Received: 8 November 2017 | Accepted: 9 April 2018

DOI: 10.1111/1365-2664.13167

RESEARCH ARTICLE

Journal of Applied Ecology | BRITISH ECOLOGICAL SOCIETY

Comparing convenience and probability sampling for urban ecology applications

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Funding information
Libera Università di Bolzano, Grant/Award Number: TN2060 - ECOBENE; Free University of Bozen-Bolzano's

Handling Editor: Cristina Garcia

Abstract

1. Urban forest ecosystems confer multiple ecosystem services. There is therefore a need to quantify ecological characteristics in terms of community structure and composition so that benefits can be better understood in ecosystem service models. Efficient sampling and monitoring methods are crucial in this process.
2. Full tree inventories are scarce due to time and financial constraints, thus a variety of sampling methods exist. Modern vegetation surveys increasingly use a stratified-random plot-based sampling to reduce the bias associated with convenience sampling, even though the latter can save time and increase species richness scores. The urban landscape, with a high degree of conspecific clustering and high species diversity, provides a unique biogeographical case for comparing these two methodological approaches.
3. We use two spatially extensive convenience samples of the urban forest of Meran (Italy), and compare the community structure, tree characteristics and ecosystem service provision with 200 random circular plots.
4. The convenience sampling resulted in a higher species diversity, incorporating more rare species. This is a result of covering more area per unit sampling time. Pseudorandom subplots were compared to the random plots revealing similar Shannon diversity and sampling comparability indices. Measured tree variables (diameter at breast height, height, tree-crown width, height to crown base) were similar between the two methods, as were ecosystem service model outputs.
5. *Synthesis and applications*. Our results suggest that convenience sampling may be a time and money saving alternative to random sampling as long as stratification by land-use type is incorporated into the design. The higher species richness can potentially improve the accuracy of urban ecological models, which rely on species-specific functional traits.

KEYWORDS
beta diversity, convenience sampling, ecosystem services, heterogeneity, probability sampling, pseudosampling, urban ecosystem, urban forest structure

1 | INTRODUCTION

There is a need to quantify complex and heterogeneous urban forest ecosystems and their structural characteristics in an efficient, robust and reproducible manner. Theoretically, a complete tree inventory, consisting of measuring species, location, height, diameter at breast height (DBH) and condition of all trees in a city, is possible. However, a medium-sized city, such as New Jersey (USA) with 270,000 inhabitants, can have an estimated 136,000 trees (Nowak, Walton, Stevens, Crane, & Hoehn, 2008). The barriers to obtaining a full inventory of such a large population are immediately apparent—time and financial constraints—not to mention the difficulties of accessing private land. According to Martin, Chappelka, Somers, Loewenstein, and Keever (2013), more research is needed to determine how much of the urban forest must be inventoried to produce an accurate estimate of the total population.

Sampling is normally undertaken using a specified number of fixed area plots allocated either randomly or systematically across the urban landscape (Nowak, Walton, Baldwin, & Bond, 2015; Nowak, Walton, et al., 2008). However, a potential barrier to effective urban tree sampling is the fact that the urban landscape is heterogeneous with the result that the beta diversity can be considered a special biogeographical case, where land use is a primary factor affecting species diversity. Public land, private gardens and ruderal wasteland all have different species assemblages. Spatial autocorrelation frequently occurs as a result of monospecific street-tree plantings, urban orchards, etc., and this particular form of conspecific clustering (Plotkin & Muller-Landau, 2002) requires careful consideration of sampling strategies.

One of the more popular standardized sampling protocols is the i-Tree suite that was developed as a management tool to quantify urban forest structure and model ecosystem services provision (i-Tree, 2017), and is used around the globe (Chaparro & Terradas, 2009; Russo, Escobedo, & Zerbe, 2016). A user of the i-Tree Eco application of the suite collects field data according to standardized guidelines (Nowak, Crane, et al., 2008; Nowak, Walton, et al., 2008) from a recommended 200 randomly, or stratified randomly, located 0.04 ha area circular plots (Nowak, Walton, et al., 2008). This number is recommended across the board because it yields an approximate 12% relative standard error on the estimate of total number of trees and further sampling of plots does not reduce this error significantly (Nowak, Walton, et al., 2008). A city with a substantial urban tree cover of 34.4% would take a field crew of two people 113 min per plot on average, meaning 200 plots would take around 14 weeks to complete (Nowak, Walton, et al., 2008), regardless of city size, heterogeneity or alpha diversity or plot density and access.

If the objective of a study is a phytosociological relevé, or to speed up study area-wide field sampling, one can reduce the statistical robustness of random plot allocation and instead sample a smaller number of complete patches. In the case of a city, this would be local neighbourhoods or city blocks, which reduce the time spent gathering plot-specific data and travelling between plots. Each patch should be of a uniform land type and stratification of the patches to proportionately cover the range of land types within a city is encouraged. In fact, urban tree data frequently already exist in this patch form because municipal tree inventories cover contiguous stretches of land such as tree-lined roads, parks and cemeteries, ignoring the trees on private land, thus producing a mosaic patchwork of sampled public land. Indeed, ecological data in general, are often collected using convenience sampling, for example along riparian areas and roads (Etikan, Musa, & Alkassim, 2016).

