

Abstract

1 The availability of pollen in urban-rural landscapes is an essential factor that influences the
2 population dynamics of insect pollinators. The amount and diversity of pollen play a pivotal
3 role in the foraging ecology of pollinators for their growth and health, but investigations on
4 the spatio-temporal patterns of foraged plants remain rare, especially in cities as neo
5 polylectic -ecosystems. Here, we explored the temporal foraging habits of a highly pollinator
6 (*Apis mellifera* L.) in Tokyo, including different landscape classes from rural to urban areas.
7 Mixed-pollen samples in each month and each location (N = 17) were analysed using DNA
8 meta-barcoding to identify plants visited by honeybees. The results showed that the landscape
9 class (rural, suburban and urban areas) explains spatial variations in pollen source-plant
10 composition foraged by honeybees, but not in taxa richness. Furthermore, pollen diversity and
11 pollen source-plant composition showed a strong seasonal dependence. A higher plant
12 richness and foraged woody taxa was found to occur in spring, which was mainly dominated
13 by the genera *Prunus* and *Acer*. In summer and autumn, the genera *Trifolium* and *Plantago* of
14 the herbaceous stratum were the most visited plants. The Fabaceae, Rosaceae, Brassicaceae,
15 Plantaginaceae, and Onagraceae plant families were the most frequently observed in all
16 combined samples. The present study contributes to a deeper understanding of the foraging
17 ecology of *A. mellifera* colonies across urban-rural gradient surrounding mega-cities such as
18 Tokyo.

19 Keywords: Pollen, metabarcoding, community structure, foraging ecology, *Apis mellifera*,
20 urban ecology

21

22 **Introduction**

23 Ongoing urbanisation is one of the main drivers of landscape degradation and pollinator
24 biodiversity loss (Ahrné et al., 2009; Concepción et al., 2015; Fortel et al., 2014; Potts et al.,
25 2010; Sánchez-Bayo and Wyckhuys, 2019). Indeed, floral resources are becoming scarcer
26 under the pressure of urban fragmentation, and the increase in impervious surfaces is
27 rendering nesting sites inaccessible to pollinators (Harrison and Winfree, 2015; Wenzel et al.,
28 2020). However, recent studies have revealed that cities can also act as a refuge for pollinators
29 (Hall et al., 2016), particularly for bees (Theodorou et al., 2020): (i) cities are less exposed to
30 pesticides (Fortel et al., 2014; Muratet and Fontaine, 2015), (ii) urban management
31 sustainably permits the maintenance of their floral resources (Baldock, 2020; Pardee and
32 Philpott, 2014), and (iii) urban areas are configured with a heterogeneity of green spaces,
33 which would be favourable to the foraging preferences of bees (Baldock et al., 2015).
34 Moreover, flowerbeds in the urban matrix are highly attractive and are a source of pollen and
35 nectar for insect pollinators (Garbuzov et al., 2015a; Garbuzov and Ratnieks, 2014). With an
36 increasing popularity in beekeeping activities in cities, honeybees (*Apis mellifera* L.)
37 contribute to urban plant pollination, generate profits of by-products, and provide
38 environmental education (Cho and Lee, 2018; Tanaka et al., 2020). However, the massive
39 introduction of urban honeybees has led to growing concerns about detrimental effects on
40 wild pollinators through an increase in floral resource competition and the spillover of shared
41 pathogen agents (Geslin et al., 2017; Ropars et al., 2019).

42 As a eusocial species, honeybees organise their floral resource collections (i.e. nectar and
43 pollen) through a complex communication system within their colonies. According to plant
44 phenology, honeybee scouts rapidly recruit their siblings to forage on rich new patches of
45 flowers using a characteristic waggle dance (von Frisch, 1965). The foraging decision-making

46 system of the colony can vary from day to day or within the same day following real-time
47 nectar and pollen availability in the surroundings. Throughout its active seasons, the colony
48 constantly maintains a balance between its biomass and energy management according to the
49 availability and the diversity of surrounding floral resources. This strategy ensures sufficient
50 food stores and energy reserves for winter (Alaux et al., 2017; Seeley, 1995). Pollen diversity
51 provides substantial resources in terms of protein, lipid, vitamin, and mineral supplies
52 (Haydak, 1970). Large amounts of pollen (15–30 kg) are collected annually, mainly for brood
53 production during summer (Avni et al., 2014, 2009; Seeley, 1995). The quality and diversity
54 of pollen are also essential for better life expectancy and immunity, as well as the parasite or
55 pathogen tolerance of the bees and the colony (Alaux et al., 2010; Di Pasquale et al., 2013;
56 Wang et al., 2014; Wilde et al., 2003).

