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Research Article

Application of UAV remote sensing and machine learning to model and map land use in urban gardens

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Abstract

Urban gardens are an integral part of urban agricultural systems, contributing to ecosystem services, biodiversity and human wellbeing. These systems occur at fine scales, can be highly complex and therefore offer the opportunity to test mechanisms of ecological patterns and processes. The capacity to confidently characterize urban gardens and their land uses is still lacking, while it could provide the basis for assessing ecosystem service provision. Land classifications from remote sensing platforms are common at the landscape scale, but imagery often lacks the resolution required to map differences in land use of fine-scale systems such as urban gardens. Here, we present a workflow to model and map land use in urban gardens using imagery from an unoccupied aerial vehicle (UAV) and machine learning. Due to high resolutions (<5 cm) from image acquisition at low altitudes, UAV remote sensing is better suited to characterize urban land use. We mapped six common land uses in 10 urban community gardens, exhibiting distinct spatial arrangements. Our models had good predictive performance, reaching 80% overall prediction accuracy in independent validation and up to 95% when assessing model performance per cover class. Extracting spatial metrics from these land use classifications, we found that at the garden and plot scale, plant species richness can be estimated by the total area and patchiness of crops. Land use classifications like these can offer an accessible tool to assess complex urban habitats and justify the importance of urban agriculture as a service-providing system, contributing to the sustainability and livability of cities.

Key words: remote sensing, UAV, urban agriculture, garden, plant diversity, land classification, machine learning

Introduction

Up to 11% of the world's urban surface could be used for urban agriculture (UA), with the potential to produce 5% of food crops globally (Clinton et al. 2018). These modeled approaches suggest that existing vegetation in urban agricultural systems provides ~$33 billion in ecosystem services, the largest proportion of which is food (Clinton et al. 2018). Although global estimates illuminate the potential of UA, we still lack research that harnesses new tools and methods to comprehensively characterize land uses within urban agricultural systems at finer spatial scales to provide more accurate assessments of both potential and realized ecosystem service provision. Some work estimates that in some cities (e.g. in the UK), 18–27% of urban areas comprise urban gardens (Loram et al. 2008), and there is large potential to revitalize urban lands for horticultural production to boost urban food security (Edmondson et al. 2020). The popularity of urban gardening as a form of multifunctional green space for biodiversity conservation, ecosystem service provision and human wellbeing means that it is imperative that we understand and are able to quantify urban agricultural land use at fine spatial scales (Lovell 2010; Lin, Philpott, and Jha 2015). This is important from an urban conservation and planning perspective to justify the significance of these systems for the environment and society and to protect and maintain these systems under urban densification in many parts of the world.

From an ecological perspective, urban agricultural systems can be highly complex and offer a system to test mechanisms driving ecological patterns and processes (Philpott and Bichier 2017). Here, researchers are often interested in testing ecological theories around ecosystem functioning and service provision in relation to land use types and composition such as crops, trees and bares soil. UA systems can be heterogeneous in vegetation and ground cover, consisting of a wide array of annual and perennial vegetation (Loram et al. 2008; Taylor and Lovell 2015) that are patchily distributed throughout the habitat (Plascencia and Philpott 2017). Garden vegetation can indicate vegetation-related ecosystem function and structure (Hooper and Vitousek 1997; Hooper et al. 2005) with implications for ecosystem service provisioning from gardens (Lin, Philpott, and Jha 2015). Because these systems are human designed, social filters such as socio-cultural characteristics can create variation in plant communities between individual garden plots (Philpott et al. 2020). In addition, spatial contagion or aggregation in vegetation patterns may drive neighborhood- to landscape-scale vegetation management, with potential impact on ecological outcomes in urban areas. For example, spatially closer front-yard urban gardens share similar aesthetic and plant composition, indicating a spatial component to fine-scale vegetation land use in city neighborhoods (Hunter and Brown 2012; Marshall, Grose, and Williams 2019).

The characterization of fine-scale vegetation heterogeneity and spatial aggregation within urban environments can challenge urban ecologists if such patterns are hard to accurately and systematically document and link to functional outcomes—at either the urban habitat or the urban landscape scale. Recent technologies are recommended to support efficient land use classification across heterogeneous urban habitats (Dennis et al. 2018; Creutzig et al. 2019). For example, different canopy elements such as patches and connectivity can be analyzed using remote sensing technology that assesses fine scale (1.5 m) spectral and structural imagery to describe the canopy network of cities (Ossola et al. 2019a). At the wildland–urban interface, object-based classifications using high-resolution aerial photography can classify land use patterns (Cleve et al. 2008). UAV technologies are also recently employed in urban ecosystems to classify urban vegetation composition (Feng, Liu, and Gong 2015) or urban forest health (Näsi et al. 2018). These works have demonstrated the high performance of hybrid methods using random forest classifiers consisting of decision trees combined with a texture analysis to accurately differentiate land uses within urban-vegetated areas (Feng, Liu, and Gong 2015). Yet, while UAV can provide an efficient approach to map and characterize urban vegetation, these methods and tools have not been utilized in a small-scale urban garden context.

In this study, our goal is to combine swift and affordable approaches and technologies in land cover mapping to rapidly classify and characterize different land uses and their spatial aggregation within urban agricultural systems (community gardens) at the very high (<5 cm) resolution and therefore fine spatial scale. We aim to first use unoccupied aerial vehicles (UAVs) to image vegetatively diverse community gardens and explore how fine-scale remote sensing technologies combined with established machine learning modeling can assist with the classification and characterization of urban garden land use, vegetation composition and vegetation spatial aggregation within a specific habitat type common in cities. Second, we aim to support UAV data with field observations and relate collected imagery to observed land use to train a machine learning algorithm in a supervised classification approach, to then predict and characterize land use and vegetation composition across gardens and garden beds. Here, we consider garden 'land use' to be the different spatially explicit vegetation arrangements, activities and inputs that take place within a garden habitat (e.g. crop production, recreation, shading), while supervised land use classification provides information on whether a garden plot is designated to food crops, trees or currently not vegetated and only covered in topsoil or mulch. Thus, while land use is often characterized and predicted at the landscape scale (e.g. a city), we propose community gardens as a model habitat to test methods of land use classification at fine scales because of high intra-system heterogeneity. We ask, (i) can we use machine learning to confidently predict land use and spatial arrangement in small-scale urban gardens from UAV imagery? (ii) Do predicted land use and vegetation spatial arrangement correlate with field observations? And (iii) can we predict indicators of species richness (i.e. number of plant species) from high-resolution remote sensing data?