Under certain conditions, data collected by nonprobability methods may be beneficial for making inferences to a larger population, especially when combined with probability sampling data once the comparability has been assessed (Cao & Hawkins, 2011). The potential for combining environmental monitoring data from different sources (Maas-Hebner et al., 2015; Overton, Young, & Overton, 1993), despite the inherent statistical problems, can assist in answering research questions. Studies on urban systems are scarce, however, Michalcová, Lvončík, Chytrý, and Hájek (2011) compared convenience (preferential) sampling of forest vegetation with a stratified random design and found higher beta diversity and more endangered species in the convenience data yet a similar alpha diversity and alien species representation. They conclude that not all the studied properties are significantly affected by the sampling method. The higher coverage of rare species in convenience sampling has been confirmed in other studies (Hédl, 2007) with contrasting conclusions of no rules for prediction of differences between sampling methods (Botta-Dukát, Kovács-Láng, Rédei, Kertész, & Garadnai, 2007), and phytosociological relevés can be biased (Diekmann, Kühne, & Isermann, 2007).

In particular, bias is the main criticism of collecting data in a nonrandom, convenience sampling manner (Brus & De Gruijter, 2003). The representativeness of the sample may be brought into question in relation to probability sampling, which aims to mitigate the effects of unbalanced covariates through random selection (Baker et al., 2013). Schreuder, Gregoire, and Weyer (1999) argue that nonprobability sample data can be very useful, even if only to describe the particular sample, and notwithstanding, much environmental data can only be collected this way due to difficult sampling processes, access and safety issues, or time and expense constraints. Purposive sampling is generally more efficient than probability sampling for dealing with spatial heterogeneity (Brus & de Gruijter, 1997), and where autocorrelation exists, model-based (purposive) sampling should be considered as long as one can obtain a medium- to large-sized sample (Wang, Haining, & Cao, 2010).

To address the dearth of information on this topic, the aim of our study is to test the comparability of probability and nonprobability sampling methods, while exemplifying their strengths and weaknesses in relation to what they reveal about urban forest ecosystem structure. We wanted to answer the following research questions:

- Are structure and composition of the urban forest similar using both approaches?
- Are ecosystem service (i.e. carbon storage and stormwater runoff) estimates similar using both approaches?

There is increasing international use of random plots to characterize urban forest ecosystem composition, structure, processes and services (i-Tree ECO, 2017; Yang et al., 2015). Accordingly, assessing and identifying more rapid, efficient and precise sampling methods are needed.

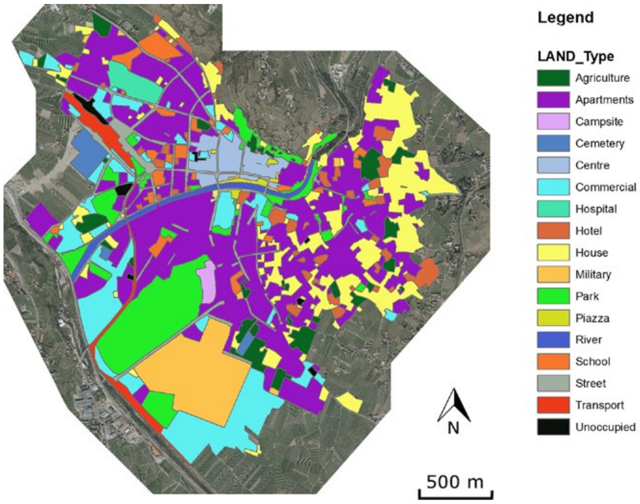

FIGURE 1 The city of Meran and the distribution of the land cover types [Colour figure can be viewed at wileyonlinelibrary.com]

2 | MATERIALS AND METHODS

2.1 | Study site

Meran, a small city of about 40,000 inhabitants (ISTAT, 2017), is located in the Autonomous Province of South Tyrol in Northern Italy (Figure 1). As the valley of the river Etsch, where Meran is situated in its upper reaches, is opening to the south, the climate is of sub-Mediterranean influence with a mean annual precipitation of *c*. 760 mm and the minimum and maximum average temperatures of 5.0 and 18.1°C, respectively (Meteo Alto Adige, 2017). It covers approximately 661 ha, however, the actual area available for study was 608 ha, due to the presence of a large military base within the city where fieldwork was prohibited (Figure 1).

The city was classified into 17 land cover types following the i-Tree land classification scheme (i-Tree ECO, 2017) but using subdivisions of the "commercial" and "institutional" land types. Plots could be characterized as being on private or public land for some analyses, to investigate differences between urban land tenure. Figure 1 shows that the city has a central commercial centre surrounded by mostly multioccupancy apartment blocks, with smaller houses situated in the more affluent east. The large park to the south is an equestrian park, which mostly consists of mowed grass with trees around the periphery.

Since the year 2000, the Meran municipality has maintained a detailed street-tree inventory containing over 5,000 trees in streets and parks, with an interactive online map (Comune di Merano, 2010). In addition to species and location, the inventory contains information on height, trunk DBH and trees' health condition. Tree species selection in Meran is driven not only by the usual requirements of, for example shade provision, longevity and litter fall, but also by a desire to include exotic and aesthetically pleasing trees, thus resulting in a high variety of native and nonnative tree species. The latter is because Meran is a popular tourist destination in the southern Alps known for its landscapes and architecture, and the botanical interest of its public trees is something the town is promoting (A. Schwarz, pers. commun., 2017).

2.2 | Approach 1: Convenience sampling

Fieldwork took place during autumn 2016. Initially, 964 trees from the three major public spaces included in the city inventory—streets, parks, and cemetery—were re-measured. The measurements in the inventory were not used because some trees had not been measured for several years, DBH had been measured at 1 m above-ground instead of 1.37 m, and additional measurements consisting of total tree height, height to crown base, crown width, percent missing crown, tree-crown condition and crown-light exposure, as outlined in the i-Tree field guide (i-Tree ECO, 2017), were required. DBH was measured with callipers and height was measured with a hypsometer (Blume-Leiss BL6) from a distance of 30 m. The DBH of trees with multiple stems was calculated as the square root of the sum of all squared DBHs. A total of 1,215 trees were measured on private land. The field data for the convenience sampling where full measurements were taken is denoted as CONV hereafter, and the addition of the species and location data from the public tree inventory provides a larger dataset called CONV+.

