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使用遙測資料探討都會地景蜘蛛多樣性之空間分布

Spatial Patterns of Spider Diversity in Urban Landscape by Using Remote Sensing Derived Indices

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本論文係尤光平君（R06625007）在國立臺灣大學森林環境暨資源研究所完成之碩士學位論文，於民國 108 年 6 月 5 日承下列考試委員審查通過及口試及格，特此證明

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中文摘要

遙測技術可以監測大空間尺度下的環境變化，使探討都市化對生物多樣性的衝擊研究更容易進行，其中，又以能夠反映棲地枝葉量多寡與初級生產力的植被指數最常被使用於描述棲地的面積以及棲地的品質；然而，有關棲地初級生產力假說和遙測資料衍生的環境因子如何影響蜘蛛這類肉食性小型節肢動物在大空間尺度下分布的研究卻較為缺乏且結果分歧。因此，本研究使用遙測資料所衍生的棲地動態指數與建蔽/裸地動態指數，探討與蜘蛛物種多樣性、科組成以及棲地偏好間的關係，並找出遙測因子能解釋最多變異的取樣尺度。本研究透過 1145 組掉落式陷阱蒐集蜘蛛樣本，並將蜘蛛物種多樣性依照 1、6.25、25、100 公頃的網格進行資料整合；另一方面，遙測資料則由大地 8 號衛星的網路公開資料庫取得，並使用廣義線性混合模式以及冗餘分析測試遙測因子和蜘蛛物種多樣性資料之間的關係。本研究發現，蜘蛛物種多樣性和棲地初級生產力呈顯著的正相關，且由於上行效應，使得蜘蛛儘管是食物鏈中上層的掠食者而非直接取食植物的初級消費者，棲地生產力假說仍能適用於牠們；且遙測因子，特別是年累積生產力，能夠顯著地解釋蜘蛛的物種多樣性以及科組成，而解釋變異的比例在 6.25 到 25 公頃的空間尺度之間達到最大。此外，狼蛛、皿蛛、姬蛛以及卵蛛這四個優勢科基於其體型、覓食策略和型態特徵的不同，棲地偏好能良好地被遙測因子所解釋。本研究提供了使用大尺度監測工具研究小型肉食節肢動物的方法，在保育策略方面，於都會綠地中營造初級生產力高且穩定的環境有助於蜘蛛多樣性的保育，除大面積綠地之外，高度都市化地區的行道樹或小型花壇亦是都會蜘蛛的重要棲地，減少殺蟲劑和除草劑的用量對於都會蜘蛛的物種多樣性保育亦有助益。

關鍵字：棲地生產力、增強植被指數、棲地動態指數、增強建蔽/裸地指數、臺灣

ABSTRACT

Through remote sensing data, monitoring the impact of urbanization on species diversity at a regional scale has become more and more convenient. Vegetation indices have been used to represent the size of habitats and habitat quality by predicting the amount of foliage and habitat productivity. However, studies on how habitat primary productivity hypothesis and remote sensing derived environmental factors (RS factors) affect spatial distribution of spiders at large spatial scales are lacking, and the relationship between spider diversity and RS factors remains unclear. Hence, the present study aimed to examine the relationship of spider species richness, family composition, and habitat preference with RS factors (Dynamic Habitat Indices and Dynamic Building/Bareness Indices) and determine the best spatial scale of sampling unit which RS factors could explain the largest variance in spider species richness and family composition. Spider species distribution data were obtained by pitfall traps in 1,145 sampling sites in an urbanization landscape in central Taiwan. Remote sensing data were obtained from Landsat 8 images. The relationships between RS factors and spider assemblage diversity were examined by generalized linear mixed models and redundancy analysis at four spatial scales: 1, 6.25, 25, and 100 ha grids. Results reveal that although spiders are predators which occupy higher trophic level, spider diversity follows habitat productivity hypothesis based on bottom-up effect, and thus could be modeled by RS factors significantly, especially cumulative Dynamic Habitat Index. The best spatial scale for studying spider diversity by RS factors was between 6.25 to 25 ha. With differences in sizes, foraging strategy, and morphological traits, habitat preferences of dominant spider families, Lycosidae, Linyphiidae, Theridiidae, and Oonopidae, could also be well explained by RS factors. Overall, the present study offers methods of modeling the spatial distribution of small carnivorous invertebrate species richness in the urbanization landscape by remote sensing data at a broad scale. For spider biodiversity conservation, maintaining high and stable habitat productivity in green areas, such as parks or school campuses, can help maintain high spider species richness. Also, Reducing the use of pesticides and herbicide at street trees and small vegetated patches in highly urbanized areas may also help on conserving spider diversity.