Methods

We used field observations of urban community gardens to assess the vegetation management characteristics of perennial and annual vegetation and used an UAV to capture imagery of urban community gardens. We studied 10 community (allotment) gardens in the Greater Metropolitan Area of Melbourne, Victoria, Australia (population 4.7 million, study area center point: 37° 500 8.6000 S 145° 20 15.3100 E; Supplementary Fig. S1). The gardens were established between 6 to 38 years ago, are between 584 and 6801 m^2 in size, and have between 25 and 124 allotment plots. The gardens are community managed, where individual gardeners lease single allotment plots to cultivate plants as they choose, under rules of the garden management. We considered two relevant spatial scales of the gardens in our study: (i) the entire garden including all allotment plots and common areas (henceforth 'garden scale'), and (ii) the individual gardener allotment plot ('plot scale'). We worked with each of the community garden managers to randomly select four garden plots distributed throughout the garden of gardeners willing to allow us access to their plot to document vegetation structure and cover ($n = 36$).

Field observation data

We assessed garden vegetation at the garden and plot scale using empirical field assessments. Specifically, we sampled plant species diversity and cover, and vegetation versus bare ground cover composition at the garden and plot scale. Assuming that all plant species play some functional role in gardens, we assessed all annual and perennial plant species, both planned (i.e. vegetable, ornamental plants) and ambient (i.e. 'weeds'). At the garden scale, we placed transects every 5 m across the width of the garden. Along the transects, we randomly placed 1 × 1 m quadrats within which we recorded the species identity of all plants present and estimated the percent of herbaceous vegetation ground cover including crop plants, weed plants and grass (i.e. versus bare soil, mulch, rock). Because gardens were of different sizes, they had varied numbers of transects and we proportionally increased the number of 1 × 1 m quadrats relative to garden size. All gardens had a minimum of eight quadrats, and we added one quadrat for every additional 500 m^2 of garden area (8–19 quadrats per garden; minimum of 2, up to 5 quadrats per transect). For each garden, we summed the total number of all plant species observed and calculated the average percent of herbaceous vegetation cover for all quadrats along the transects (i.e. garden scale measurements). At the plot scale, we similarly sampled the species identity of plants present, and estimated the percent of herbaceous vegetation cover in the entire plot. Total number of plant species and average vegetation cover were calculated for each garden plot (i.e. plot scale measurements). Collectively, these data provided us with observed field vegetation measurements (e.g. number of plant species, vegetation cover) commonly collected at the garden and plot scale.

UAV imagery collection

Aerial imagery of each garden was collected using an autonomous commercial Mavic Pro multirotor UAV (DJI, Shenzhen, China) during field surveys (summer 2018). The UAV flight paths for each garden were planned and executed using Ground Station Pro (DJI, Shenzhen, China), directed by the authors. The flight altitude was 70 m above the ground and 30 m away from any individuals on the ground in accordance with the Australian Civil Aviation Safety Authority (CASA 2019). All auto-piloted flights were carried out in overcast weather within 8 h on the same calendar day to maintain consistent ambient light conditions and avoid shadows of tall buildings or vegetation on our target cover classes. Shadows can alter the target classes' spectral reflectance and lead to misclassifications if a supervised classification model is trained on areas that have received shadows. Flying on overcast days or under diffuse light conditions avoids this problem, ensures similar light conditions for all images and may enhance spectral features of vegetation (Arroyo-Mora et al. 2021). The 70 m flight altitude resulted in an image resolution of ~2.5 cm per pixel across all gardens. Further details regarding flight and imagery collection can be found in Supplementary Table S1.

Image processing and variable compilation

We processed images using Metashape (Agisoft, St. Petersburg, Russia), utilizing Structure from Motion to estimate 3D structure from 2D overlapping image sequences through photogrammetry (Ullman 1979). The image processing resulted in 3D point clouds for each garden, which we then used to derive orthomosaics of the three available color bands [red, green and blue (RGB) reflectance; Fig. 1A] and to compute a canopy height model (CHM) of each garden (Fig. 1B). We processed all UAV data products using the *raster*, *sf* and *lidR* packages (Hijmans et al. 2017; Pebesma 2018; Roussel and Auty 2019) in the R statistical environment (R Development Core Team 2019). First, point clouds were normalized to a 0 m ground elevation. Using the grid_canopy function from *lidR*, we calculated a digital terrain model (DTM) and a digital surface model (DSM) that express both the ground elevation and point elevation above ground. A CHM is the difference between DSM and DTM (CHM = DSM—DTM) and calculated to a 2D raster, expressing each pixel's height above ground in meters. Our CHMs had a resolution of 0.5 m and were subsequently smoothed by a sub-circle algorithm adding a 0.5 m disk around each pixel to close empty pixels resulting from the respective point density (Khosravipour et al. 2014).

To test additional independent variables for land use classification available from the orthomosaic apart from visual light reflectance, we carried out a texture analysis on the imagery of each garden, adding common variables from object-based image analysis (OBIA) to our supervised classification model. Image texture may represent pixel patterns that are generally not characterized by spectral reflectance and can therefore enhance the image classification accuracy in supervised classification approaches by Herold, Liu, and Clarke (2003), Thomas, Hendrix, and Congalton (2003), Cleve et al. (2008), Szantoi et al. (2013) and Feng, Liu, and Gong (2015). Texture was derived from grey-level co-occurrence matrices (GLCM) of the green band. The matrices are indicating the likelihood that values of pixel-pairs co-occur in a certain direction and lag distance within each image, termed texture similarity (Haralick, Shanmugam, and Dinstein 1973; see Fig. 1C). All texture analyses were carried out using the package *glcm* (Zvoleff 2019) in R. Due to the nature of strong intercorrelation between many measures of texture (Haralick, Shanmugam, and Dinstein 1973; Szantoi et al. 2013; Feng, Liu, and Gong 2015), we only derived the eight least correlated texture layers on a 31×31 pixel moving window size. The choice of moving window size and variables was based on findings from Feng, Liu, and Gong (2015), identifying the lowest model error rates for spatially predicting urban vegetation cover from UAV imagery using these metrics. The 3 initial spectral bands (RGB reflectance) and height from the CHM along with texture layers produced 12 predictor variables, which were then compiled as multi-layer raster-stacks for each garden to be used as variable candidates in predicting land use.

