoid further contamination and particles falling, and then to the lab for further analysis.

Fig. 2. The sampling location for three species, located in the Olympic Forest Park in Beijing.

a: Examples of classification results-AA

b: Examples of classification results-FC

c: Examples of classification results-SM

Fig. 3. Examples of classification results. AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.). The magnification of these pictures is 2000. The yellow parts represent the particles recognized by software eCognition. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.2. Scanning electron microscopy

We randomly chose fifteen healthy leaves to represent those three species, five leaves for each species. For each leaf, one square sample of approximately $1\text{ cm} \times 1\text{ cm}$ was cut out from the middle part of the leaf avoiding the veins. The samples were coated with gold to increase productivity. After the pretreatment, we photographed the samples under a field emission scanning electron microscope (FESEM, Hitachi SU-8020) at an accelerating voltage of 3–5 kV at magnification of 2000; seventy-five images were taken, five images for each sample. The pixel amount for each picture was 1,228,800, and each pixel was $0.05\text{ }\mu\text{m}$ in size. The area of one pixel was $25 \times 10^{-4}\text{ }\mu\text{m}^2$, and the total area for one image was $3072\text{ }\mu\text{m}^2$.

2.3. Object-based classifications

We used the object-based classification method to extract the particles from the SEM micrographs automatically (Yan et al., 2016b). These micrographs were imported into eCognition Developer™ software. The eCognition Developer™ software is a widely used remote sensing software which can be used to conduct the classification for remote sensed images. The object-based method embedded in the eCognition is effective in classification, overcoming some of the shortages of pixel-based classification methods (Yu et al., 2006). Initially, the optimal segmentation scale, color, and shape parameter were set to conduct a multi-resolution segmentation algorithm. We then applied the ruleset-based classification to the entire micrograph for particle matter identification. Finally, we merged the adjacent image objects of the same class to get the particles and, the result was exported as vector files for further analysis. Examples of the classification are shown in Fig. 3.

2.4. Landscape analysis

The vector files were imported into R. According to the width and length of particles extracted by eCognition Developer™ software, the diameter was the average of width and length. Based on the geometrical diameter, the particles were divided into four classes: PM_{10} (diameter $\leq 10\text{ }\mu\text{m}$), $\text{PM}_{2.5}$ ($1\text{ }\mu\text{m} < \text{diameter} \leq 2.5\text{ }\mu\text{m}$), PM_{10} ($2.5\text{ }\mu\text{m} < \text{diameter} \leq 10\text{ }\mu\text{m}$), Large (diameter $> 10\text{ }\mu\text{m}$).

We rasterized the vector files using the raster function and exported the results as .tiff by using the writeRaster function in R package raster (Hijmans, 2015) in the R base version 3.1.2 (R Core Team, 2014), resulting in 49931 particles. To calculate the landscape metrics, the rasterized files were imported into Fragstats v4.2.1 (McGarigal et al., 2012). Metrics representing the particle number, the particle area, the shape characteristic of particles, and proximity of class particles were chosen from the metrics provided by Fragstats (Table 1).

There are several principles in selecting the metrics. First, core area metrics were not chosen because they need the definition of the width of the edge whereas there was neither practical meaning for leaf particle nor standard for edge width. Second, contrast metrics which describe the degree of dissimilarity of adjacent patches (patches share part of their edges) were not chosen because adjacent particles were merged into one particle. Similarly, all metrics based on adjacent matrix were not chosen such as contag, iji, clumpy and PLADJ. Third, the aggregation, subdivision and isolation metrics were not chosen because they are pixel based metrics describing both size and shape which was of irrelevant meaning for leaf particles. Fourth, metrics representing the fragmentation were not chosen (such as split and cohesion), because they have no explicit meaning for leaf particles. Some measurement unit transformations from SEM pictures to real data were made to accurately reflect the landscape metrics based on the

Table 1
Description of landscape metrics transformed and evaluated.