Keywords: Habitat productivity, EVI, Dynamic Habitat Indices, EBBI, Taiwan

CONTENTS

LIST OF FIGURES

doi:10.6342/NTU201902479

doi:10.6342/NTU201902479

doi:10.6342/NTU201902479

LIST OF TABLES

doi:10.6342/NTU201902479

doi:10.6342/NTU201902479

Introduction

In the recent decades, urban areas expand dramatically (United Nation, 2018), and urbanization has thought to be one of the leading causes of biodiversity loss (Marzluff, 2001; Li *et al.*, 2005; McKinney, 2008). Therefore, evaluating the influences of urbanization and the spatial distribution of biodiversity in urban areas are essential keys to conservation (McKinney, 2008; De Mas *et al.*, 2009; Zhang *et al.*, 2018a).

Spiders are very sensitive to environmental changes both at large and small spatial scales, which make them an excellent environmental indicator (Pearson, 1994; Fan, 2007; Chapman, 2009; Lowe *et al.*, 2017), and their species richness can be benefitted by both local and regional scale conservation works (Lowe *et al.*, 2017). Besides, as the main arthropod predator in the terrestrial ecosystems, spiders can benefit human society by serving as capable pest controllers (Nyffeler, 1987; Marc *et al.*, 1999; Denno *et al.*,2003).

Spider is taxa vary in size and foraging strategy (Uetz *et al.*, 1999; Cardoso *et al.*, 2011). Therefore, urbanization might cause different effects on different spider families and functional guilds (Miyashita *et al.*,1998; Magura *et al.*, 2010; Varet *et al.*, 2014). Large-sized spiders are often the main victims of urbanization. Natural habitats with complex vertical vegetation structures where harbor higher prey diversity and biomass

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are more likely to support high energy cost of large-sized spiders (Miyashita *et al.*,1998; Floren and Deleman-Reinhold, 2005; Finch, 2005; Barlow *et al.*, 2007; Hung *et al.*, 2008; Pinto-Leite *et al.*, 2008; Yekwayo *et al.*, 2016; Setiawan *et al.*, 2016; Lowe *et al.*, 2017). On the other hands, small-sized space web builders, for example, Theridiidae, prefer highly urbanized habitats and sometimes become dominant taxon due to their low energy cost and tolerance to low humidity (Magura *et al.*, 2010). Similar preferences can also be found in some ground wandering spider taxa (Magura *et al.*, 2010). Orb wed builder prefer edge habitats or open areas because of their unique spatial needs for orb web weaving (Miyashita *et al.*,1998; Petcharad *et al.*, 2016). However, previous studies also showed that these urban taxa tend to present smaller body size and web width than those in natural habitats due to the lower prey biomass (Miyashita *et al.*,1998; Dahirel *et al.*, 2018). Nevertheless, like most of the wildlife, urbanization could cause negative influences on overall spider species richness (Miyashita *et al.*,1998; McKinney, 2008; Varet *et al.*, 2014).

Remote sensing data can serve as proper tool to monitor the relationship between broad-scale environmental changes and wildlife species richness (McFeeters, 1996; Liu *et al.*, 2004; Schowengerdt and Robert, 2007; Mohapatra *et al.*, 2014; Lu *et al.*, 2015). By satellite or aircraft carried sensors, such as Moderate Resolution Imaging Spectroradiometer (MODIS), remote sensing can record electromagnetic wave emitted or reflected from the surface instantly (Schowengerdt and Robert, 2007; Lu *et al.*, 2015). Based on remote sensing data, researchers can derive important environmental indices to wildlife by calculating the albedo differences between several different spectral bands reflect from the ground surfaces (McFeeters, 1996; Mohapatra *et al.*, 2014; Yan *et al.*, 2019).