Garden land use classifications and spatial arrangement

To train a model to predict garden land use and spatial arrangements of all land uses, we created training polygons on true color (RGB) representations of each garden's orthomosaic (Fig. 2A), classifying the gardens into six major land use classes: impervious surfaces (Class 1), bare ground (e.g. major garden paths (Class 2)), bare plots (e.g. bare soil, Class 3), large trees (Class 4), crops (Class 5) and grasses and weeds (Class 6). Polygons were placed and assigned land use classes through image interpretation. As fine resolution imagery in homogenous landscapes requires a larger number of pixels to derive accurate classification (Chen and Stow 2002), a minimum of 20 polygons per class and garden were placed. These were then used to extract all pixel data from the predictor variable raster-stacks and train a random forests model (Breiman 2001) of garden land use through supervised classification. All analyses were carried out in R using the packages *randomforest* and *caret* (Liaw and Wiener 2002; Wing et al. 2019).

We pooled extracted pixels from all gardens together to create a universal model of land use. Extracted pixels were paired with their respective identified land use class, randomly subsampled to 6000 pixels per class (3600 pixels per garden in total) and then split into a training (80% of the total dataset) and testing dataset (20% of the total dataset), based on the Pareto principle (Newman 2005). We created an initial random forests model using the default number of trees (500) on the training dataset of each garden stack, using all available raster bands ($n = 12$) as predictor and the land use class as response variable (Pal 2005; Gislason, Benediktsson, and Sveinsson 2006). Subsequently, we observed variable importance and model performance of this model and removed variables with a Gini index <1300 to create a less complex model, while preserving (or increasing) model performance. In decision trees and data prediction, the Gini Index (or "Gini impurity") represents the probability of a specific feature that is classified incorrectly if selected randomly. Here, a Gini value of 0 is equal to 'pure'

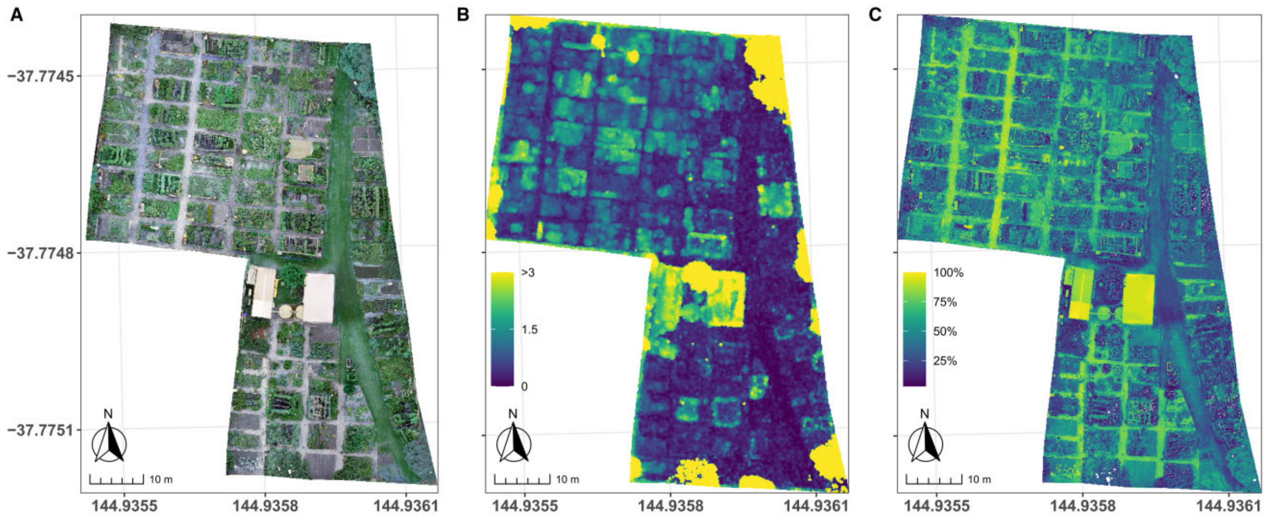

Figure 1: Spatial data products from UAV imagery used for predicting garden land cover—(A) Garden-scale true-color orthomosaic compiled of RGB reflectance bands, (B) CHM derived from UAV point cloud in meters and (C) mean texture similarity per pixel in %.

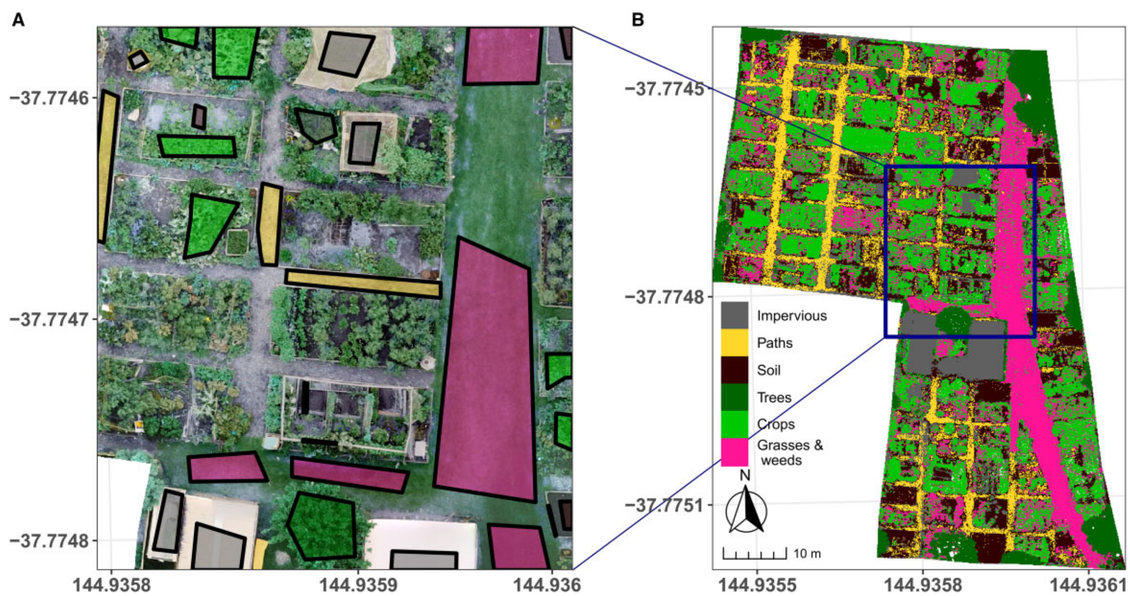

Figure 2: Example of training polygons placed using image interpretation on the RGB orthomosaic for the six land use classes (A) and final land cover classification for the Essendon community garden (B).