To account for spatial heterogeneity in the city, for the CONV sampling, we targeted homogenous areas with the aim of proportionately covering the different land cover types. Areas of the city were sampled in blocks that is sampling several neighbouring apartment complexes or small residential houses (Figure 2). These sampling units are based on the patch concept (Forman, 1995), a fundamental measurement unit for landscape analysis which implies a discrete spatial pattern in the form of urban land parcels. The sampling is classed as convenience because the patches were convenient to sample that is the field personnel walk through the urban landscape and choose patches adjacent to the route. The first available patch on the route is included. Once access is granted to a particular patch of land tenure, all the trees on that land are available to sample. True convenience sampling operates without a priori sampling design; however, to be more precise, the method used in this study utilizes a semistratified approach because the walking routes through the city were chosen to proportionately include the different land types after calculating their areal coverage of the city.

Permission was always sought from the landowner. On the infrequent occasions where permission was not granted, the next neighbouring unit was measured. The patch sizes for CONV range from 250 m^2 (a single house and garden) to 5.9 ha on public land (cemetery) and 5.5 ha on private land (several adjacent apartment blocks), and there were 48 patches in total. The clustering of patches to the west of the city is coincidental and does not detract from land type coverage. Tree species were identified mostly to species level and occasionally to genus level using Phillips (1978). Tree locations were drawn on a map and transferred to a geodatabase within ArcMap 10.4.1 using high-resolution aerial photography from 2013 obtained from the online Geocatalogue (Geocatalogo, 2017). The native

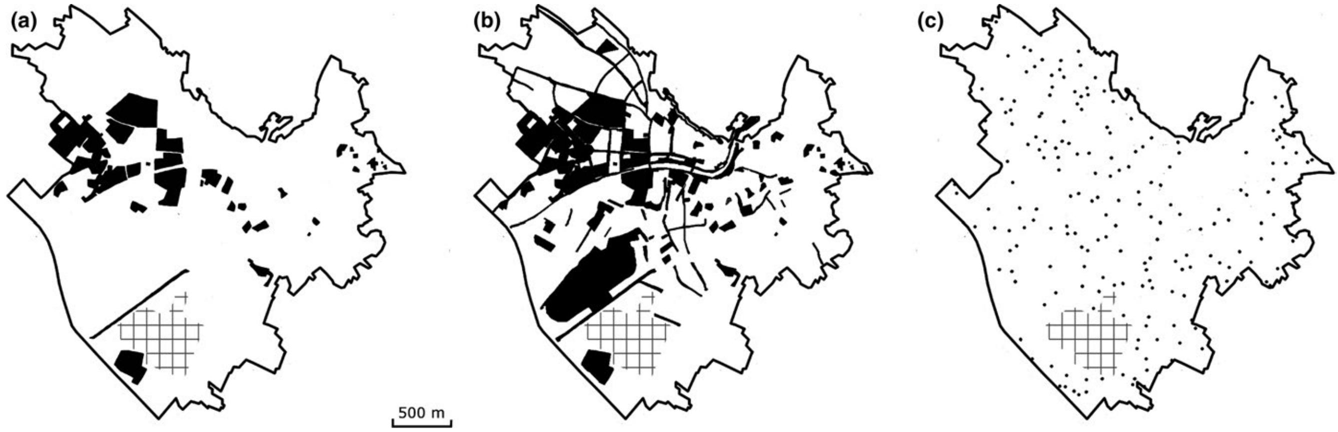

FIGURE 2 Extent of the areas sampled by the three different sampling strategies (a) CONV, (b) CONV+ and (c) RAND

status of each tree species in Italy was obtained from Pignatti (2017) as was the growth strategy that is evergreen or deciduous.

2.3 | Approach 2: Random sampling

A total of 250 random, nonstratified 0.04 ha plots was generated in ArcMap and 200 of these were sampled in spring 2017 as suggested by the standardized i-Tree ECO guidelines (i-Tree ECO, 2017). The same data were collected as for the convenience sampling. When plots were located on private land, permission was requested from the landowner. On the infrequent occasions where permission was not granted, another random plot was picked from the surplus 50 plots making sure it was in the same land type to avoid developing a bias towards public land types with easy access. The field personnel was different than for the convenience sampling; however, the two personnel carried out sampling of pilot sites to encourage convergence of the slightly more subjective measurement techniques such as tree-crown condition estimation.

2.4 | Data analysis

In order to compare tree species and quantitative measurements between the two different sampling methods, it was first necessary to generate pseudorandom 0.04 ha plots within CONV and CONV+ to replicate the RAND sampling approach within the convenience sampled patches. This was achieved by creating a layer of random points in ArcMap and allocating trees located within an 11.28 m radius to that pseudoplot. A program was written using R (version 3.3.3) which randomly sampled a given number of these pseudoplots with trees without repetition of individual trees.

In order to quantify the comparability of the tree population samples collected with different sampling methods, one must account for the effects of within-site sampling variability and differences in sampling effort (Cao & Hawkins, 2011). This can be done using a classification strength quantification technique (mean similarity analysis) defined as sampling-method comparability (SMC) according to Cao, Hawkins, and Storey (2005) which is

$$\mathrm{SMC} = 100 \times (S_{\mathrm{between}}{}^{2}/(S_{\mathrm{1within}} + S_{\mathrm{2within}}))$$

where S_{between} is the mean similarity between two sets of replicate samples collected with the two sampling methods, and S_{1within} and S_{2within} are the mean similarities between two replicate samples collected with CONV and RAND, respectively.