57 The preservation of ecosystem functioning relies on the mutualistic networks of pollinators
58 and plants. Several methods are used to assess these interactions: the observation of floral
59 visits, digital tracking systems to capture floral visits, chemical signatures of pollen, pollen
60 genetic sequencing, and pollen light microscopy (Cornman et al., 2015). Identifying a pollen
61 species or genus by light microscopy from mixed pollen samples, also known as
62 melissopalynology (Ohe et al., 2004), is a time-consuming process, even for well-trained
63 experts (De França Alves and De Assis Ribeiro DosSantos, 2014) that results in low
64 taxonomic resolution, usually at the family or genus rank at best (Bell et al., 2016;
65 Kaškonienė and Venskutonis, 2010; Rahl, 2008; Richardson et al., 2015a). With the advent of
66 high-throughput sequencing (HTS) techniques, DNA meta-barcoding approaches have
67 become reliable methods to obtain faster taxonomic profiles with higher resolution of mixed
68 pollen collected from bees or flowers (Bell et al., 2017; Pornon et al., 2016; Sickel et al.,
69 2015). To elucidate the plant taxonomic composition of mixed-pollen samples, the meta-
70 barcoding process can be based on different genetic markers, such as the *rbcLa*, *matK*, *trnH*-

71 *psbA*, *trnL*, and *ITS* regions (mainly *ITS2*), which require high inter-specific and low
72 intraspecific variability (Galimberti et al., 2014; Hawkins et al., 2015; Kraaijeveld et al.,
73 2014; Richardson et al., 2015a; Sickel et al., 2015). These selected loci, the primer set and the
74 differences in available plant reference sequences for each marker used for amplification
75 drive the range of taxonomic inferences (Bell et al., 2016).

76 The floral plant composition of agricultural or urban landscapes heavily impacts the foraging
77 ecology of honeybee workers (Danner et al., 2017; Lucek et al., 2019; Richardson et al.,
78 2021). Indeed, the fragmentation of urban matrix usually leads to the creation of small,
79 remote, and intensely maintained green spaces (Bastin and Thomas, 1999), which could
80 influence the foraging distance of honeybee workers (Garbuzov et al., 2015b). As the most
81 polylectic bee forager (Butz Huryn, 1997), honeybees can adapt to shortages in floral
82 resources by enlarging their foraging area (Danner et al., 2016; Steffan-Dewenter and Kuhn,
83 2003). Moreover, seasonal shifts greatly impact the pollen availability for honeybee colonies,
84 according to the phenology of the floral resources (Danner et al., 2017; Sponsler et al., 2020).
85 In temperate climates, the foraged plant characteristics also vary according to the course of
86 the seasons: spring is dominated by trees and shrubs, summer has more herbaceous species,
87 and autumn is characterized by woody vines (Sponsler et al., 2020). Nonetheless, the space-
88 time effects combined with plant characteristics in the foraged plant community have yet to
89 be studied extensively (Richardson et al., 2021). Understanding the floral range dynamics of
90 honeybee colonies according to urbanization gradient would help to better determine the
91 foraging ecology of the honeybee colonies in cities.

92 To achieve this aim, the taxonomy of pollen foraged by honeybees was identified over the
93 seasons along an urban-rural gradient from different locations in the Kanto region, Tokyo,
94 and its surroundings in Japan. The research questions addressed were as follows: (i) How

95 does the composition of the foraged flower community (and the foraged plant characteristics)
96 vary along an urban-rural gradient? (ii) How does the composition of foraged flower
97 communities and characteristics of pollen forage plants vary according to the course of the
98 seasons?

99 **Material and methods**

100 **Study area and experimental set-up**

101 We selected 17 apiary locations, with homogeneous climatic and altitudinal conditions (Table
102 S1), distributed along an urbanisation gradient in the Kanto region of Japan (Fig. 1). One hive
103 per apiary was used for pollen sampling. From March to September 2019, pollen samples
104 were collected using pollen traps at the entrance of the same hive (Fig. S1). This experimental
105 setup was used to collect pollen balls from the hind legs of honeybee foragers with a
106 standardised honeybee-size mesh and tray (Mahmood et al., 2017). Then, the contents of the
107 pollen traps were discharged into labelled 50-ml conical tubes and stored at -20°C . However,
108 due to meteorological conditions and the personal schedules of the beekeepers, the sampling
109 date, collection frequency, and operational time of the pollen trap varied from site to site for a
110 total of 143 collected pollen samples (Table S2). Each corbiculate pollen sample was
111 thoroughly mixed by lightly kneading all collected pollen with a [mortar and pestle](#). Then, all
112 samples were sent to the private company, Bioengineering Lab. Co., Ltd.
113 (<https://www.gikenbio.com/>, consulted on 20/07/2020) for the processing of the meta-
114 barcoding of the mixed pollen samples.