classification of a single class, whereas the maximum value is equal to completely random distribution across all predicted classes. The cutoff at 1300 was chosen due to the clear contrast in performance between the five least important and six most important variables (Fig. 3). The mean decrease in accuracy illustrates how much accuracy the model would lose, if the respective variable was removed. The final model selected was based on six predictor variables. We then used the model to predict (i) to the test dataset of ∼7000 pixels (20% of total dataset, 1200 pixels per Class 1–5, 1080 for Class 6, which was not present in one garden) for model evaluation and (ii) to each garden's raster stack, to create classified images for further analysis of spatial arrangement of gardens and garden plots. We illustrate and explain a simplified version of our workflow of training polygon creation, data extraction and model building and evaluation in the form of a tutorial in Supplementary Appendix S2.

Universal model performance was evaluated from the prediction to the test dataset (independent validation), using (i) model accuracy, based on average absolute model error, and (ii) Cohen's Kappa, a measure of model reliability based on confusion matrices (Elith et al. 2006; Cohen 1960). To quantify accuracy of predictions per use-class, we assessed sensitivity (true positive rate; TPR) and specificity (true negative rate; TNR). Further, we derived the true skill statistic [TSS = (TPR + TNR) − 1], representing matches and mismatches between observations and predictions (Allouche et al., 2006). TSS values range from 0 to 1 and permit similar inferences as the Kappa statistic, without being dependent on prevalence (Somodi et al. 2017). Furthermore, we tested the performance of the universal model in each garden separately through cross-validation, by extracting the predicted land use class from the final garden classification (Fig. 2B) with the polygon masks and comparing the predicted values with the assigned values from image

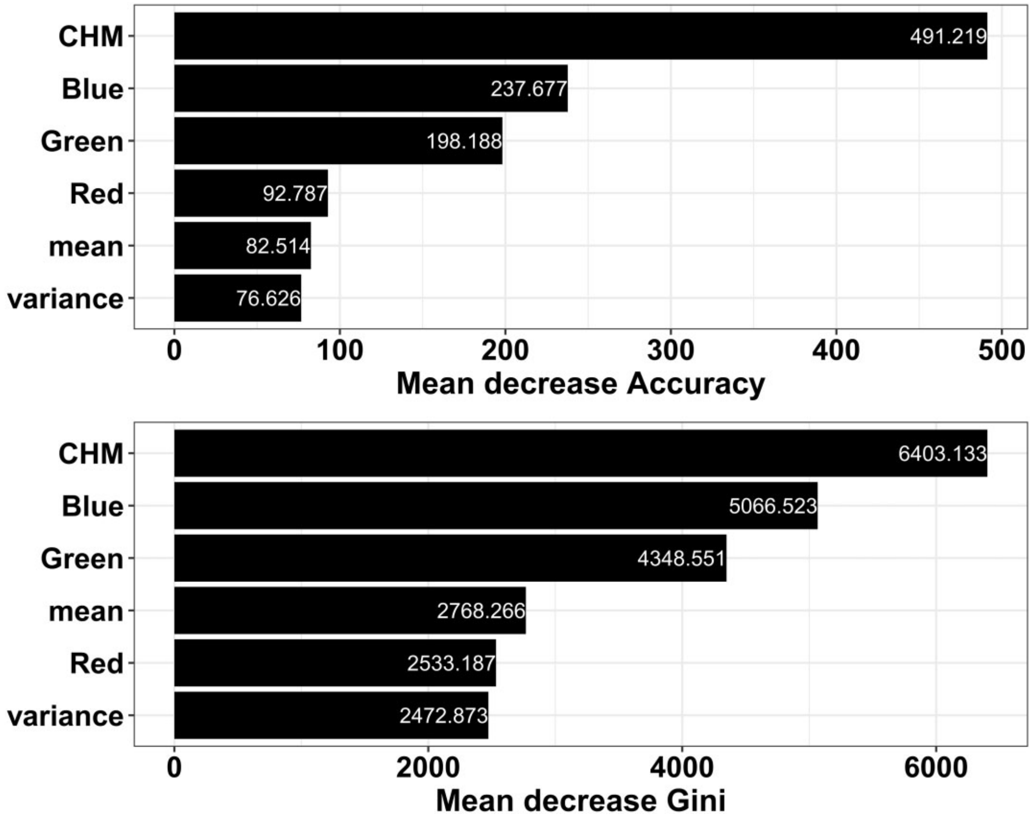

Figure 3: Variable importance according to mean decrease in model accuracy if the respective variable was removed (top) and Gini impurity index (bottom).

interpretation in a confusion matrix, using the same evaluation metrics as in independent validation.

Relationship between field and aerial survey data

To test for relationships between field survey data and garden classifications from UAV imagery, we calculated the area and projected cover of each class on both the garden ($n = 10$) and plot ($n = 36$) scale. We further derived the number of patches, mean patch area and clumpiness as measures of connectivity and spatial aggregation of each class using *landscapemetrics* (Hesselbarth et al. 2019). A large number of patches or low clumpiness value (on a scale from 0 to 1) indicates low aggregation of land classes, whereas low patch number or high clumpiness indicate highly aggregated and connected classes (Hesselbarth et al. 2019). We used generalized linear models (GLMs) to test the relationships and correlations between field and aerial survey data.

Results

Results of the field survey

Plant species richness (number of species per plot or garden), vegetation height and cover measured in the field varied among the garden plots and the community gardens. Total plant species richness observed across all of the gardens was 32 species. Mean plant species richness observed within garden plots was 19 species. Gardens and garden plots exhibited high variability in plant species (±8 species). The mean vegetation cover averaged at 67.65% (±25.9%) at the garden scale, and 97.3% (±25.4%) at the plot scale. A majority of the gardens and plots had vegetation that averaged around 1 m in height, with the average maximum height within plots around 2 m. Bare ground (no vegetation) was also present in gardens, with bare ground averaged at 33% of plot cover (±24.8%). Most garden plots harbored low vegetation under 0.5 m in height.