A randomization procedure was used to generate 1,000 replicates of varying sample size that is varying number of plots to pool into one sample. The sample size was restricted by the number of plots with trees in the RAND data. SMC can then be estimated based on the average similarities of these replicates. The Bray–Curtis index was used as a similarity index because abundance data were available. The R Vegan package was used for the ecological analyses (Oksanen et al., 2017). The two methods are considered comparable if they have an SMC value of 100 because it measures the overall similarity in assemblage composition or structure (Cao et al., 2005). The Shannon–Wiener diversity index at the species level was also calculated 1,000 times using the maximum sample size possible and a mean average obtained.

The same random pseudosample generation technique was used for statistically comparing the quantitative tree measurement data using maximum sample size of 22 for public, 88 for private and 110 for the whole area. Data were nonnormal so the nonparametric Mann–Whitney *U* test determined whether the pseudosamples were selected from populations with the same distribution. The same pseudosampling method generated one lot of 200 plots within the CONV field area. These were treated as input data for the i-Tree Eco v6 modelling software, as were the 200 plots from RAND. Additional data were needed for the model—percent tree-crown cover, shrub and plantable space—and these were estimated visually from a high-resolution (5 × 5 cm) orthophotograph in ArcMap. Hourly air pollution concentration and meteorological data for Meran for the year 2013 (Meteo Alto Adige, 2017) were submitted to the i-Tree database and included in the latest software update (v. 6.0.7). To independently compare and evaluate i-Tree output, we also estimated tree cover using a visual tree-cover mapping tool from the US Geological Survey

(Cotillon & Mathis, 2016) that was applied to the orthophotograph in ArcMap. The same 200 plots, plus a further 200 pseudosampled plots from CONV+, were used to carry out rarefaction and extrapolation with Hill numbers using the R package iNEXT (Hsieh, Ma, & Chao, 2016). The plots with trees were treated as sampling-unit-based incidence data.

TABLE 1 Descriptive data for the three sampling strategies in Meran, Italy

	RAND	CONV	CONV+
Area covered hectares	8.1	57.9	101.2
Area covered % of total city—excluding military	1.2	9.5	16.6
Number of plots with trees (*SD*)	110	123 (5.7)	121 (6.9)
Number of plots public land with trees (*SD*)	22	84 (27)	90 (7)
Number of plots private land with trees (*SD*)	88	87 (14)	50 (6)
Number of plots total public (*SD*)	34	111 (7)	146 (7)
Number of plots total private (*SD*)	166	99 (7)	72 (6)
Time taken (days)	11	21	—
Trees per day	28.3	103.7	—
Total trees	311	2,179	6,371
Trees private	225	1,215	1,215
Trees public	86	964	5,156
Species richness	72	179	222
Number of unique species	7 4 against CONV+	115	156
Genus richness	49	82	92
Number of unique genus	5 2 against CONV+	38	46
Family richness	25	36	40
Number of unique Family	1 0 against CONV+	12	15
Order richness	15	21	21
Number of unique order	0 0 against CONV+	6	6
% Native private	48.9	45.2	45.1
% Native public	38.4	36.4	45.1
% Evergreen private	44.4	50.4	50.4
% Evergreen public	31.4	45.1	23.5

3 | RESULTS

The plot areas sampled within each of the 16 land types correlate well with the total land type area for the city for RAND (Spearman's $\rho = 0.89$, $p < 0.001$) and moderately well for CONV ($\rho = 0.51$, $p = 0.04$). This indicates that both the stratified convenience sampling and the randomly generated plots were able to proportionately sample the land cover type diversity in the city. However, as expected, the correlation for CONV+ falls to $\rho = 0.45$ ($p = 0.12$) due to the strong bias towards the public areas in the city inventory. The CONV+, however, covers 12.5 times as much city area as RAND, while CONV covers seven times as much yet only taking approximately double the time to survey (Table 1), 21 working days as opposed to 11. In other words, it is 3.5 times more efficient. In terms of numbers of trees, CONV also includes seven times as many but CONV+ includes 20.5 times as many trees.

3.1 | Forest composition

CONV and CONV+ resulted in a much higher species richness than for RAND with many more unique species also (Table 2). RAND contains only seven unique species (species not found with the other sampling method) when compared to CONV and four when compared to CONV+, whereas even at the tree order level the convenience sampling and tree inventory contain much more taxonomic diversity. The total species richness when all the data are combined is 230. Table 2 shows how much overlap there is between the tree communities with RAND when the generation of pseudoplots allows for statistical comparison with CONV, with 59.2% of species shared by number, and 69.4% shared by abundance. Within the raw data, there were a few instances where trees could only be identified to genus level, for example for *Tilia* and *Ulmus*. When comparing the populations at the genus level, the similarity in community structure increased to 75.6% by number and 93.8% by abundance. Similarity decreased when comparing to CONV+ due to the higher species richness in the public tree inventory. However, Table 3 shows that actually the top 20 most abundant species in RAND do not have much overlap with CONV (7) and CONV+ (6).