Landscape metrics (full name)	Level	Description in landscape ecology	Transformation	Meaning in particles on the leaf
NP(Number of Patch)	Landscape, Class	NP equals the number of patches of the landscape and corresponding patch type (class).	$\div 3072 \times (10^6)$	Number of particles per unit mm^2
CA(Class Area)	Class	CA equals the sum of the areas (m^2) of all patches of the corresponding patch type divided by 10,000 (to convert to hectares). It is a measure of landscape composition.	$\times 10000 \times 0.05 \times 0.05 \div 3072$	Proportion of leaf area covered by the class particles
TA(Total Area)	Landscape	TA equals the total area (m^2) of the landscape, divided by 10,000 (to convert to hectares). Note, total landscape area (A) includes any internal	$\times 10000 \times 0.05 \times 0.05 \div 3072$	Proportion of leaf area covered by all the particles
Area_MN, AREA	Class, Patch	AREA equals the area (m^2) of the patch, divided by 10,000 (to convert to hectares).	$\times 10000 \times 0.05 \times 0.05$	The area of the particles (μm^2)
SHAPE_MN, SHAPE	Class, Patch	SHAPE equals patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant to adjust for a square standard.	none	Shape index of particles
FRAC_MN(Fractal Dimension Index), FRAC	Class, Patch	FRAC equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter.	none	Fractal dimension index of particles
PROX_MN(proximity Index)	Class	PROX equals the sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch. Note, when the search buffer extends beyond the landscape boundary, only patches contained within the landscape are considered in the computations. In addition, note that the edge-to-edge distances are from cell center to cell center.	none	proximity index of particles

Note: MN (Mean) equals the sum, across all patches of the corresponding patch type, of the corresponding patch metric values, divided by the number of patches of the same type. MN is given in the same units as the corresponding patch metric.

Fig. 4. Box plots of number, area and weight of particles on leaves per unit leaf area of three species. NP: number of particles of unit leaf area, N/mm^2 . TA: the proportion of leaf area covered by particles, unitless. Weight: the weight of particles of unit leaf area, mg/mm^2 . AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.).

information in 2.2, and the details of the transformation process are in Table 1.

The particle weight was calculated based on the diameters. First, the particle was assumed to be spherical, and the diameter was divided by two to get the radius. Second the particle volume was

calculated using the radius. Third, the weight was the product of the volume and density $2\text{g}/\text{cm}^3$ (Zhang and He, 2014). Graphs for comparing those metrics were drawn using R package ggplot2 (Wickham, 2009).

Fig. 5. Box plots of AREA, SHAPE and FRAC of particles on leaves of three species. AREA: the area of each particles, μm^2 . SHAPE: shape indicator, equals patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant to adjust for a square standard, unitless. FRAC: fractal dimension, the range is 1–2, unitless. AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.).

3. Results

3.1. Amount, area, and weight of particles

As shown in Fig. 4, the SM accumulated the most particles in terms of amount, area and weight per unit leaf surface. The median value of the number of patch (NP) of SM ($569987/\text{mm}^2$) was approximately 10 times that of FC ($49805/\text{mm}^2$) and 8 times of AA ($75846/\text{mm}^2$). Moreover, the NP variation of SM is the largest, whereas that of FC is the smallest. The biggest particles appeared in SM.

The medians of total area (TA) for AA, FC, and SM were 4.6%, 10.7%, and 19.4%, respectively; therefore, SM had the highest leaf coverage of particles among the three species, and AA had the lowest. The variation of TA of SM was the highest, and the variation of TA of FC was the lowest.

The median weight for AA, FC, and SM were 189, 530, and $573 \text{ ng}/\text{mm}^2$, respectively. SM had the highest particle weight per unit leaf area and AA had the lowest. The picture that the particles' weight was the most showed up in SM. The variation of weight of SM was the highest, whereas that of FC was the lowest.

3.2. The characteristics of particle area and shape indexes

3.2.1. Particle AREA, SHAPE, and FRAC

As shown in Fig. 5, the median value of area of each particle (AREA) for SM was $0.0575 \mu\text{m}^2$, which is the smallest among the three species; moreover, it was approximately half that of AA ($0.1025 \mu\text{m}^2$) and one-third that of FC ($0.1725 \mu\text{m}^2$). Meanwhile, the variation of the AREA of FC was the highest (the interquartile range was 0.5750), whereas that of SM was the smallest (the interquartile range was 0.0875).

As for the shape, the SHAPE index median values of the three species were close, ranging from 1.182 (SM) to 1.231 (AA); therefore, most of the particles were similar in shape complexity. The SHAPE of FC particles (the interquartile range was 0.2750) had a higher variation than AA (0.2571) and SM (0.2220).