Model selection and variable importance

The final model to predict garden land use classes was selected based on highest model accuracy and Cohen's Kappa, as well as superior sensitivity (TPR) and specificity (TNR) compared with models with all or other predictor variable combinations. The best model utilized six variables, out of which height above ground derived from the CHM was the most important based on both mean decrease accuracy (490) and mean decrease Gini (6402) (Fig. 3). Visible light reflectance on all available bands (RGB) were together equally important in distinguishing land classes from one another, while out of eight texture variables, only two (mean and variance of pixel co-occurrence) were found to improve model performance.

Model performance

Independent validation of the universal model documented good model performance with overall prediction accuracy at 79.6% and a Cohen's Kappa of 0.75, indicating substantial agreement between observed and predicted values across classes (Table 1). The best predictions were recorded for Classes 1 and 4 (impervious surfaces and trees), with TSS = 0.91, respectively, indicating near perfect agreement. Crops (Class 5) and grasses and weeds (Class 6) were predicted with substantial agreement (TSS = 0.73 and 0.75, respectively). We observed the lowest accuracy for bare soil (Class 3) and path cover classes (Class 2), where ~15% of pixels were classified incorrectly.

Table 1: Model validation results for independent and cross-validation[a]

Model validation	Garden[b]	Metric	Value
Independent validation	All	Accuracy	0.8
		Kappa	0.76
	Ashburton	Accuracy	0.84
		Kappa	0.80
	Balwyn	Accuracy	0.86
		Kappa	0.82
	Box Hill	Accuracy	0.73
		Kappa	0.66
	Essendon	Accuracy	0.86
		Kappa	0.83
Cross-validation	Flemington	Accuracy	0.85
		Kappa	0.81
	Hawthorn	Accuracy	0.76
		Kappa	0.70
	Jolimont	Accuracy	0.78
		Kappa	0.70
	Rushall	Accuracy	0.83
		Kappa	0.78
	Slater	Accuracy	0.74
		Kappa	0.67
	Western Brunswick	Accuracy	0.81
		Kappa	0.75

[a]Both accuracy and Cohen's Kappa are on a scale from 0 to 1 where 1 means 100% accuracy or perfect agreement.
[b]Garden is the name of each garden site examined.

Nevertheless, both classes reached TSS > 0.6 and were therefore predicted with moderate agreement across all gardens (Fig. 4 and Table 2).

Testing the model on the garden scale through cross-validation revealed that a universal model based on a sample of pixels from multiple gardens can be used to predict land classes across different garden landscapes. Although performance varied, we observed high prediction accuracies between 73% and 86% and Kappa values of 0.65–0.8. The model performed best in the Essendon community garden, reaching both maximum accuracy and Kappa values. Although still performing to a level of substantial agreement between prediction and observed land class, both Slater and Box Hill gardens had the least accurate predictions ($\sim$70% accuracy and a Kappa of 0.66 each; Table 1). Best performances by cover class were observed for the gardens Flemington, Essendon and Balwyn for Class 4 (large trees), all reaching TSS $\geq$ 0.95. In Balwyn we also observed the highest TSS for crops (Class 5) with 0.93, as well as the lowest prediction performance by class (TSS $=$ 0.13 for grasses and weeds; Supplementary Fig. S2 and Table S2). Mean observed TSS by class throughout all gardens was 0.72 ($\pm$0.19).

Land use and garden arrangement from spatial predictions

An analysis of land use based on our spatial land use classifications (Fig. 2B) for the 10 urban gardens revealed similar distribution of land use classes between gardens, with crops (Class 5) covering on average the largest area (by proportion), followed by pathways (Class 2, Fig 5A). Based on the clumpiness metric from *landscapemetrics*, the most aggregated class on the garden level was tree crowns, with values close to maximum aggregation (i). The least aggregated and most patchy class was 'grasses and weeds' (Class 6, Fig. 5B and C). Crops were less patchy, with an average clumpiness of 0.88 ($\pm$0.03). Similar patterns were observed on the plot level (Supplementary Fig. S3 and Table S3).

Correlation between field and aerial survey data

When comparing land use metrics such as area or percentage cover that were collected on the ground and derived from the imagery, we found some relationships between remotely sensed land use classes and field survey data both at garden scale and at the plot scale. Observed bare soil cover in the field was estimated by multiple land use metrics such as area of the 'bare' land use class or area of the 'paths' and 'soil' use classes. Grass cover measured in field surveys was predicted by percent area of the remotely sensed 'grasses and weeds' land use class. Surprisingly, no direct relationships were found between crop or vegetation cover field survey measurements and remotely sensed classes.

Using GLMs, we found that derived landscape metrics from the predicted land use classes were useful to estimate observed plant species richness on both garden and plot scale. There was a significant relationship ($P < 0.001$, $R^2 = 0.45$) between (log-transformed) number of patches and observed species richness in field surveys. Here, species richness increased in gardens with an increasing number of patches and thus a spatial disaggregation of crop vegetation cover (Fig. 6A). Similarly, the predicted (and log-transformed) class area of crops (Class 5) was also positively correlated to species richness ($P < 0.05$, $R^2 = 0.53$), where the number of species increased with increasing crop area (Fig. 6B). We found similar relationships also held true on the plot scale for these vegetation variables. The number of species in each plot was significantly related to the number of patches as well as vegetation class area ($P < 0.01$). At this scale, crop area was not significant in describing species richness and the explained variability was lower than at the garden scale ($R^2 = 0.17$).

Discussion

Heterogeneous and fine-scale land use systems in urban areas can be predicted from high-resolution aerial imagery collected by a commercial UAV. We found that a universal supervised classification model can be trained on a random sample of pixels from aerial imagery, which was assigned land use classes through image interpretation. The universality of our model demonstrates that a small subset of data may accurately predict land use in a range of other or potential future data sets. The results have great potential for applications to other urban green systems with high plant diversity and high patchiness in land use. Importantly, however, while overall performance can be meaningful, we also suggest that model classification and performance should be conducted for each system separately. This study builds upon previous work in other urban systems and agroecosystems on the application of UAVs and predictive modeling approaches to rapidly assess and predict urban land uses and their spatial characteristics (Feng, Ling, and Gong 2015; De Luca et al. 2019; Vilar et al. 2020; Gibril et al. 2020), important metrics related to ecosystem function and services.