TABLE 2 Mean average species and genus in common between the sampling strategies from 1,000 generations of 200 plots without repetition of trees

	Species		Genus	
	CONV	CONV+	CONV	CONV+
Number shared with RAND (*SD*)	45 (3)	46 (3)	35 (2)	35 (2)
% shared with RAND (*SD*)	59.2 (3.5)	53.8 (3.4)	75.6 (4.2)	73.1 (4)
% shared with RAND by abundance (*SD*)	69.4 (3.4)	63.3 (3.7)	93.8 (1.6)	93.7 (1.5)

TABLE 3 The top 20 most abundant species in Meran, Italy, for the three datasets. Bold = shared with RAND

RAND	*n*	CONV	*n*	CONV+	*n*
Tilia americana	24	***Cedrus deodara***	145	*Tilia europaea*	696
Chamaecyparis lawsoniana	20	*Tilia europaea*	110	*Tilia* sp.	365
Cupressus sempervirens	17	***Platycladus orientalis***	106	***Aesculus hippocastanum***	353
Prunus avium	15	***Cupressus sempervirens***	92	***Cedrus deodara***	259
Thuja occidentalis	12	***Thuja occidentalis***	86	*Platanus acerifolia*	208
Cedrus deodora	10	*Pinus nigra*	81	*Acer platanoides*	205
Ficus carica	10	*Betula pendula*	77	*Populus nigra*	202
Aesculus hippocastanum	9	***Tilia americana***	65	***Cupressus sempervirens***	151
Malus domestica	7	***Picea abies***	64	*Pinus nigra*	150
Sambucus nigra	7	*Magnolia grandiflora*	52	*Tilia platyphyllos*	144
Platycladus orientalis	7	*Taxus baccata*	49	***Celtis australis***	136
Cedrus libani	6	*Tilia platyphyllos*	48	*Tilia cordata*	128
Celtis australis	6	***Chamaecyparis lawsoniana***	45	***Platycladus orientalis***	114
Fagus sylvatica	6	*Cupressus arizonica*	44	*Betula pendula*	108
Olea europaea	6	*Prunus cerasus*	42	*Acer pseudoplatanus*	105
Picea abies	6	*Cedrus atlantica*	38	*Magnolia grandiflora*	100
Prunus domestica	6	*Acer pseudoplatanus*	37	*Ginkgo biloba*	93
Prunus laurocerasus	6	*Prunus cerasifera*	37	***Thuja occidentalis***	93
Prunus persica	6	*Acer negundo*	35	*Prunus cerasifera*	85

Figure 3 shows similarities in the community structure between RAND and the fixed 200 plots sampled from CONV, with both methods showing a small number of frequent species and over a third of species only occurring once. With regard to conspecific clustering, on plots with more than one tree, 37% of RAND plots have more than one tree of the same species, and 15% of the plots are monospecific. For CONV, this is also 37%, and CONV+ this is 49% (due to extensive presence of monospecific street trees).

The Shannon diversity indices are very similar for RAND (3.88), CONV (3.81, *SD* 0.1) and CONV+ (3.95, *SD* 0.1) and any differences are not significant between RAND and CONV (stat = 0.28, $p = 0.23$) and RAND and CONV+ (stat = 0.31, $p = 0.52$) using the "oecosimu" function testing the nonrandomness of the Shannon statistic against a null model with 2,000 iterations (R package Vegan). The Shannon evenness is higher for RAND (0.91) than for CONV (0.69, *SD* 0.02) and CONV+ (0.68, *SD* 0.01) undoubtedly due to a larger number of rarer species in the latter datasets. In Table 4, the within and between Bray–Curtis similarities are fairly low (mostly around 0.2); however, the SMC scores when comparing RAND to CONV are acceptably high for the whole dataset (81%) and public land (93%), and lower (64%) when looking at private land only. These fall when the public area inventory trees in CONV+ are included.

Figure 4 shows the extrapolated species diversity in terms of richness for the three sampling approaches. The confidence bands overlap in the extrapolation to double the sample size, indicating there are no significant differences between the three approaches for this snapshot of pseudo-samples of CONV and CONV+ compared to RAND.

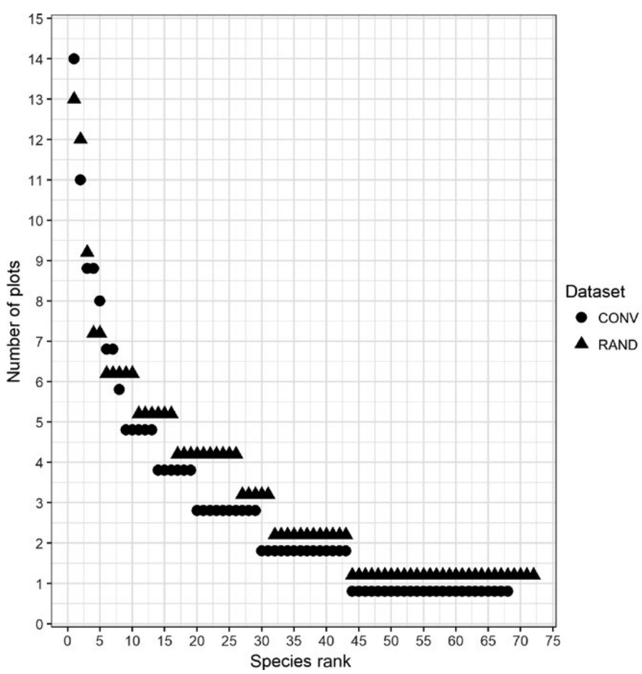

FIGURE 3 The number of plots out of 200 (110 with trees for RAND, 122 with trees for CONV) in which all the species were found

3.2 | Tree structure

Figure 5a–d show the continuous data collected using the i-Tree model protocol are all positively skewed and generally fairly comparable; however,

	Within *S* RAND	Within *S*	Between *S*	SMC (%)
CONV				
Public	0.2	0.1	0.14	93
Private	0.32	0.2	0.16	64
Whole	0.35	0.12	0.19	81
CONV+				
Public	0.2	0.24	0.15	68
Whole	0.35	0.54	0.21	47