115 **Landscape analysis**

116 Using remote sensing techniques, the landscape structure was investigated within a 6-km
117 radius around each hive location (Table 1); this distance enclosed 95% of the forage area per

118 colony (Seeley, 1995). With the help of Planet Labs Inc. (Planet Core Team, 2020), we used
119 multi-spectral images (RGB, NIR) with 3-m pixel resolution. To fully exploit the potential of
120 the data, the cloud cover condition was set to a maximum of 5%. Planet data are relevant for
121 computing and mapping high-resolution terrestrial above-ground vegetation at the landscape
122 scale (Miller et al., 2019). For each planet image, the normalised difference vegetation index
123 (NDVI) was computed using the red and near-infrared bands based on band rationing, which
124 allowed for the delineation of the vegetation cover from other types of land cover (Xue and
125 Su, 2017). Classes were created with the function *reclassified* from the *raster* package in R
126 (Hijmans et al., 2020) by defining the NDVI threshold values to distinguish the water (NDVI:
127 from -1 to -0.2), the impervious surface (NDVI: from -0.199 to 0.199) and the vegetation
128 (NDVI: from 0.2 to 1) (Hashim et al., 2019; Taufik et al., 2016). A majority filter, with a $6 \times$
129 6 filter kernel size, from the *whitebox* package in R (Lindsay, 2016), was applied to smooth
130 the result and aggregate regions of high uncertainty. Landscape classifications at the site level
131 were performed using demographic data (i.e. number of inhabitants per admin units) and
132 landscape metrics from the *lconnect* (Mestre and Silva, 2019) and *landscape metrics*
133 (Hesselbarth et al., 2019) packages in R. To classify our sites along an urban-rural gradient
134 (Bastin and Thomas, 1999; Hadley and Betts, 2012), we retained selected data: number of
135 inhabitants per km² (dpop), the integral index of connectivity (IIC) (Saura and Pascual-Hortal,
136 2007), the effective mesh size (MESH) (Spanowicz and Jaeger, 2019), Shannon's evenness
137 index (SHEI) (Shannon, 1948), the vegetation cover proportion (veg cover), the vegetation
138 patch density (Threlfall et al., 2015), and the median vegetation class NDVI (NDVI median)
139 (Table S3).

140 We conducted principal component analysis (PCA) of the landscape dataset to visualise the
141 differences among our study sites. The unsupervised k-means clustering method was applied
142 to delineate the landscape category along the urban-rural gradient into k groups. Before

143 initiating the analysis, the data were standardised using the *scale* function in R to make
144 variables comparable. As a result, the clustering algorithm was independent of any variable
145 unit. The number of k groups required to be defined as the first step was determined using the
146 elbow method (Kodinariya and Makwana, 2013). The k-means partitioning analysis was
147 performed using the *k-means* function with 25 random sets (Strickland, 2014) and the
148 *factoextra* package in R for PCA graphical representations (Kassambara and Fabian, 2020).

149 **Molecular techniques**

150 *DNA extraction*

151 First, pollen samples (0.5 g) were lyophilized using a lyophilizer freeze dryer VD-250R
152 (TAITEC, Koshigaya, Saitama, Japan). After being ground at 1500 rpm for 2 min using a
153 ShakeMaster NEO homogeniser (bms, Shinjyuku, Tokyo, Japan), DNA was extracted using
154 the protocol of MPure Bacterial DNA Extraction Kit (MP Biomedicals, Irvine, CA, USA).
155 DNA purification of the samples was performed using the MPure-12 Automated Nucleic Acid
156 Purification System (MP Biomedicals, Irvine, CA, USA). Quality control of DNA extracts
157 was conducted using Synergy H1 (BioTek, Winooski, VT, USA) and QuantiFluor dsDNA
158 System (Promega, Madison, WI, USA).

159 *Library preparation and DNA sequencing*

160 One hundred and **forty-three** libraries were produced using a 2-step tailed polymerase chain
161 reaction (PCR) method. The first PCR amplification was conducted using internal transcribed
162 spacer (ITS1) primers designed by Masamura *et al.*, (2014) (Table S4), coupled with MiSeq-
163 specific adapters. This primer pair was selected for its effectiveness (Maeda and Takahashi,
164 2017) to identify more Japanese plant species compared to ITS 1 and ITS 2 region designed
165 by Cheng *et al.* (2016). The second PCR amplification was conducted using index primers.

166 PCR reactions were carried out in a reaction volume of 10 μ L containing 1.0 μ L of 10 \times Ex
167 Buffer, 0.8 μ L of nucleoside triphosphate dNTPs (each at 2.5 mM), 0.5 μ L for both forward
168 and reverse primer at a concentration of 10 μ M, 2.0 μ L of DNA template normalized at 0.5
169 ng/ μ L, 0.1 μ L of DNA polymerase ExTaq at 5 U/ μ L (TaKaRa, Otsu, Shiga, Japan) and 5.1 μ L
170 of double-distilled water. The PCR profile was as follows: 2 min of denaturation at 94°C,
171 followed by 30 cycles with 30 s of denaturation at 94°C, 30 s of annealing at 57°C, 30 s of
172 elongation at 72°C, and a final elongation at 72°C for 5 min. [The PCR products were purified](#)
173 [using MPure XP with ratio of beads of 0.7x](#) (Beckman Coulter, Brea, CA, USA). The second
174 PCR profile was follows: 2 min of denaturation at 94°C, followed by 10 cycles with 30 s of
175 denaturation at 94°C, 30 s of annealing at 60°C, 30 s of elongation at 72°C, and a final
176 elongation at 72°C for 5 min. Library concentrations were determined using a Synergy H1
177 microplate reader (BioTek, Winooski, VT, USA) and a QuantiFluor dsDNA System
178 (Promega). Library quality was evaluated using a fragment analyser (Advanced Analytical
179 Technologies, Ankeny, IA, USA) with a dsDNA 915 Reagent Kit (Agilent, Santa Clara, CA,
180 USA). The generated library was sequenced using MiSeq Illumina technology (Illumina, San
181 Diego, CA, USA) through a 2 \times 300 paired-end run.