Vegetation Indices are one of the most commonly used remote sensing derived environmental indices which are derived from albedo ratio between red (564–580 nm) and near-infrared (750–950 nm) lights (Liu *et al.*, 2004; Phillips *et al.*, 2010). These indices are designed to predict the amount of foliage and vegetation density on the ground (Liu *et al.*, 2004; Phillips *et al.*, 2010) and can also be used on quantifying the main impacts of urbanization on biodiversity: habitat loss and habitat degradation (McFeeters, 1996; Li *et al.*, 2005; As-syakur *et al.*, 2012; Mohapatra *et al.*, 2014; Zhang *et al.*, 2018b).

Based on the albedo ratio, there are several types of formulae to derive vegetation indices (Liu *et al.*, 2004). Among all vegetation indices, Normalized Difference Vegetation Index (NDVI) has been the most commonly used vegetation index (Liu *et al.*, 2004). Derived by red and infrared bands only, NDVI is the most straightforward vegetation index, which can be calculated easily (Liu *et al.*, 2004). However, NDVI also has several shortages. For example, soil and airborne particle noises can heavily influence the accuracy of NDVI (Liu *et al.*, 2004). Besides, a nonlinear relationship is presented between the index and real foliage amount. The NDVI saturates at condense vegetation, such as broadleaf forests (Liu *et al.*, 2004; Phillips *et al.*, 2010; Hobi *et al.*, 2017). Despite many disadvantages, NDVI is still a sensitive index in habitats with low to medium vegetation density (Liu *et al.*, 2004; Phillips *et al.*, 2010).

Enhance Vegetation Index (EVI) was then constructed in order to fix the shortages of NDVI (Hobi *et al.*, 2017; Philpot, 2017). Intaking an additional blue band and two constants to calibrate soil and practical biases, EVI is more accurate than NDVI for dense vegetation (Phillips *et al.*, 2010). Therefore, EVI could present linear correlations to real foliage amount and vegetation density, which make EVI better predictors of foliage amount than NDVI in tropical and subtropical landscapes (Hobi *et al.*, 2017; Philpot, 2017). However, no matter how precise a vegetation index is, it does not fully equal to ground truth foliage amount (Liu *et al.*, 2004; Phillips *et al.*, 2010; Hobi *et al.*, 2017).

Further, vegetation types and their phenology can be inferred by combining vegetation indices at different temporal scales (Berry *et al.*, 2007). Dynamic Habitat Indices (DHIs) are designed to describe vegetation phenology through times base on vegetation indices (Berry *et al.*, 2007). The DHIs include three different indices, Cumulative DHI, Minimum DHI, and Variation DHI (Berry *et al.*, 2007). Within a year,

doi:10.6342/NTU201902479

Cumulative DHI represents the total amount of foliage of the habitat in the whole year, Minimum DHI represents the amount of foliage in non-growing season of the habitat, and Variation DHI is the differences in the amount of foliage between growing and non-growing season of the habitat (Berry *et al.*, 2007; Andrew *et al.*, 2012; Hobi *et al.*, 2017). By comparing DHIs in different habitats, vegetation types and their phenology can be inferred. For example, within one year, temperate deciduous forest presents high cumulative DHI, high variation DHI, and low minimum DHI because of the dense foliage in growing season and defoliation in the non-growing season (Hobi *et al.*, 2017). On the other hand, all three DHIs are low in temperate grassland due to its stable, but sparse foliage amount (Hobi *et al.*, 2017).

Through vegetation indices and DHIs, researchers can also predict habitat productivity, which has been thought to be one of the most important environmental factors to species diversity (Clark *et al.*, 2001; Amthor and Baldocchi, 2001; Liu *et al.*, 2004; Lu *et al.*, 2015). Habitat productivity is defined as the total inorganic energy fixed by producers (Amthor and Baldocchi, 2001; Clark *et al.*, 2001). Habitat productivity hypothesis is an important theory which states that species richness increases with increasing habitat productivity. However, there are many exceptions which have rejected habitat productivity hypothesis (McGoff *et al.*, 2013; Vilar *et al.*, 2014; Bicudo *et al.*, 2016; Zorzal-Almeida *et al.*, 2017). One of the famous cases is eutrophication in

doi:10.6342/NTU201902479

aquatic ecosystems, high productivity sometimes leads to explosive growth of bacteria and algae which consume all the oxygen and cause suffocation to other organisms (McGoff *et al.*, 2013; Vilar *et al.*, 2014; Bicudo *et al.*, 2016; Zorzal-Almeida *et al.*, 2017).