In sum, our work in an increasingly relevant and heterogeneous urban land use system provides three new contributions to the field: (i) commercial drone technology can be used to accurately predict and map common land uses in urban gardens; (ii) all predictor variables of urban garden land use can be derived from standard aerial photo images without the need for

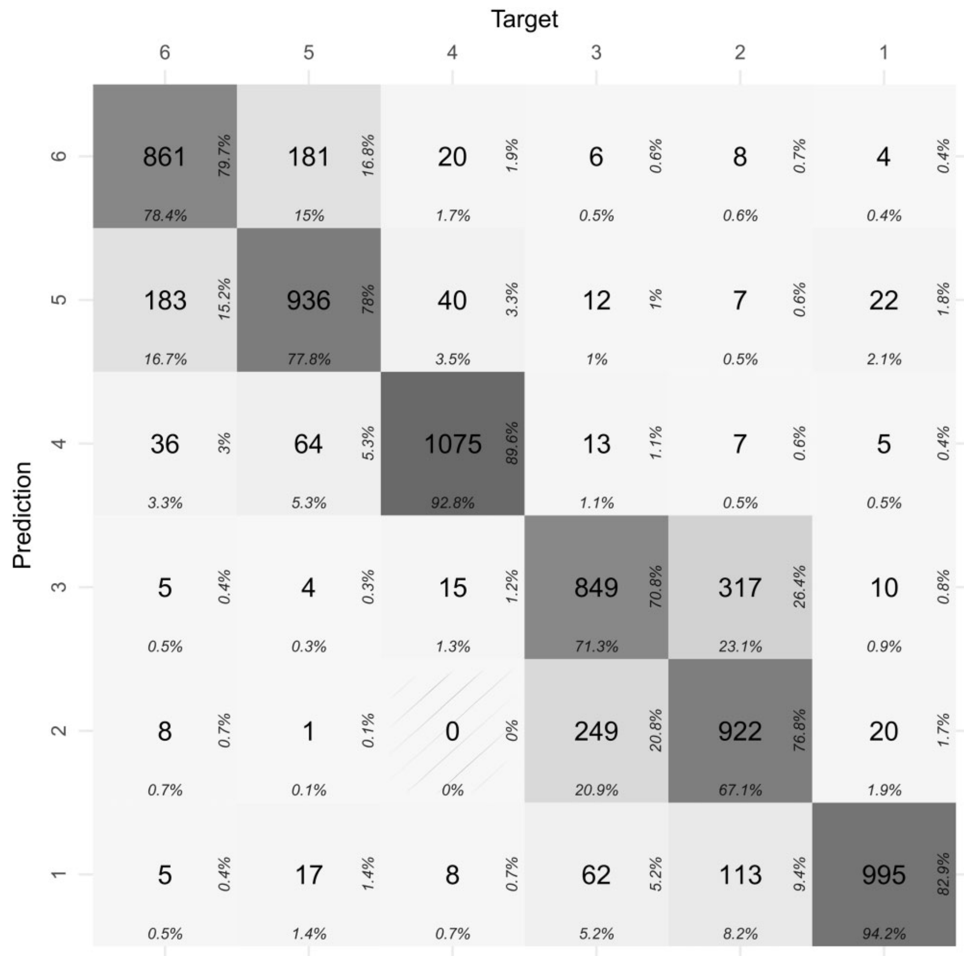

Figure 4: Confusion matrix of independent model validation of the six land cover classes, comparing observed and predicted pixels for the six land cover classes. Numbers are pixel counts with color gradient indicating into which class combination the majority of pixels were classified to. Right percentages in tiles indicate the fraction of pixels in each row this tile makes up, lower percentages the fraction of pixels per column. Larger numbers, percentages and darker shades in the center indicate correct predictions, where observed and predicted land cover class matched. For example, the top-left tile shows that 861 pixels were correctly classified as class 6–grasses and weeds, (~78.4% of all pixels in that column and 79.7% in the row), whereas the tile below indicates that 183 pixels, observed to be in class 6 were falsely predicted to be class 5 - crops (~16% of all pixels in column and row).

Table 2: Classification evaluation for land cover classes (Classes 1–6) from the independent validation confusion matrix[a]

Cover class	Sensitivity	Specificity	Balanced accuracy	TSS
Impervious	0.94	0.97	0.95	0.91
Paths	0.67	0.95	0.81	0.62
Soil	0.71	0.94	0.83	0.65
Trees	0.93	0.98	0.95	0.91
Crops	0.78	0.96	0.87	0.73
Grasses and weeds	0.78	0.96	0.87	0.75

[a]All evaluation metrics are scaled from 0 to 1 where 1 is the highest possible performance or evaluation agreement.

costly sensor technology; and (iii) plant species richness (number of species) can be estimated from these spatial predictions with implications for future survey methods.

Important predictors of urban garden land use and model performance

We successfully modeled and spatially mapped land use in urban garden systems using UAV remote sensing of visible light reflectance (RGB bands), canopy height and image texture. Vegetation or structural height from the UAV CHM was the most meaningful predictor to distinguish different cover classes. Land use classes such as grasses and weeds, crops or trees all expressed distinct differences in heights above the ground, even if sharing similar light reflectance (Fig. 1A and B), which may explain the importance of this variable. CHMs have been used to improve land use classification in other ecosystems such as forests (Räsänen et al. 2014), whereas generally they are employed for tree detection approaches from photogrammetry or LiDAR (see e.g. Stone et al. 2016; Mohan et al. 2017; Swinfield et al. 2019). Their usefulness in classifying mostly tree-less systems with very low canopy heights is promising and should be further explored. Nevertheless, for cover classes that had less distinguishable height differences, such as bare ground in garden plots and paths between plots, our model had lower accuracy. This illustrates why we produced high accuracies for classes with distinct differences in height and highlights the limitation of this variable. These limitations may be overcome by adding spatial restraints and neighborhood dependencies to classifications. As high-resolution image pixels are much smaller than the entities targeted by modeling and mapping