182 *Data processing*

183 For subsequent analysis, the sampling dates were discretely pooled by month and analysed in
184 R version 4.0.2 (R Core Team, 2020). We used Spearman's rank-order correlation between
185 the number of taxa per sample and the sampling length in hours to test whether the data could
186 be treated independently of the sampling length. Furthermore, we used "FASTX Barcode
187 Splitter" from Fastx toolkit, a short-reads pre-processing tool, to extract only the target and
188 index sequences from MiSeq reads (Hannon, 2010). Next, the reads were denoised and
189 filtered using Sickle software (Joshi and Fass, 2011) with an overlap quality value of 20.

190 Trimmed reads with fewer than 150 bases were discarded. The remaining reads were merged
191 using FLASH (version 1.2.11) paired-end merge script (Magoč and Salzberg, 2011) using the
192 following conditions: fragment length after merging of 420 bases, read fragment length of 280
193 bases, and minimum overlap length of 10 bases. The open-source [bioinformatic](#) pipeline
194 Qiime 2.0 (Bolyen et al., 2019) workflow script was used for taxa creation and taxonomic
195 assignment for the filtered reads. The filtered read pairs were clustered with USEARCH
196 9.0.2132 (Edgar et al., 2011) to remove low quality data with more than 97% sequence
197 identity. Taxon sequences were searched on the 1st February 2020 against the NCBI
198 nucleotide database (Benson et al., 2013) using BLASTN ver. 2.9.0. and the 10 best matches
199 were retained. Only the top 1 taxon was considered if it belongs to Tracheophyta group (i.e.
200 vascular plants), other taxa belonging to other kingdoms were removed. Following the
201 taxonomy classification step, taxa-abundance data and operational taxonomic unit (OTU) data
202 were applied to the R environment (R Core Team, 2020). First, the assignment of all OTUs
203 below the identity threshold of 97% was discarded (Danner et al., 2017; Smart et al., 2017).
204 Next, the number of reads was sorted by genus and sample (i.e. site and collection date), and
205 was then expressed as the ratio between the read count and the sum of read number per
206 sample for each genus. Genera accounting for less than 0.05% of the total number of reads for
207 a single sample were excluded to prevent false positives and two samples were removed
208 because it accounted for less than 1000 reads to limit inferences from insufficient sequencing
209 depth (Sponsler et al., 2020).

210 **Taxonomic analysis**

211 [Read-matches to plant taxa were classified to genus, where possible, because ITS1 reference](#)
212 [sequences were not enough to identify some species in the region. They were treated as](#)
213 [incidence \(i.e. presence/absence binary arrays\) data because PCR biases \(Bell et al., 2021\).](#)

214 The richness of the pollen samples (i.e. the number of distinct taxa of foraged plants) was
215 analysed as a function of the month (i.e. converted in integer variable) and landscape
216 variables (i.e. explanatory variables). The non-collinearity among the predictors was assessed
217 using Pearson's correlation coefficients with a range value from -0.7 to 0.7 as selection
218 criteria (Dormann et al., 2013). Four landscape variables were selected: dpop, SHEI, the
219 proportion of impervious surface (Cov_urb) and the urban patch density (pd_urb) (Fig. S2).
220 Given that the independence of our measurements could not be controlled because of the
221 pseudoreplication of the temporal data (Table S2) and the unbalanced experimental design,
222 general mixed-effects models (GLMMs) were used (Grueber et al., 2011; Harrison et al.,
223 2018). The pollen collection sites were specified as random effects (1| site). Negative
224 binomial distribution was chosen as link function to explain the distribution error of the
225 foraged plant richness (Lindén and Mäntyniemi, 2011) using *glmmTMB* R package (Brooks et
226 al., 2017). The selected predictors were specified as fixed effects as a function of the months
227 and landscape variables (i.e. explanatory variables). For the model selection, Akaike
228 Information Criterion (AIC) and Bayesian Information Criterion (BIC) metrics were assessed.
229 The lowest values of these metrics optimize the trade-off between the fit and the complexity
230 of the constructed models (Richards, 2008). Finally, the residual distributions of all mixed-
231 effects models assumptions (i.e. over- underdispersion, deviance) were inspected and checked
232 with *DHARMA* R package (Hartig, 2021).