Besides species richness, community dissimilarity can also be explained by habitat productivity (Harrison *et al.*, 2006; Andrew *et al.*, 2012; Johnson and Angeler, 2014). In habitats with high productivity, community dissimilarity between sampling sites are larger than those in habitat with low productivity (Harrison *et al.*, 2006; Andrew *et al.*, 2012; Johnson and Angeler, 2014). Further, Andrew *et al.* (2012) stated that dissimilarity is driven by inter-species competition in productive habitats due to the competition on resources. On the other hand, dissimilarity in less productive habitats are driven by environmental filtering since only a few strong species are present in harsh habitats (Andrew *et al.*, 2012).

Although spiders are small-sized carnivores, their species richness and assemblage composition are heavily influenced by bottom-up effect, prey biomass and vertical vegetation structure (Greenstone, 1984; Tso, 2003; Fan, 2007; Scharf *et al.*, 2011; Štokmane and Spuņģis, 2014). Therefore, habitat productivity hypothesis can also apply on spider species richness (De Mas *et al.* 2009; Birkhofer and Wolters, 2012; Turrini *et al.*, 2015). Turrini *et al.* (2015) even stated that green areas in highly urbanized landscape with high NDVI value can harbor higher spider species richness than that in rural farmland. Besides species richness, prey diversity to spiders also increases with increasing productivity at a global scale (Birkhofer and Wolters, 2012). However, in some cases, spider species richness cannot be well explained or predicted by vegetation indices (Jiménez-Valverde and Lobo, 2006; Lafage *et al.*, 2014). Lafage *et al.* (2014) suggest that the results may be caused by the higher trophic levels that spiders occupied (Girard *et al.*, 2011). Thus their diversity is not heavily influenced by vegetation productivity in less productive habitats such as temperate floodplains (Lafage *et al.*, 2014).

DHIs are good environmental predictors which contain not just spatial, but also temporal productivity features. To many taxa, habitats with high cumulative, high minimum productivity, and low productivity variation can harbor higher species richness, abundance, and larger body size (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Birkhofer and Wolters, 2012; Michaud *et al.*, 2014; Suttidate, 2016; Hobi *et al.*, 2017; Khlifa *et al.*, 2017; Tiede *et al.*, 2018). However, different taxa and functional groups might prefer habitats which had different productivity features. To North American birds, vegetation indices derived DHIs are valid predictors (Hobi *et al.*, 2017). For forest nesting birds, cumulative DHI has the best predictive power and presents positive correlation relationship (Hobi *et al.*, 2017). On the other hand,

doi:10.6342/NTU201902479

minimum and variation DHI are better predictors for grassland nesting birds, and habitat had low minimum and high productivity variation harbor higher grassland nesting birds (Hobi *et al.*, 2017). To spiders, however, the relationship between DHIs and the habitat preferences of each family or functional guilds was seldom studied.

Habitat preferences of wildlife taxa and functional guilds are not the only reason which might cause different relationship between habitat productivity and species richness. Habitat productivity hypothesis is a scale-dependent hypothesis, several previous studies indicated that the hypothesis is more likely to be applied at broader spatial scales, while the correlation between habitat productivity and species richness might become neutral, or even negative and less significant at finer spatial scales (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Birkhofer and Wolters, 2012; Michaud *et al.*, 2014; Suttidate, 2016; Hobi *et al.*, 2017; Khlifa *et al.*, 2017). Therefore, spatial scale shall also be considered as an important factor when modeling species richness by habitat productivity. On the other hand, the scale of sampling unit is also important when using remote sensing data to derived environmental factors (Liu *et al.*, 2004; De Mas *et al.* 2009; Phillips *et al.*, 2010). Under remote sensing, differences within sampling units are shrunk into a single value, which may cause two distinct habitats had the same environmental factors (Liu *et al.*, 2004; De Mas *et al.* 2009; Phillips *et al.*, 2010). To spiders, De Mas *et al.* (2009) indicated that spider species

doi:10.6342/NTU201902479

richness in the mountains in the Mediterranean climate could be well predicted by NDVI and the area ratio of different vegetation types. They also stated that the proper spatial scale to predict spider species richness and assemblage composition is in 220-meter pixel size, and the efficiency decreases at other spatial scales (De Mas *et al.* 2009).