Another shape indicator was FRAC. The FRAC median values of the three species were close, ranging from 1.106 (FC) to 1.129 (SM). Moreover, the FRAC of SM particles (the interquartile range was 0.1150) had a higher variation than FC (0.0633) and AA (0.0834).

3.2.2. Distribution of particle AREA, SHAPE, and FRAC

As shown in Fig. 6, regarding particle size, the SM distribution curve is sharp, indicating that the particle area distribution was centralized; moreover, the value peaked at approximately $0.03 \mu\text{m}^2$. In contrast, the shapes of AA and FC were similar and had moderately high value intervals from 0.04 to 0.09 and 0.04–0.07, respectively.

Regarding the SHAPE of particles, valleys occurred at approximately 1.02 for all the three species. The first peaks appeared at approximately 1, with SM having the highest peak; therefore, the particle proportion with SHAPE value surrounding 1 was higher than those of AA and FC. Moreover, among the three species, a moderately high value interval occurred: 1.1–1.2, demonstrating that particles in that range were abundant for all three species.

The FRAC curves were similar, suggesting that the FRAC values of the particles of the three species coincided. The high value interval was 1.00–1.20, with two peaks occurring for each species.

3.3. Class level characteristics based on landscape analysis

3.3.1. Characteristics of the particles at four class levels

As illustrated in Fig. 7, regarding CA characteristic, AA and FC displayed similar trends: the median values of class particles monotonically increased with the particle diameter. Large particles had high median values (3% and 5.8% for AA and FC, respectively) and PM_1 had low median values (0.9% and 0.6% for AA and FC, respectively). For SM, however, the CA median values of PM_{10} (6.6%) was the highest among the four classes, followed by PM_{10} , Large (5.2%), PM_1 (4.5%), and $\text{PM}_{2.5}$ (2.7%). Regarding NP, the median value decreased as the particle diameter increased. PM_1 had high median values: 57943, 38086, and 543294 for AA, FC, and SM, respectively. Large particles had low median values: 325, 325, and 1320 for AA, FC, and SM, respectively. The number of PM_1 was 100–400 times that of Large particles. As for AREA_MN, the median value SM was the lowest among the four classes, whereas that of FC was the highest. SM and AA have close median values of AREA_MN of PM_{10} . The highest difference occurred in Large class, FC ($131.05 \mu\text{m}^2$) tripled SM ($40.36 \mu\text{m}^2$). Except for AA, the shape complexity increased with the class level. Among the four classes, PM_1 had the simplest shape throughout three species; AA had particles with more complicated shapes than SM and FC. In classes $\text{PM}_{2.5}$, PM_{10} , and Large, SM generally had complicated particles, whereas AA and FC had relatively simple particles. Regarding

Weight, that of corresponding class particles increased as the class level increased. For the Large class, FC had high weight. For PM₁, PM_{2.5}, and PM₁₀, SM had the highest weight.

3.3.2. Proportion of four class particles in NP, CA, and weight

As shown in Fig. 8, in terms of NP, PM₁ was the predominant class. Overall, PM₁ accounted for 70%–95%; PM_{2.5} accounted for 5%–20%; PM₁₀ accounted for 1.5%–8%, and Large accounted for 0.1%–0.8%. In terms of CA, PM₁₀ and Large were the predominant classes. In general, PM₁ accounted for 5%–25%, PM_{2.5} accounted for 10%–16%, PM₁₀ accounted for 30%–40%, and Large accounted for 20%–45%. In terms of Weight, Large was the predominant class. Generally, PM₁ accounted for 0.3%–2%, PM_{2.5} accounted for 1.5%–4%, PM₁₀ accounted for 20%–30%, and Large accounted for 65%–75%.

Fig. 6. The PM AREA, SHAPE and FRAC distributions. The small pictures inside the big ones were drawn from subset data of the big ones: data smaller than the third quantile was contained to show the details of the distributions. AREA: the area of each particles, μm^2 . SHAPE: shape indicator, equals patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant to adjust for a square standard, unitless. FRAC: fractal dimension, the range is 1–2, unitless. AA: *Ailanthus altissima* (Mill.) Swingle; FC: *Fraxinus chinensis* Roxb.; SM: *Salix matsudana* Koidz.).