233 For multivariate analysis, the pollen source-plant taxonomic composition of the samples was
234 studied across sites, sampling periods and landscape classes using the Jaccard dissimilarity
235 metric from the *vegan* package in R (Oksanen et al., 2019). This asymmetric distance
236 coefficient addresses the problem of double zero, which is essential when studying data on
237 community composition along a gradient. Differences in pollen source-plant composition
238 between sampling periods and landscape classes were investigated by permutation-based

239 multivariate analysis (N = 999) of variance using the *adonis* function (Anderson, 2001). If the
240 PERMANOVA results were significant, a post-hoc multilevel pairwise analysis with
241 Bonferroni correction was performed using the *pairwiseAdonis* package in R (Martinez
242 Arbizu, 2020). The dissimilarities in the structures of pollinated plant communities were
243 displayed using non-metric multidimensional scaling (NMDS) with 999 permutations. All
244 graphics were generated using the *ggplot2* package in R (Wickham, 2016).

245 **Indicator species and trait-based analysis**

246 Similarity percentage (SIMPER) analysis was applied to identify how the taxonomic
247 composition differed from the environmental conditions (landscape type) and changes
248 (season). This step allowed us to identify the sampled taxa that contributed significantly to the
249 dissimilarities among the months or landscapes. Finally, to analyse the characteristics of
250 pollen forage plants, taxa were further classified by their traits including herbaceous (no
251 woody stems above ground) or woody taxon (tree, shrub, liana), and including native, alien,
252 or cultivar taxa. The plant trait database was built using information from Ylist (Yonekura
253 and Kajita, 2007) and ©Species2000 (Roskov et al., 2019) for the Japanese plant dataset. To
254 determine if the proportion between the different traits varied with the seasons and landscape
255 types, the G-test of independence for contingency table was performed using the
256 *RVAideMemoire* package in R (Hervé, 2020). The G-test is based on the log likelihood ratio
257 and tests whether the relative proportions of one categorical variable (i.e. plant nature or
258 native status) are independent of the second categorical variable (i.e. season or landscape).
259 Next, post-hoc pairwise comparisons were conducted between pairs of proportions using the
260 Bonferroni correction of the p-values (MacDonald and Gardner, 2000).

261 **Results**

262 **Landscape classification**

263 The method of differentiating vegetation from impervious surfaces using NDVI provided
264 convincing results after crosschecking, even in the complex environment of an urban matrix.
265 The two first dimensions of the landscape PCA from landscape variables of our sampling sites
266 described a high percentage of the variance (axis 1 = 81.6% and axis 2 = 11.0%; Fig. 2).
267 According to the elbow method (Fig. S3) of the k-means partitioning, we classified our
268 sampling sites into four landscape classes according to a rural-urban gradient: rural (N = 3),
269 suburban (N = 3), urban (N = 5), and urban centre (N = 6). The urbanised locations were
270 driven by a much higher demographic density compared to the other landscapes (Fig. S4).
271 Moreover, following the decrease in the proportion of vegetation along the rural-urban
272 gradient, it can be assumed that the higher patch density in the cities was induced by the
273 presence of many smaller plots, such as private garden patches. In contrast, the rural sites
274 demonstrated a higher connectivity between the patches.

275 **Taxonomic analysis**

276 Illumina sequencing generated a total of 8,179,602 paired-end raw reads for the 143 pollen
277 samples from the 17 sites throughout the 7 months of pollen sampling. After assembling and
278 filtering, 6,799,314 reads (83.2%) were obtained for analysis, with a mean count of $47,548 \pm$
279 $27,464$ (SD) reads per sample. After taxonomic assignment of the meta-barcoding dataset, we
280 identified 307 plant flower taxa from 74 families and 187 genera. Prior to the analysis, the
281 richness was not correlated with the duration of sampling (Table S2), showing a very weak
282 relationship ($r_s [143] = -0.17, p < 0.05$), allowing us to consider the statistical independence
283 of all our pollen samples. Plant richness ranged between 3 and 42 pollinated plant taxa per
284 sample, with an average of 12 ($SD = 6.2$). GLMMs were not able to detect a significant
285 interaction between landscape variables and collection time on taxa richness (Table 1). Only,
286 the pollen richness diminished significantly as the seasons progressed (Table 1, Fig. 3A)
287 while the impervious surface proportion has no impact on the pollen richness (Fig. 3B).

288 NMDS displayed high variability in the composition of foraged pollen across the months and
289 seasons (Fig. 4). The greatest discontinuity separated spring (March, April, and May) from
290 autumn (September). Concerning the floral composition foraged by the honeybees, May and
291 August served as transition months to subsequent seasons. The permutation tests revealed that
292 the month period ($F = 6.87$; $R^2 = 0.23$; $p < 0.001$), site ($F = 1.27$; $R^2 = 0.1$; $p < 0.01$), and
293 landscape class ($F = 2.01$; $R^2 = 0.03$; $p < 0.001$) were significant explanatory variables of
294 pollen source-plant composition in the samples; however, the sampling period was attributed
295 a larger proportion of the variance. From pairwise comparisons (i.e. letters from Fig. 4), the
296 urbanised sites hosted similar plant communities. Moreover, the structure of the plant
297 communities varied significantly over the months until late summer and early autumn (i.e.
298 August and September), when the floral composition harboured similar foraged plant
299 communities.