Not just vegetation indices can quantify the effect of urbanization, building indices, based on albedos differences between short wave infrared (2000 – 2500 nm) and thermal infrared (1000 – 1200 nm), are indices sensitive in detecting concrete, asphalt, and most of the artificial surfaces (McFeeters, 1996; As-syakur *et al.*, 2012; Mohapatra *et al.*, 2014). Therefore, scientists can map level of urbanization by deriving indices such as Enhance Build-Up/Bareness Index (EBBI) (As-syakur *et al.*, 2012). However, only a few studies have focused on the relationship between building indices and species richness (Shih, 2018). After all, modeling spatial distribution of species richness at regional scale has become more important to conservation works, especially to those in urban areas (Turrini *et al.*, 2015; Buchholz *et al.*, 2018; Lowe *et al.*, 2018). Through burgeoning remote sensing technology, environmental factors which used to cost many resources to record are now easier to reach (McFeeters, 1996; Liu *et al.*, 2004; Schowengerdt and Robert, 2007; Mohapatra *et al.*, 2014; Lu *et al.*, 2015). However, algorithms and conservation strategy were still remaining ambiguous to taxa which

doi:10.6342/NTU201902479

attracted less attention, such as spiders (Nyffeler, 1987; Marc *et al*., 1999; Denno *et al.*,2003; McKinney, 2008). Therefore, the present study aimed to test the possibility of studying species richness and family composition of ground-dwelling arthropods predator in urbanization landscape by remote sensing data. Further, are spiders in different families in urbanization landscapes all prefer habitats with the same productivity features? Also, is the best scale of sampling units for studying spider diversity in the present study the same to that stated in Lafage *et al.* (2014) in mountains in Mediterranean climate (220 m^2)? After all, could any conservation strategy be stated through the present study?

Specifically, the present study aimed to (1) examine differences in spider family composition in a subtropical urbanization landscape, (2) define habitat preferences of dominant spider families by remote sensing derived environmental factors (RS factors) (EVI derived DHIs, and EBBI derived Dynamic Building/Bareness Indices (DBIs)), (3) explain these spider family composition differences by RS factors, (4) determine appropriate spatial scale of the sampling units that RS factor(s) can explain the largest proportion of variance of spider family composition variances, (5) examine relationships between RS factors and spider species richness in subtropical urbanization landscape, (6) explore the possibility of modeling spider species richness by RS factors, and (7) determine best RS factors subset and spatial scale of the sampling units that spider species richness can be modeled by RS factor(s).

Methods

GREEnS data set

Global Research & Education on Environment and Society (GREEnS) was a project supported by the Board of Directors of Tunghai University, and conducted by Tunghai University from the year 2012 to 2015. One of the main aims of the project was to test the suitability and validity of studying spider and plants species diversity in different land use types by using an environmental indicator which has been widely used in gardening and urban planning, Biotype Area Factor (BAF).

Therefore, a broad urbanization landscape (about 3,500 km^2) located in central Taiwan was selected as the study area of GREEnS project (Figure 1). Within this study area, a total of 1,232 sampling sites were conducted under 53 patches with four different land use types, which included 8 school campus, 11 industrial areas, 30 parks, and 4 paddy areas (Appendix 1). Sampling sites was at least 100 m apart and a sampling plot of 100 m^2 quadrat was established for recording both spider and vegetation species diversity data.