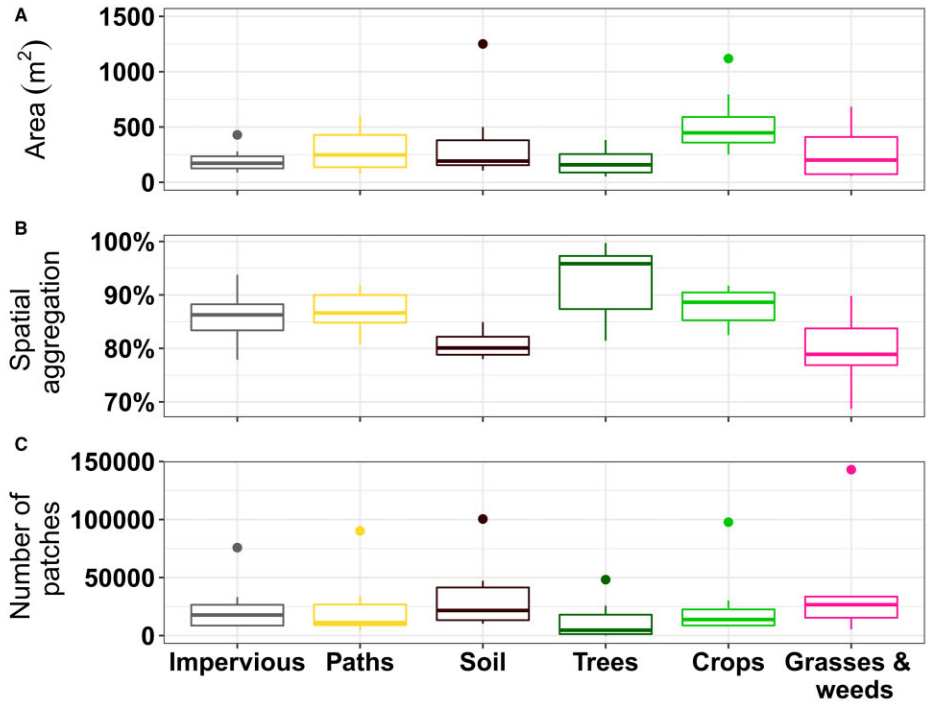

Figure 5: Spatial arrangement statistics from spatial land cover predictions, extracted at the garden scale ($n = 10$) for the six predicted cover classes.

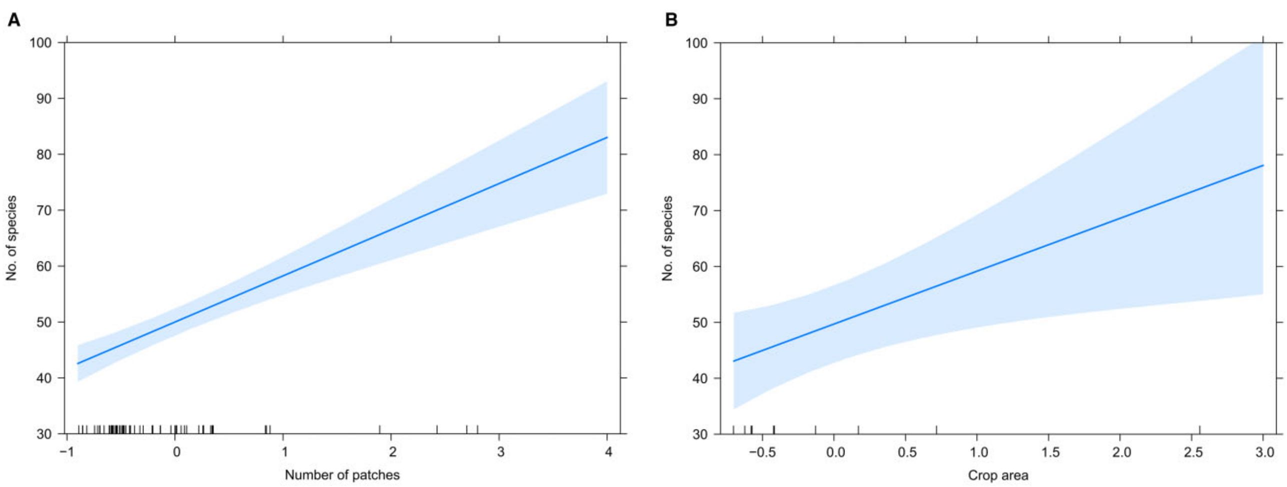

Figure 6: Variable dependence plots for GLM models of species richness using number of patches (A) and crop area (B) on the garden scale from spatial land classifications as predictor variables. Both number of patches and crop area are standardized (scaled to mean and standard deviation of the respective variables).

cover classes, a grouping of pixels into objects before classifying them, may increase accuracy in predicting classes that are similar in height and/or topography. Here, OBIA is an option (Herold, Liu, and Clarke 2003; Thomas, Hendrix, and Congalton 2003; Cleve et al. 2008), aspects of which we covered by adding texture variables to our supervised classification model. However, when optimizing model performance, the final model contained only two metrics of image texture (mean and variance of texture similarity), which were the least important predictors (Fig. 3). Nevertheless, future research should focus on improving prediction accuracy in urban gardens by exploring and comparing further methods of image classification. Visible light reflectance was together equally important in distinguishing cover classes as the CHM (Fig. 3). The RGB bands are the most easily acquired and processed data from commercial UAV imagery. They were found to be capable of distinguishing even similarly reflecting land use at the very high resolutions achievable from UAV or satellite imagery, when coupled with aspects of OBIA, such as measures of texture from GLCM, as e.g. demonstrated by Feng, Liu and Gong (2015) or Ayhan and Kwan (2020), which we could also confirm in this study for a new urban environment.

Predictive capacity in relation to field surveys

Our findings help to understand and predict plant species diversity with a spatially explicit perspective. The best land use classes predicted by our models included bare ground cover and tree cover, providing evidence for a rapid assessment of either no vegetation or high vegetation within gardens. These land use classes in turn relate to ecosystem functions such as microclimate regulation (Lin et al. 2018), invertebrate habitat (Quistberg, Bichier, and Philpott 2016), or the potential for increasing production capacity (Clinton et al. 2018). Similarly, the predicted class area of crops and vegetation was positively correlated to species richness, suggesting that as the area of crop increased, the number of species also increased. This species–area relationship has implications for space use and function in urban gardens by supporting the idea that provided more space to cultivate, gardeners may plant more plant species which in turn support biodiversity (van Heezik et al. 2013; Clucas, Parker, and Feldpausch-Parker 2018) and ecosystem functions and services (Lin, Philpott, and Jha 2015). Indeed, home gardens may be more diverse than forest ecosystems in some urban contexts due to the mix of native remnant vegetation and ornamental and crop plants and this may e.g. support native bee fitness (Kaluza et al. 2018). Greater crop heterogeneity may also reduce (or dilute) pest populations and support natural enemies (Lowenstein and Minor 2018) and pest control in UA (Arnold, Egerer, and Daane 2019). Thus, the capacity to quickly characterize such species–area relationships within urban vegetation communities could allow rapid assessments of (or at least informed speculation about) pollination and pest control services.