300 **Indicator species and trait-based analysis**

301 The characteristics of pollen forage plants varied significantly according to their stratum ($G =$
302 99.0 , $p < 0.001$) and native status ($G = 69.1$, $p < 0.001$) over the study months (Fig. 5B),
303 while only the plant strata showed significant differences ($G = 10.7$, $p < 0.05$) according to
304 the landscape classes (Fig. 5A).

305 *Effect of landscape*

306 Significantly more herbaceous plant taxa structured the rural landscape (Fig. 5A), even if
307 pollen source-plant composition traits were independent of landscape type. A total of 35 plant
308 taxa were shared among all the landscapes over the sampling months such as some *Trifolium*
309 spp. or *Plantago asiatica* L., while 151 plant taxa were exclusively related to specific
310 landscapes, corresponding to 27%, 22%, 24%, and 26% of the total plant taxa for rural,

311 suburban, urban, and urban centre landscapes, respectively (Fig. S5). *Sagittaria natans* Pall.
312 and *S. trifolia* L. taxa are tied to rural areas. Plant families, such as Fabaceae, Rosaceae,
313 Brassicaceae, Asteraceae, Plantaginaceae, and Onagraceae, were the most frequent taxonomic
314 families encountered in all samples. However, their proportions varied according to the
315 landscape (Fig. S6). In urban and urban centre areas, leguminous plants prevailed more than
316 in rural and suburban landscapes. However, the suburban landscape showed a higher
317 frequency for the Brassicaceae, Ranunculaceae, and Rosaceae plant families. Surprisingly,
318 anemophilous plants of the Poaceae family were more frequently foraged in the urbanised
319 landscape than in the countryside (Fig. S6). *Trifolium* genus showed constant occurrence
320 throughout the landscape classes while other main genera foraged by honeybees were more
321 frequent in distinct landscapes such as *Allium*, *Sagittaria* and *Helianthus* taxa for rural
322 landscapes, *Veronica* and *Papaver* taxa for suburban areas, *Plantago* and *Oryza* taxa for
323 urban center landscape (Fig. 6A).

324 *Effect of sampling period*

325 The proportion of foraged woody taxa decreased significantly over the seasons ($G = 87.5$, $p <$
326 0.001), with a peak of 46% in April and a low of 10% in September. Over the sampling
327 months, honeybees foraged mainly on alien plant taxa (Fig. 5B). Cultivar taxa were more
328 foraged in spring than in the other two seasons ($G = 32.9$, $p < 0.001$). The most visited plant
329 genera in March and April included *Prunus*, *Helleborus*, *Brassica*, and *Acer* taxa (Fig. 6B). In
330 contrast, four of the 11 most frequent genera emerged in late spring in May. Between April
331 and June, a noticeable phenological turnover in the pollen composition (Fig. 6B) was
332 observed, with May serving as a transition bridge. This has already been highlighted by the
333 discontinuities in the NMDS ordination (Fig 4). Following this shift, the genus *Trifolium* spp.
334 was highly dominant in the June and July samples. In addition, the herbaceous genera

335 *Plantago* and *Oenothera* spp. were also found in large proportions in combination with the
336 woody genera *Mallotus* and *Hydrangea* spp. In August, the taxa from the genus *Oenothera*
337 were the most represented with *Trifolium*, despite a reduction in its occurrence. A shift in
338 pollen composition trends, with a reduction in highly proportional occurrence genera, was
339 observed in August and September. In other words, plants detected in August and September
340 were more distributed between the genera. Only the genus *Allium* showed an increase from
341 August to September. Finally, *Trifolium* spp., *Rosa* spp., and *Allium* spp. were the only genera
342 that were observed throughout the study period.

343

344

345 **Discussion**

346 This study revealed interesting patterns of honeybee foraging habits along the urban-rural
347 gradient throughout their active season. In the present study, we used an unconventional
348 approach, namely k-means clustering from landscape metrics, to categorise our sampling sites
349 into four landscape classes. These landscape variables allowed the estimation of the effects of
350 some ecological processes at the landscape level (i.e. foraging and plant dispersal) in
351 assessing the diversity, connectivity, and aggregation of the patches (Baguette et al., 2012;
352 Doherty and Driscoll, 2018). Despite the convincing results of the grouping method, several
353 reservations are worth mentioning. First, the selected foraging radius of 6 km accentuated the
354 spatial autocorrelation issues on the landscape variables by increasing the foraging area
355 overlaps among the sites (Plant, 2012). This was not tested in the present study because we
356 considered that there was no spatial influence on foraged plant communities between each
357 sampling colony due to the high variations in their foraging behaviour (Oldroyd et al., 1992;
358 Visscher and Seeley, 1982), even at the local scale for colonies of the same apiary (De Vere et
359 al., 2017). Indeed, the foraging behaviour of honeybee colonies is mainly driven by: (i) the
360 temporal colony needs; (ii) the high density of pollen and nectar resources available near the
361 colony; (iii) the rapid decision making by colony for the most profitable flower patches; and
362 (iv) the ability to tightly modulate its pollen reserves to protect the colony from seasonal
363 pollen breaks (e.g. long rainy periods, rarefaction of floral resources at the end of summer)
364 (Seeley, 1995). Second, the 3-image resolution from satellites may result in some limitations,
365 especially in complex landscapes, such as urban matrices. Therefore, this spatial resolution
366 issue could be counterbalanced with the use of specific cameras, such as red-green-blue
367 (RGB) or multispectral cameras, mounted on unmanned aerial vehicles to characterise floral
368 identification and surfaces (Chen et al., 2019; Librán-Embid et al., 2020). Nonetheless, this
369 research domain is still in its infancy, particularly in the data processing of imagery