doi:10.6342/NTU201902479

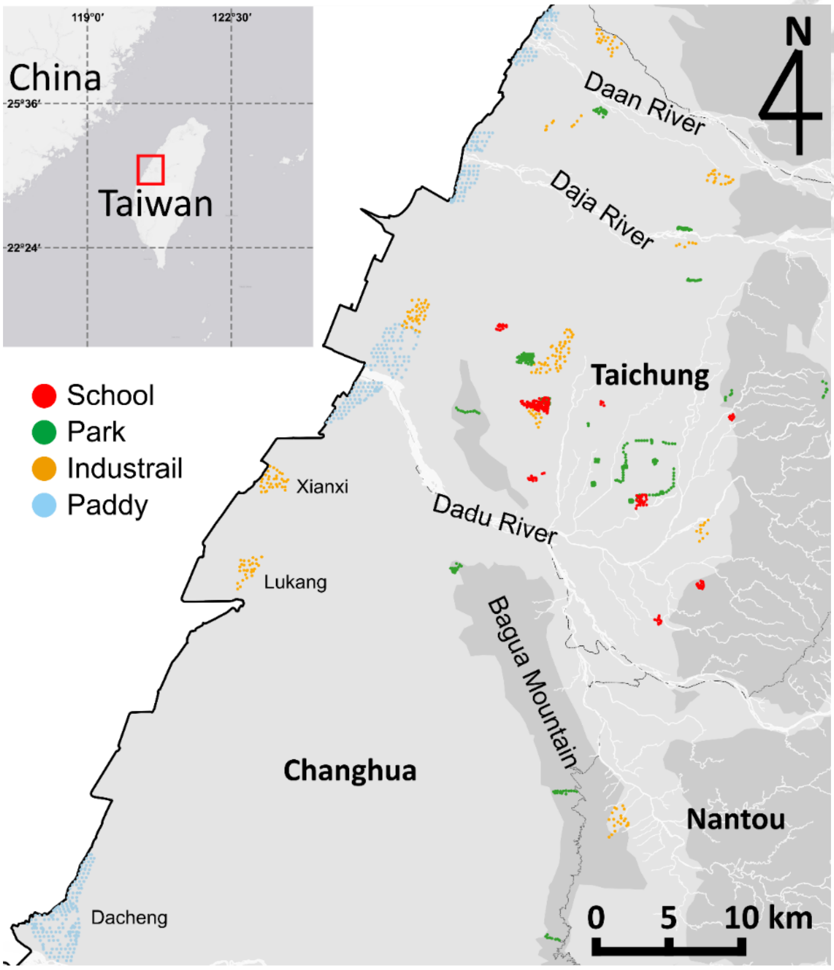

Figure 1 The study area located in central Taiwan; each dot represent one sampling site and colors of the dots represent different land use types in Global Research & Education on Environment and Society project.

Species diversity data

During the growing seasons (March to June) from 2012 to 2015, pitfall traps were established in the field to record spider species richness and abundance data at every sampling site and without repeat survey. A set pitfall trap consisted of five 50 ml centrifuge tubes. Each tube was filled with 30 ml 70% ethanol and left in the field for no more than a week to reach the highest capture efficiency (Schirmel *et al.*, 2010). All the trapped spider individuals were the removed from the traps and preserved in 70% ethanol and identified to morphological species level by comparing their genitals. A total of 1849 spider individuals that belong to 196 morphological species, 27 families were recorded in the data set (Appendix 2). The present study only included sampling sites with mature spider individuals and sampling sites with only one juvenile individual, which was treat as one morphological species at that site. In a total of 1,145 sampling sites were included for further analysis.

On the other hand, vegetation diversity data, including both wood and herb plants, were surveyed within the 10×10 m sampling plot. For woody plants, individuals with its diameter at breast height (DBH) larger than 1 cm were identified to species level, and their DBH were also recorded. For herbs, individuals were identified to species level, and percentage of coverage of each herb species was also recorded.

In order to determine suitable spatial scale to explain spider species richness and family composition by RS factors, I rearranged the spider and vegetation diversity data into four different grid systems, 1ha (100 m diameter buffer of each sampling site), 6.25 ha (250m × 250m grid), 25 ha (500 m × 500 m grid), and 100 ha (1,000 m × 1,000 m grid) (Table 1). Spider and vegetation diversity data were combined in each grid.

Besides, since no repeat survey was done to both spider and vegetation data.