TABLE 4 Sampling method comparability sampling-method comparability (SMC); Cao et al., 2005) when CONV and CONV+ are compared to RAND in Meran, Italy. *S* is average Bray–Curtis similarity index from 1,000 runs

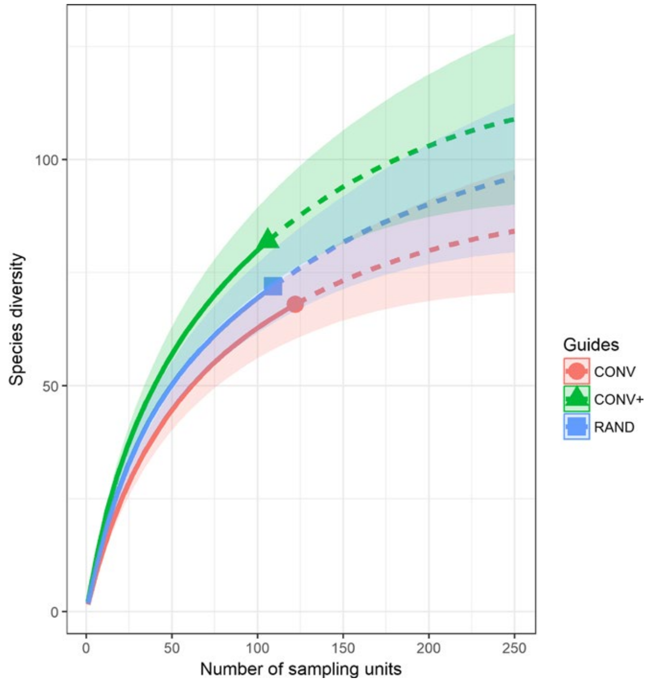

FIGURE 4 Sample-size-based rarefaction (solid lines) and extrapolation (dashed lines) curves for tree diversity. The 95% confidence intervals were obtained by a bootstrap method based on 200 replications [Colour figure can be viewed at wileyonlinelibrary.com]

the mode is lower for the RAND dataset, and median is also lower for height and DBH. This is due to the RAND plots containing multiple individuals of smaller shrub-like evergreen trees such as *Chamaecyparis lawsoniana* and *Thuja* spp. commonly used as hedging for privacy in gardens (Cariñanos & Casares-Porcel, 2011). The CONV dataset also contains several instances of these gardens; however, the fixed 200 plots randomly generated from CONV contained more trees with larger DBHs. The percentage of significant statistical comparisons (Table 5) were around two thirds of the simulations at $p = 0.05$ and roughly a half at $p = 0.01$, with the exception of tree-crown width, which had only a sixth of the simulations significant at $p = 0.05$. Therefore, we cannot confidently say the sampling methods sampled different populations all the time.

3.3 | Ecosystem service estimates

The output from the i-Tree model (Table 6) shows the estimates of carbon storage and runoff when the trees are extrapolated to the whole city area are fairly comparable. The estimated tree covers are especially close at 23.5% and 24.7%, and also close to the independent estimate of 21.4% obtained by the independent orthophoto analysis. Avoided runoff are higher for CONV despite a lower total tree estimate due to the presence of a larger number of large leaf area species, as defined by the ECO model, in the 200 fixed plots, such as *Cedrus deodar*.

4 | DISCUSSION

4.1 | Forest composition

The two field datasets RAND and CONV are statistically similar when using for urban forest ecology applications, despite being presented as different and separate approaches to sampling the city. They have similar Shannon diversity and the SMC scores are acceptably high at 93% for public, 64% for private and 81% for the city-wide dataset. Cao et al. (2005) suggest user discretion based on the study goals when deciding what is an acceptable SMC and for the purposes of comparing these two methods; that said 81% comparability is satisfactory. The community structures in RAND and CONV are also very similar having comparable abundance distributions of the dominant and rare species, and both exhibiting a similar level of conspecific clustering. Extrapolation of the sample-size-based rarefaction curves indicate the three sampling methods have no significant differences between them (Figure 4). In terms of the actual species sampled by the two methods, there is again some similarity, with all of the 72 species sampled in RAND appearing in CONV apart from seven (three of which appear in CONV+). Each of the seven species unique to RAND is only encountered once, apart from *Pyrus communis* with five individuals, all found in private gardens. Of the species unique to CONV, only 16% had more than 10 individuals and these were mostly common street trees such as *Tilia europaea* and *Acer pseudoplatanus*, and common garden trees such as *Eriobotrya japonica* and *Cercis canadensis*. This demonstrates one of the advantages of the convenience sampling; when a wider area is covered there is a lower probability of missing some of the common trees. Despite the species similarities mentioned above, RAND and CONV did not share that many of the most abundant species (Table 3). RAND failed to sample some of the widespread public tree species such as *T. europaea* and private land species such as *Magnolia grandiflora*.