370 classification by deep learning (Pritt and Chern, 2017). However, despite these spatial
371 limitations, the approach led to satisfactory classification, which paves the way for further
372 investigations. The use of DNA meta-barcoding with one pair of ITS1 primers (Masamura et
373 al., 2014) allowed for the identification of a great diversity of plant resources and highlights
374 foraging patterns, regardless of the landscape variables or classes. This method yields to the
375 identification of 307 taxa, which is higher than previous studies (Danner et al., 2017;
376 Richardson et al., 2021). This could be explained by the important sampling effort of pollen
377 samples (N = 143) over the seasons combined with contrasting landscapes (i.e. urban to rural
378 landscapes). Moreover, the lack of a Tokyo regional plant list and associated ITS1 references
379 to compare our sequences with could have increased the number of detected taxa by
380 introducing false-positive BLAST alignments (Richardson et al., 2015a).

381 We observed a strong seasonal effect on plant richness (Fig 3), the foraged plant community,
382 and plant characteristics (Fig 4 and 5B). We observed higher plant richness and foraged
383 woody taxa in spring than in the other two seasons (Fig 3 and 5B), as reported previously
384 (Brodschneider et al., 2019; Lau et al., 2019; Sponsler et al., 2020). The genera *Prunus* spp.
385 and *Acer* spp. (Fig 5D) dominate the foraged woody stratum during this season, as these taxa
386 constitute an important source of pollen for the early season (Brodschneider et al., 2019;
387 Requier et al., 2015; Richardson et al., 2015b; Sponsler et al., 2020). Indeed, bee breads with
388 high proportions of both genera were positively correlated with a higher protein content
389 (Donkersley et al., 2017). Particularly, the complexity and high range of foraged plants is
390 known to be beneficial to the “nutritional value” of these bee bread stocks, and thus to
391 honeybee immunity (Alaux et al., 2010). After the spring period, the proportion of foraged
392 herbaceous strata gradually substituted woody taxa to reach approximately 90% of
393 herbaceous foraged taxa in September, in agreement with previous studies (Brodschneider et
394 al., 2019; Sponsler et al., 2020). This growing herbaceous stratum is mainly dominated by

395 *Trifolium* spp. and *Plantago* spp. which, because of their long flowering period, might explain
396 the lower richness of taxa foraged in summer and autumn (Brodschneider et al., 2019;
397 Donaldson-Matasci and Dornhaus, 2012; Liolios et al., 2015). Also late summer and early
398 autumn are known to be characterized by a depletion of floral resources in temperate regions
399 which could explain specific foraging on the remaining floral communities such as *Trifolium*
400 or *Allium* genera (Requier et al., 2015; Sponsler et al., 2020). Moreover, clover species (i.e.
401 *Trifolium* spp.) are highly ubiquitous in grasslands, such as meadows for rural areas or parks
402 and gardens for urban areas (Brodschneider et al., 2019; Critchley et al., 2007) and may
403 contribute to the concentration effect of amino acid content (Donkersley et al., 2017).
404 Concerning the temporal dynamics of the biogeographic traits, the observations point to a
405 decrease in the frequency of cultivars in favour of exotic taxa, which contradicts previous
406 studies (Urbanowicz et al., 2020; Williams et al., 2011). The highly anthropized and
407 fragmented environments of the Tokyo region and its surroundings could explain the
408 predominance of non-native floral species. However, this statement should be mitigated and
409 requires further investigation, such as a complete plant inventory of the study site. Finally, we
410 observed a transitional change from August by a collapse of the dominant flower prevalence,
411 which may correspond to the seasonal dearth of floral resources (Fig 4 and 5B)
412 (Brodschneider et al., 2019; Park and Nieh, 2017). The honeybees mitigate this effect by
413 increasing their foraging range, requiring extra effort for sometimes worthless rewards (Park
414 and Nieh, 2017). Finally, the study of other co-variables, such as brood monitoring or
415 estimating the pollen collection/reserve of each colony, could be used to compare the
416 conditions of each sampled colony and improve our understanding of the foraging patterns of
417 the colonies (Delaplane et al., 2013).