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Hence, to correct the possible bias of the data set, I adopted species richness estimation by using Chao (1984) index (CHAO1), which is a species richness estimator suitable for estimating invertebrate richness at genus level or lower (Basualdo, 2011). CHAO1 is derived by the cumulative species richness rarefaction curve and the number of rare species recorded in sampling sites and is suitable for. The correction method was applied to spider species richness at every spatial scale (grid size) and to tree and herb species richness in grids larger than 1 ha (Table 1)

Table 1 Sites compilation by buffer zones and grids at different spatial scale; CHAO1: Chao (1984) index estimated species richness; GLM: generalized linear model; GLMM: generalized linear mix model

Unit size	**Sample size**	**CHAO1**	**Model**	**Radom factor**	**N.O. of site(s) per grid**
1 ha	1,145	Spider Richness	GLM	None	1
6.25 ha	805	Spider, Wood, Herb Richness	GLMM	N.O. of sites per grid	1–9
25 ha	407				1–29
100 ha	186				1–49

Remote sensing data

I downloaded five cloud-free images, four from the four seasons of the year 2014 and one from the winter of the year 2013 (Table 2), of the study area (Path: 118, Row: 43) from National Aeronautics and Space Administration (NASA), Landsat 8 mission level two product online open access (Resolution: 30m × 30m). Based on the images, Enhance Vegetation Index (EVI) and Enhanced Built-Up and Bareness Index (EBBI) were calculated through the following formulae (NIR: near infrared band; RED: red band; BLUE: blue band; SWIR: short wave infrared; TIR: thermal infrared).

$$\mathrm{EVI} = 6 \times \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + 6 \times \mathrm{RED} - 7.2 \times \mathrm{BLUE} + 1} \qquad \mathrm{EBBI} = \frac{\mathrm{SWIR} - \mathrm{NIR}}{10\sqrt{(\mathrm{SWIR} + \mathrm{TIR})}}$$

Table 2 Landsat 8 images selected in this study

Date of the image	**Season represented**
December 3rd, 2013	2013 Winter
March 25th, 2014	2014 Spring
August 16th, 2014	2014 Summer
October 19th, 2014	2014 Fall
December 22nd, 2014	2014 Winter

Using the EVI and EBBI values in each season, I derived Dynamic Habitat Indices (DHIs), and Dynamic Building/Bareness Indices (DBIs). Dynamic Habitat Indices include cumulated annual productivity (Cumulative DHI), minimum annual productivity (Minimum DHI), and seasonal coefficient (Variation DHI) (Figure 2). On the other hand, DBIs is consists of cumulated annual build-up/bareness (Cumulative DBI), maximum annual build-up/bareness (Maximum DBI), and seasonal coefficient (Variation DBI) (Figure 3).

Both Cumulative DHI and DBI were calculated by integrating EVI and EBBI value from the winter of the year 2013 to the winter of the year 2014 (Table 3). On the other hand, Variation DHI and DBI were calculated by the standard deviation of EVI and EBBI value divided by the average of EVI and EBBI value (Table 3). Minimum DHI was the lowest EVI value of the year, and Maximum DBI was the largest EBBI value of the year. All the calculations were done using QGIS version 2.18.15.

However, strong collinearity was found between Cumulative DHI and Minimum DHI (Pearson correlation coefficient = 0.95), and also between Cumulative DBI and Maximum DBI (Pearson correlation coefficient = 0.83) (Table 3). Therefore, I excluded Minimum DHI and Cumulative DBI from the following statistical analyses.

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Table 3 Pearson correlation coefficient between six remote sensing derived environmental factors; bold characters represent factor pairs with correlation coefficient over 0.7. Cum_DHI: Cumulative Dynamic Habitat Index; Min_DHI: Minimum Dynamic Habitat Index; Var_DHI: Variation Dynamic Habitat Index; Cum_DBI: Cumulative Dynamic Building/Bareness Index; Max_DBI: Minimum Dynamic Building/Bareness Index; Var_DBI: Variation Dynamic Building/Bareness Index.