3.3.3. Characteristics particulate matter spatial distribution on leaves

As shown in Fig. 9, the PROX of PM₁ of AA and FC increased when the searching radius reached 1 μm ; whereas that of SM remained high even at a searching radius was 0.5 μm , and increased as the searching radius elevated. The PROX of PM_{2.5} of AA, FC, and SM increased with searching radii of 5, 5, and 1 μm , respectively. The PROX of PM₁₀ of AA, FC, and SM increased at 10, 5, and 1 μm , respectively. Moreover, the PROX of Large of AA was not high under the seven searching radii. The PROX of Large of FC and SM increased at searching radii of 20 and 5 μm , respectively.

PM of different classes have different proximity characteristics. In general, Large had the lowest proximity. For AA, under all the seven searching radii, the proximity of the class particles decreased as the particle class levels rose. For FC, when the search radius was higher than 5 μm , from PM₁, PM_{2.5}, and PM₁₀, the proximity rose. For SM, in general, the PM₁₀ had the highest proximity, followed by PM₁ and PM_{2.5}.

4. Discussion

4.1. Size and shape distribution

The leaf surface particles were quantified and described synthetically from four aspects: number, size, shape, and spatial position. SM is efficient in accumulating particles, judging from number, mass, and size distribution; this might be because of the trichome (Beckett et al., 2000a; Räsänen et al., 2013). Moreover, the leaf grooves have a coarse surface that can facilitate particle deposition on the leaf (Beckett et al., 2000b; Liang et al., 2016).

4.1.1. Weight and size distribution both embody the air cleaning ability of vegetation

Small particles, especially fine and ultrafine particles, can be harmful. Small particles are difficult to clear away (Pui et al., 2014). Moreover, fine particles have a relatively high surface area that could absorb toxic materials and increase toxicity (Kelly and Fussell, 2012).

Besides the toxicity, fine particles can reach deep to the respiratory system (Sierra-Vargas and Teran, 2012), thereby causing severe pulmonary conditions (Makkonen et al., 2010; Oberdörster, 2000). Particle number concentrations are correlated with airway inflammation and lung injury (Strak et al., 2012). The PM₁ and PM_{2.5} account for most of the total particle number; however, they account for only a tiny proportion of the total weight. Consequently, evaluating the value of PM cleaning of vegetation using weight might be biased. For example, AA has less weight than FC, but the PM₁ proportion was higher. Therefore, based on mass and size distribution, AA is probably a more efficient species than FC.

4.1.2. Estimation the element source appointment of the particles

Shape distribution combined with size distribution can be used to estimate the element of particles and facilitate source appointment of the particles. Chemical characteristics of the particles may be inferred by size distribution because differences in size fractions are caused by different components (Grantz et al., 2003). Obtaining the diameter of each particle enables investigation of the sources, the elements contains, and pollutant levels of the particles on the leaf. For example, particles greater than 1 μm are mostly generated from natural sources and those less than 1 μm are mostly from human activities (Makkonen et al., 2010).

From the ecosystem perspective, particle-polluted leaves could be a source of non-point pollution for urban ecosystems during precipitation (Feng et al., 2001), which is critical in the pollutant transfer from the air to soil and affects biogeochemical cycling

Fig. 7. Class level particle characteristics: comparison of PM₁, PM_{2.5}, PM₁₀ and Large. NP: number of particles of unit leaf area, N/mm^2 . AREA_MN: the mean area of the particles, μm^2 . CA: proportion of leaf area covered by the class particles, unitless. SHAPE_MN: the mean value of the shape index of the particles, unitless. FRAC_MN: the mean fractal dimension index of the particles, the range is 1–2, unitless. Weight: the weight of particles of unit leaf area, mg/mm^2 . AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.).

(Fowler et al., 2009). The results of this study will help high temporal and spatial resolution monitoring (Sgrigna et al., 2016; Zampieri et al., 2013).

4.2. Class level characteristics

Large particles, on average, had relatively complicated shapes, with PM₁ having the simplest shape. This phenomenon might be because PM₁ has mostly anthropogenic sources, such as high temperature combustion (Akram et al., 2014). Moreover, the mean area of SM class particles was the lowest across the four classes and three species, showing that SM probably prefers small particles. Regarding the proportion of particles from different fractions, in general, ultrafine and fine particles are dominant in number, which is consistent with previous studies (Cao et al., 2011; Song et al., 2015). This may be caused by the composition of atmospheric particulate matter: the number concentrations of ultrafine and fine particles are larger than coarse particles. PM₁₀ and Large were dominant in area cover percentage. Large were dominate in weight.