Despite some strong relationships between field observations and drone surveys, inconsistent relationships may argue for improving field observations at appropriate scales to then better support model predictions using machine learning. In our study, conflicting methods of assessing land cover and use might have been used, which may be incompatible with remotely sensed data. For example, our results highlight the importance of spatial scale in such research (Wang et al. 2009; Cavender-Bares et al. 2017), where relationships depend on the scale at which habitat features were measured. Previous studies in urban forests argue for spatial scale correction to fix misclassification of land use types by UAVs (Feng, Liu, and Gong 2015). Furthermore, because the size and structure of a plant (e.g. thin and tall) may reduce a UAV sensor's capacity to capture the vegetation, future research that combines field survey observations with remote sensing should aim to systematically measure multiple layers of vegetation (Egerer et al. 2020).

Predicting spatial arrangement of land use

Spatial arrangement and aggregation of land uses were strongly associated with plant species richness observed in the field. The ability to predict and relate spatial aggregation in relation to species diversity in urban gardens provides just a starting point to predict and look at relationships between land uses within the system. Patchiness and land use spatial arrangements are important in relation to biodiversity and ecosystem functions, especially in urban agricultural systems and urban habitats that can exhibit abundant and diverse insect populations (Lin, Liu, and Gong 2015; Egerer, Bichier, and Philpott 2017; Baldock et al. 2019). In urban areas, spatial aggregation in vegetation patterns is largely driven by social factors, where vegetation management decisions are influenced by residents' preferences for urban vegetation as a function of certain attitudes about the form and function of said vegetation, but also social norms (Ives and Kendal 2014). Front yards have different vegetation patterns than back yards (Locke et al. 2018), whereas neighbors share similar and spatially aggregated vegetation and land use patterns (Marshall, Grose, and Williams 2019). This spatial aggregation of vegetation patterns at a yard to neighborhood scale can further scale up to the city scale (Ossola et al. 2019b). Thus, our work further supports and works to elucidate the spatial characteristics of urban vegetation.

Implications for urban ecosystem service provision and future directions

Our model results suggest that methods of supervised land classification could be widely applied to other gardens and urban ecosystems. The land use classes we assessed have important implications for biodiversity conservation and ecosystem service provision in urban agricultural systems. For example, the aggregation and spatial arrangements of bare soil- or flower patches may strongly influence bee diversity and abundance in a garden through impacts on nesting and flower resource availability (Plascencia and Philpott 2017). Bee habitat provision may in turn have implications for crop pollination services (Werrell et al. 2009; Cohen et al. 2021). Predicting canopy cover of trees or tall crops allows drawing implications for climate regulation (Lin et al. 2018; Rost et al. 2020) and aesthetic benefits (Fernandes et al. 2019; Egerer et al. 2019). A rapid assessments of crop land use can inform the food production capacity of an individual garden or multiple gardens within a city to inform food provision and security benefits. This may be especially important in the Global South and cities where UA highly contributes to food security but is difficult to assess and quantify its land use and social impact. Spatial predictions of land use in urban gardens could be further improved with the use of multi- or hyperspectral sensors allowing a plant genus- or species-level classification of individual areas (see e.g. Zhang and Qui 2012; Hakkenberg et al., 2017; Liu et al., 2017). Although such sensors would decrease accessibility and affordability in efforts to derive more detailed spatial classification of urban ecosystems, they would allow additional measures of vegetation complexity such as plant cover or density or remote predictions of plant alpha- and beta diversity, which would greatly improve our understanding and ability to monitor these small scale but highly heterogenous landscapes.

In addition, it would be important to employ gardener survey questionnaires to determine relationships between remote sensing, ecological field surveys and people's reported experience and benefits within a space. Furthermore, this method offers excellent potential to continuously survey land use change to quantify and characterize changes in seasonal land use, as the crops grown in gardens and land uses within gardens change throughout the year. Although we were limited to one image per garden during the growing season, the benefits of affordable commercial UAVs that can be harnessed in future work are to collect multiple sets of images over the course of a growing season or entire year and to allow for spectral contrasts between seasons, which may enhance class discrimination. Multi-season data collection may therefore be another way to improve classification and help quantify changes in plant species diversity and crop productivity. Thus, an important consideration for future research is to avoid compensating accuracy for e.g. more survey sites or repeated assessments; finer spatial scales are still recommended for the best assessments possible.

Conclusion

We demonstrate that methods in spatial land use analysis can be effective to predict small scale and highly heterogeneous (urban) habitat patches in the form of urban community gardens. Land classifications have never been done before using UAVs in urban gardens— ecosystems that highly vary in land use, spatial arrangement and function—to offer a novel contribution to the literature in urban environments. The increasing relevance and utility of urban ecosystem service assessments for urban planners and city policy makers means that such land use classification and characterization methods could offer an important, increasingly accessible and cheap tool to map and assess complex urban habitats and landscapes. Having customizable, UAV-enabled opportunities to monitor important and growing urban land use such as UA could be extremely helpful to researchers, planners and designers at different urban scales. Furthermore, such assessments can justify the importance and value of urban gardens and UA generally as service providing systems that contribute to the sustainability and livability of cities—what urban planners seek to achieve.

Ethical statement

There are no conflicts of ethics to declare. All sites were sampled and surveyed with written or verbal permission from land managers.

Data accessibility statement

Datasets and code supporting this article can be accessed at https://github.com/BennyWag/urbandrones. Due to large file sizes, original UAV imagery and other spatial data is available upon request to the authors. A working tutorial with code examples and data from this study to the garden cover modeling can be found in Supplementary Appendix S2.

Authors' contributions

Both authors conceived of the study. M.E. carried out the field surveys. B.W. and M.E. collected aerial imagery. B.W. processed aerial imagery and spatial data. B.W. and M.E analyzed the data. M.E. and B.W. jointly drafted the article. Both authors contributed equally to this work.

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Conflict of interest statement. None declared.

Supplementary data

Supplementary data are available at *JUECOL* online.

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