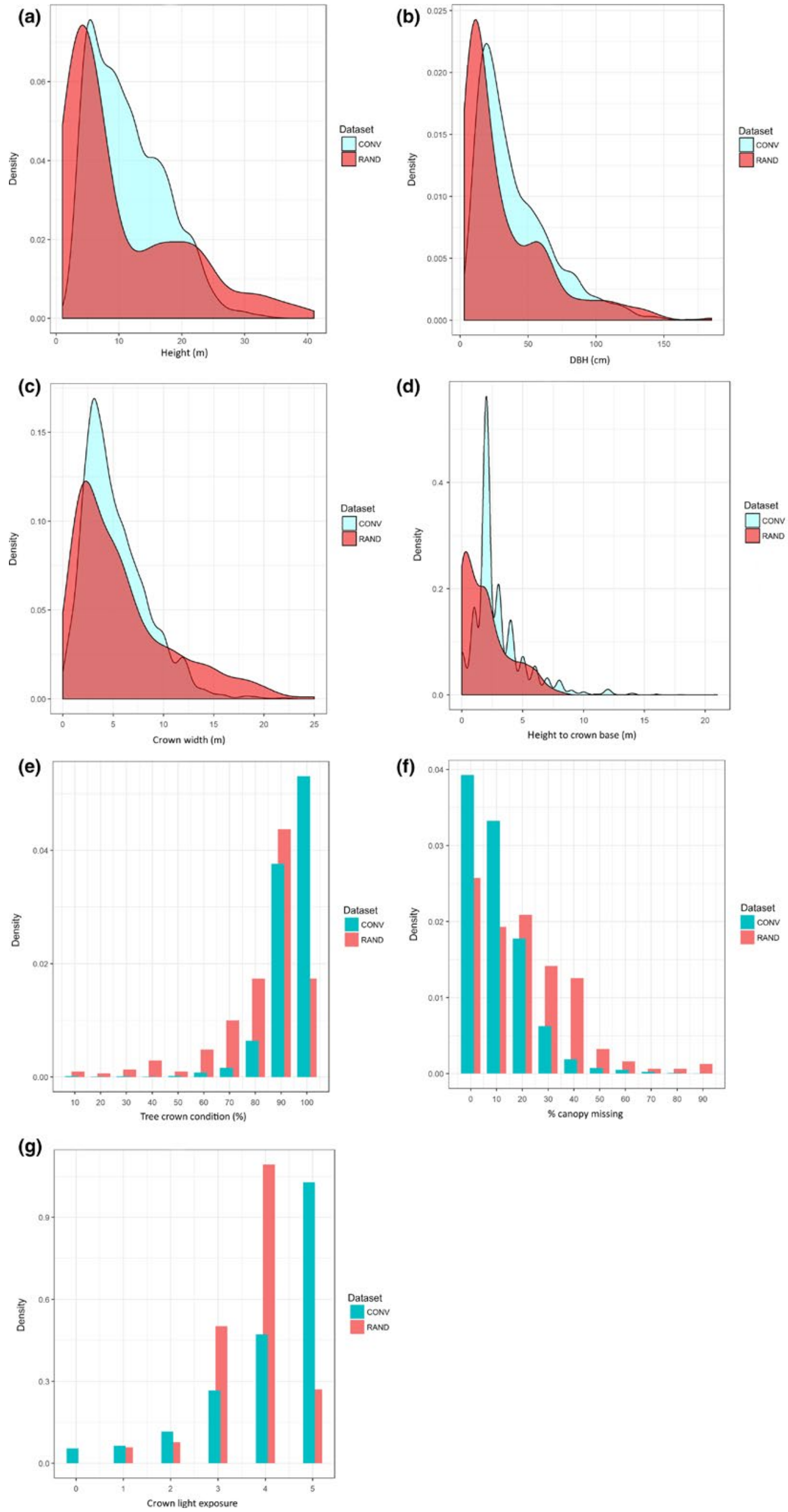

FIGURE 5 Density curves and histograms for (a) height, (b) DBH, (c) crown width, (d) height to crown base, (e) crown condition, (f) % crown missing and (g) crown light exposure for RAND and CONV [Colour figure can be viewed at wileyonlinelibrary.com]

A sampling strategy that aims to provide a comprehensive picture of the particular species richness and diversity of a city should take into consideration that 200 random plots will miss many species, and this will be especially true for larger cities. Meran is a fairly small-sized city, 1% of which could be covered by the 200 plots method (Table 1). A sample of projects using i-Tree plots in larger cities reveals much lower percentage areal coverage of the study areas. For example, Pickering borough of Toronto, 0.0014% (219 plots, 99 species; TRCA, 2012), Barcelona, 0.002% (579 plots, 138 species; Chaparro & Terradas, 2009), Brooklyn, 0.0004% (202 plots, 58 species; USDA, 2002) and Santiago in Chile, 0.00008% (200 plots, 108 species; Luz de la Maza, Hernández, Bown, Rodríguez, & Escobedo, 2002). Stratification of these samples may help them cover the main land types adequately but the lack of

TABLE 5 Mean and modal average tree measurements of 1,000 comparisons of 110 randomly generated plots using convenience sampling (CONV) to match random (RAND) sampling. The percentage of comparisons where difference was significant with the Mann–Whitney *U* test are shown at $^*p = 0.05$, $^{**}p = 0.01$

	RAND	CONV
Diameter at breast height cm (*SD*)	32.2 (31.6)	40.7 (26.9)
Mode	8	15
Median	17	32
% significant	68.6* 51.6**	
Height m (*SD*)	10.4 (9.2)	12 (6.4)
Mode	2	5
Median	6	10
% significant	57.7* 37.9**	
Crown width m (*SD*)	5.9 (5.1)	5.3 (3)
Mode	2	3
Median	5	4
% significant	15.7* 6.6**	
Height to crown m (*SD*)	1.9 (1.9)	2.9 (2)
Mode	0.1	2
Median	2	2
% significant	68.1* 52.8**	

TABLE 6 i-Tree Eco model structure and ecosystem services estimates for Meran, Italy, using convenience (CONV) and random (RAND) sampling

	RAND	CONV
Total tree estimate	23,590	21,680
Tree cover estimate (%)	23.5	24.7
Carbon storage (1,000 t)	11.68	11.37
Avoided runoff (1,000 cubic feet/year)	437.5	508.1

spatial coverage will confer a lack of robustness for species richness and diversity estimates.