Large particles contained most of the weight (65%–75%), however, they accounted for less than 1% in total. Moreover, PM₁ accounted for the highest number (70%–95%), however, they accounted for less than 2% in weight.

4.3. Proximity

Patterns reflect a specific process. Different species have various canopy and leaf characteristics that may confer distinct spatial characteristics. Moreover, particle proximity is not necessarily congruent with the number of particles. For example, the proximity of PM₁₀ of FC was higher than that of PM₁. Moreover, except for large particles, no determinate relationship exists between the proximity and size of particles. The thick trichomes can maintain a stabilized air layer thus bring about selectively deposition of small particles ($\leq 1 \mu m$) (Martell, 1974). Similarly, from the particulate matter deposition dynamic perspective, particles already deposited on the leaf surface may affect subsequent particle deposition. Particles in different classes combined with different leaf surface

Fig. 8. Percent contributions from different class type to the total NP, CA and Weight of three species. NP: number of particles of unit leaf area, N/mm^2 . CA: proportion of leaf area covered by the class particles, unitless. Weight: the weight of particles of unit leaf area, mg/mm^2 . AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.).

structures may play different roles in fixing of new particles. The particles on the leaf may proceed or resist new particles around them. Further studies should be conducted to explore the effects of spatial pattern on particle deposition.

4.4. Limitations and recommendations for future studies

This study has several limitations thereby are needed to be clarified by future studies. First, more tree level individuals should be sampled in various environments: both near a source like these samples and perhaps in more regional areas where the particulate loading is more likely similar and not influenced by a particular source and location like in our study which was conducted in a highly heterogeneous environment for particle deposition. Second, the seasonal effect can affect particulate removal because of comprehensive effect of various factors like wind speed, rainfall, PM concentration and particle size distribution, humidity and so on. In Guangzhou in China, the dust retention was higher in the dry season (Liu et al., 2013). Seasonal variation of dust retention also showed up in Beijing. Different species showed different dust retention responses to the season, some accumulated more particulate matter in spring whereas some accumulated more in the summer to autumn (Chen et al., 2017).

5. Conclusion

Fragstats was used in this study to calculate the metrics, including traditional indexes, such as size, shape, and spatial distribution in different diameter intervals, and to evaluate the

characteristics of the leaf surface particles. Landscape metrics were modified to indicate the leaf particle characteristics.

Landscape ecology framework, exemplified in our study, can facilitate the understanding of leaf particles. Fragstats, a landscape analysis software, can be applied to examine leaf particles. Landscape metrics after transformation can also quantify the particles on plants in terms of comprehensive metrics, namely: size, shape, and spatial characteristics. The spatial concept was introduced and initially quantified in this particle deposition on leaf surface research.

Weight alone is insufficient to quantify the importance of vegetation on particle deposition because particle size distribution size should be considered. *S. matsudana* is an efficient species for particle accumulation in terms of quantity and quality. *A. altissima* performed better than *Fraxinus chinensis* Roxb did. Particles exhibit different shapes and sizes. In general, small particles have simple shapes and large particles usually have complex shapes. A new phenomenon was detected in this study. In particular, PM of different classes from various species show distinct proximity characteristics. Large particles have lower proximity than other classes. The PM_{10} have relatively higher proximity than other classes.

Our study may facilitate further research on the mechanism of particle retention by vegetation and the assessment and prediction of airborne particle deposition locally, regionally, and globally. The proposed technology can be used to identify the particles in situ and quantify the position between particles and specific leaf structures, such as the stoma. This technology may also be utilized to examine the effects of particles on leaves and plant physiology.

Fig. 9. The proximity in different searching radius of particles of four classes (i.e. PM1, PM2.5, PM10, and Large). logPROX: log value of the proximity index of particles, unitless. AA: ailanthus (*Ailanthus altissima* (Mill.) Swingle); FC: ash (*Fraxinus chinensis* Roxb.); SM: willow (*Salix matsudana* Koidz.).

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