418 The landscape variables did not influence forage plant richness, as reported in previous
419 studies (Danner et al., 2017; Steffan-Dewenter and Kuhn, 2003). However, considering the

420 spatial variation of taxa composition among the sites of our area of interest (i.e. beta diversity)
421 (Legendre, 2014), our results showed a spatial structure of foraged plant communities in
422 countryside, suburban, and urban environments (i.e. by merging the urban and urban centre
423 areas) (Fig 4). It is likely that honeybee colonies modify their foraging preferences due to the
424 high prevalence of unattractive ornamental flowers in urban landscapes (Garbuzov et al.,
425 2015a). The urban matrix also offers smaller spread patches and less dense floral resources,
426 which contribute to the foraging change of workers (De Vere et al., 2017; Lucek et al., 2019).
427 This shift in the prospected flora is also coupled to fulfil the nutritional demand with a diverse
428 and complementary floral diet (Donkersley et al., 2017; Hendriksma and Shafir, 2016).
429 Therefore, it shows the importance of taking beta diversity and not only the local richness into
430 account to understand the community structure of foraged plants throughout space and time
431 scales (Richardson et al., 2021; Socolar et al., 2016). Despite the landscape structure of the
432 foraged plant community, the trait-based analysis revealed no significant pollinated plants
433 traits for honeybee colonies, except for herbaceous plants in rural landscapes (Fig 5A).
434 However, the forest cover is high in rural areas (Enokisawa and Kuwata=42.2%,
435 Ichihara=35%), mainly composed of artificial forest stands (Enokisawa and Kuwata=53%,
436 Ichihara= 33%) (Chiba, 2022). Artificial forest mainly consists of conifers *Cryptomeria*
437 *japonica* (L. f.) D.Don and *Chamaecyparis obtusa* (Siebold & Zucc.) Endl. which do not
438 provide floral resources for bees, meaning that the attraction of herbaceous plants would be
439 facilitated. Moreover, the inconclusive result of trait-based analysis can be explained by the
440 number and selection of functional traits selected from the foraged plants. The selected
441 characteristics of pollen forage plants are few and not very informative in the context of plant-
442 pollinator relationships. An evaluation of the functional structure of foraged plants with
443 relevant floral characteristics (which honeybee colonies depends on) such as floral symmetry,

444 floral shape, etc. would have helped to refine the understanding of the attractive floral
445 structure (E-Vojtkó et al., 2020; Fornoff et al., 2017).

446 In all the samples, 35 plant taxa were shared throughout all the landscapes studied,
447 corresponding to 45% of all read counts. The top three plant families were Fabaceae,
448 Rosaceae, and Brassicaceae which are known to be in the foraging preference of honeybee
449 (Richardson et al., 2021; Sponsler et al., 2020). The presence of grasses (Poaceae) may seem
450 surprising among the most frequent families in the samples, given that these plants are
451 considered unsuitable for *A. mellifera* resource needs (Decourtye et al., 2010). In view of their
452 dominance, it seems unlikely that anemophilic pollen is the result of contamination by pollen
453 blown from flowers onto the body of the bees, such as the rice paddy field in Japan (Kimura
454 et al., 2014). Other recent studies have shown that pollinators (i.e. bees and syrphids),
455 particularly *Apis* bees, interact with wind-pollinated plant species for their nutrient or nesting
456 requirements (Saunders, 2018). Honeybees foraged floral resources ranging from 28 to 45
457 taxa, specific to each defined landscape. For example, some parts of rural landscapes in our
458 study correspond to wetlands which are suitable to the population development of *S. natans*
459 and *S. trifolia* (Chen, 1989).

460

461 **Conclusion**

462 This study has shown that the foraged plant richness was mainly explained by the season
463 progression. In addition, it reflects large plant communities dominated by the occurrence of
464 alien species independently of the landscape classes. Woody species offered an important
465 source of pollen to the honeybees in the early growth season while herbaceous plants
466 dominated foraged plant structure in summer and autumn. The cultivar species occurrence
467 tends to decrease constantly over the seasons, while native species are sparsely foraged. These
468 findings are consistent with the literature addressing this topic with similar datasets (Requier
469 et al., 2015; Sponsler et al., 2020). Our work revealed that the foraged floral composition is
470 also driven by the landscape context suggesting that bee diet is locally constrained by
471 ecological drivers although 35 foraged plant taxa were exploited by honeybees in all defined
472 landscapes. During periods of floral dearth, honeybees increase their foraging radius and their
473 number of floral sites which require extra effort from the foragers sometimes for worthless
474 rewards (Park and Nieh, 2017). Indeed, the nutritional need for the colony is a pivotal factor
475 for the colony health which is mainly affected by the variations in pollen depletion and
476 quality rather than its pollen richness (Di Pasquale et al., 2016). Therefore, in an urban
477 greening context, it would be relevant to put in place measures to alleviate this seasonal
478 dearth by ensuring enough high-quality floral resources close to the apiaries which may also
479 benefit in their tolerance against pathogens or pesticides (Barascou et al., 2021; Di Pasquale et
480 al., 2013).

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