The high species richness gained by the larger sample size of CONV is a definite advantage to the convenience sampling approach. Yang et al. (2015) undertook a meta-analysis of 38 papers that used the i-Tree methodology and found a median species richness of 77, which is similar to the 72 for RAND. Higher sampling efforts can uncover much more species. For example, Jim and Liu (2001) found 254 species in a convenience sample of 115,140 trees (35 plots covering 597 ha) in all the public areas and some private areas of Guangzhou, China. The higher species richness from these larger samples, can be a useful statistic used in combination with abundance and tree measurement data (Fleishmann, Noss, & Noon, 2006), and may be useful for calculating urban forest diversity or carbon sequestration estimates with greater confidence. However, convenience sampling produces higher species richness simply as a result of covering more area, and thus increasing the likelihood of including new species. The improvement arises from covering more area per unit sampling time, and not necessarily an improvement in sampling approach.

4.2 | Tree structure

The comparisons of the quantitative measures, again, demonstrated the potential limitations of restricting the sampled area as in RAND. The density plots in Figure 4 show that the general distributions of the measured quantities were overall quite similar, yet two thirds of the statistical test simulations indicated that the samples came from different populations, with the exception of tree-crown width. RAND and CONV sampled several gardens containing clusters of smaller trees used as hedging (*C. lawsoniana*, *Thuja occidentalis* and *Platycladus orientalis*) but the larger sample in CONV contained overall much more larger trees raising the mean and modal averages. Lowering the sample sizes used for the comparisons resulted in the samples being statistically likely to be from the same population for all the measurements at around 33 plots—around a third of the plots that had trees in RAND.

Some of the differences noticed for the more subjective measures (condition, crown light exposure) may be due to inconsistencies and biases in the field researchers, despite a priori quality control training and practicing the field techniques. In Figure 5g, the researcher in RAND allocated more trees with a crown light exposure of four than five, and vice versa for CONV. In addition, the field researcher for RAND was seemingly less likely to allocate a condition of 100% (Figure 5). Fortunately, these differences will have a minimal impact on any modelling results. These researcher subjectivities are not envisioned for the taxon richness. Ostermiller and Hawkins (2004) showed that sampling crews were similar in capturing taxa as long as the crews were well trained and undertook quality control measures.

4.3 | Ecosystem service assessment

The outputs from the i-Tree ECO model are very similar, apart from those, which rely more on the specific species composition, such as carbon and runoff prevention. This is a situation where it may be important to increase the sample size to more adequately capture the species present in a city, if the model outputs are sensitive to species abundances. Martin et al. (2013) completed a full inventory for a 300 ha campus in Alabama, USA which allowed an investigation of the 200 plots protocol for estimating ecosystem services. To achieve a plot-based estimate with a ±10% error of the total inventory estimate, it was found that 870, 622, 483 and 258 plots were needed for carbon storage, air pollution removal, carbon sequestration and number of trees, respectively. Our study provides further evidence that the 200 plot protocol may not be well founded and sampling strategies that uncover a more complete picture of species richness and diversity may be preferable. Another way that the time taken to sample urban forests could be reduced is to only identify trees to the genus level. Depending on the level of complexity required for subsequent modelling work, and irrespective of the ability of convenience sampling to increase species richness, this may be sufficient. For example, the i-Tree model frequently uses the same parameters and allometric equations for members of the same genus (I-Tree ECO, 2017). Future research could investigate the differences in ecosystem service model output between genus and species level inventories.

In conclusion, the number of species in a community can rarely be completely observed, especially where there are many rare or elusive species. However, a convenience sampling method allows for rapid sampling (nearly four times the number of trees per day in this study) and provides a more complete picture of the richness and abundance of an urban forest. The reduction in survey time and costs would be very appealing to urban forest managers and researchers alike. Indeed, inventories of other natural resources, such as rare or endangered flora in tropical jungle ecosystems, or wild crop relatives in European meadows, may benefit from the advantages of convenience sampling. The lack of randomness can be ameliorated to some extent by careful stratified sampling by land type, which goes some way towards replacing subjective decisions with described and repeatable criteria (Michalcová et al., (2011). Many cities already have convenience/block sampled inventories and these datasets can be utilized, potentially alongside probability samples. This could be important for modelling studies where the modelling outputs such as carbon storage, pollen production and BVOC production are highly species sensitive.

It must be noted, however, that while convenience sampling has been demonstrated to be an efficient alternative to probability sampling for the city of Meran, this may not be true for other cities, especially larger cities. Meran is a compact, alpine city and the more land which is sampled, the more the samples converge to a complete census, regardless of how they were collected.

ACKNOWLEDGEMENTS

The study (project ECOBENE) was funded by the Free University of Bozen-Bolzano's internal research funds. We thank the municipality of Meran council, in particular Ms Anni Schwarz, and we are grateful to Hajo Späthe for his efforts in the field.

AUTHORS' CONTRIBUTIONS

S.Z., F.J.E. and A.R. conceived the ideas and advised continually throughout the research design stage; A.S. designed the methodology, collected and analysed the data, and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

DATA ACCESSIBILITY

Data available from the Dryad Digital Repository https://doi.org/10.5061/dryad.bs1f7c3 (Speak, Russo, Escobedo, & Zerbe, 2018).

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How to cite this article: Speak A, Escobedo FJ, Russo A, Zerbe S. Comparing convenience and probability sampling for urban ecology applications. *J Appl Ecol*. 2018;55:2332–2342. https://doi.org/10.1111/1365-2664.13167