	Cum_DHI	Min_DHI	Var_DHI	**Cum_DBI**	Max_DBI	Var_DBI
Cum_DHI	–	–	–	–	–	–
Min_DHI	0.95	–	–	–	–	–
Var_DHI	-0.37	-0.57	–	–	–	–
Cum_DBI	-0.21	-0.24	0.20	–	–	–
Max_DBI	-0.14	-0.27	0.37	0.83	–	–
Var_DBI	-0.33	-0.47	0.52	0.37	0.65	–

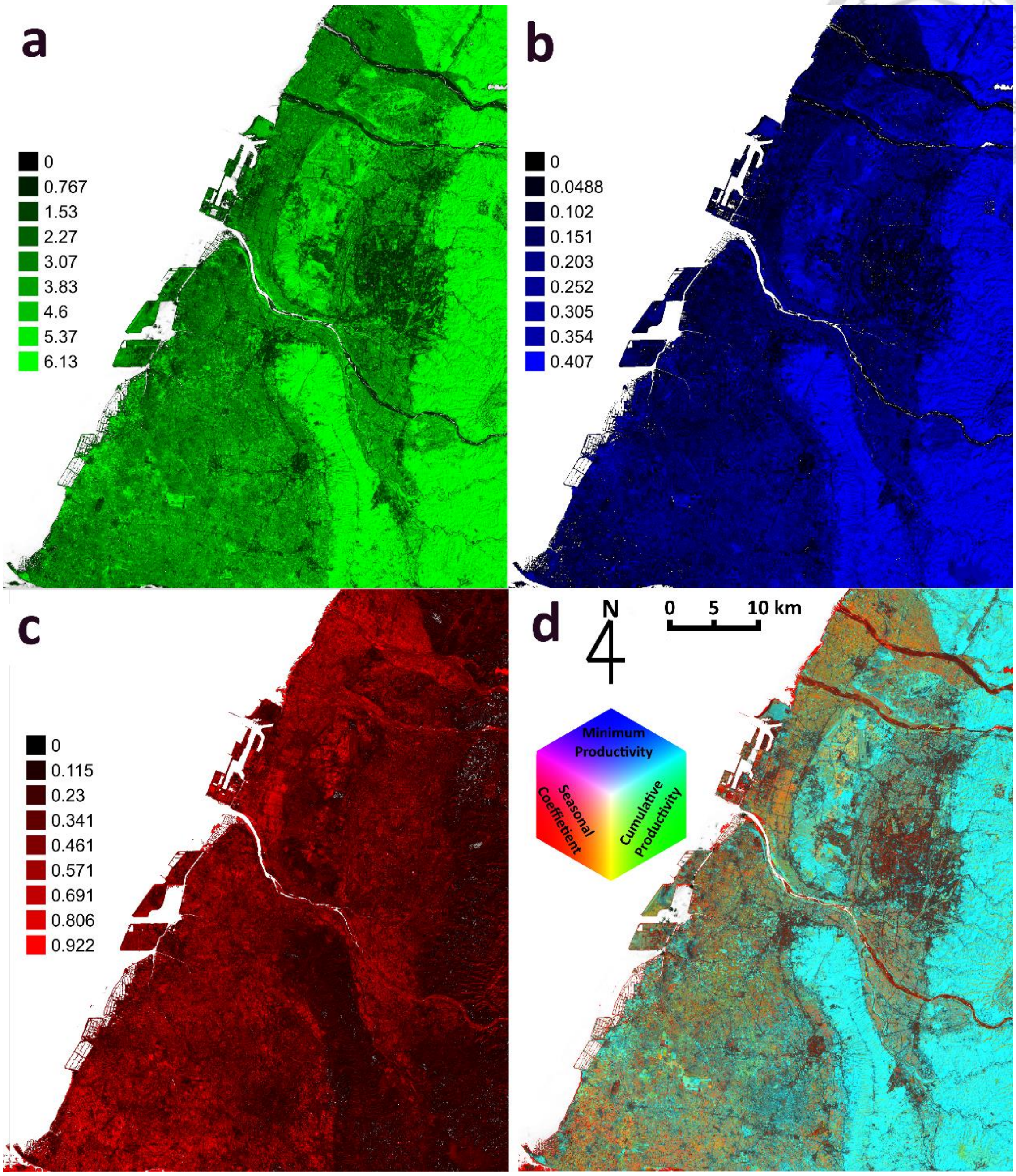

Figure 2 Dynamic Habitat Indices (DHIs) of the study area derived by Enhance Vegetation Index. (a) cumulative DHI, (b) minimum DHI, (c) variation DHI, (d) combined DHIs were transformed into RGB color on the map (Red: Variation DHI; Green: Cumulative DHI; Blue: Minimum DHI)

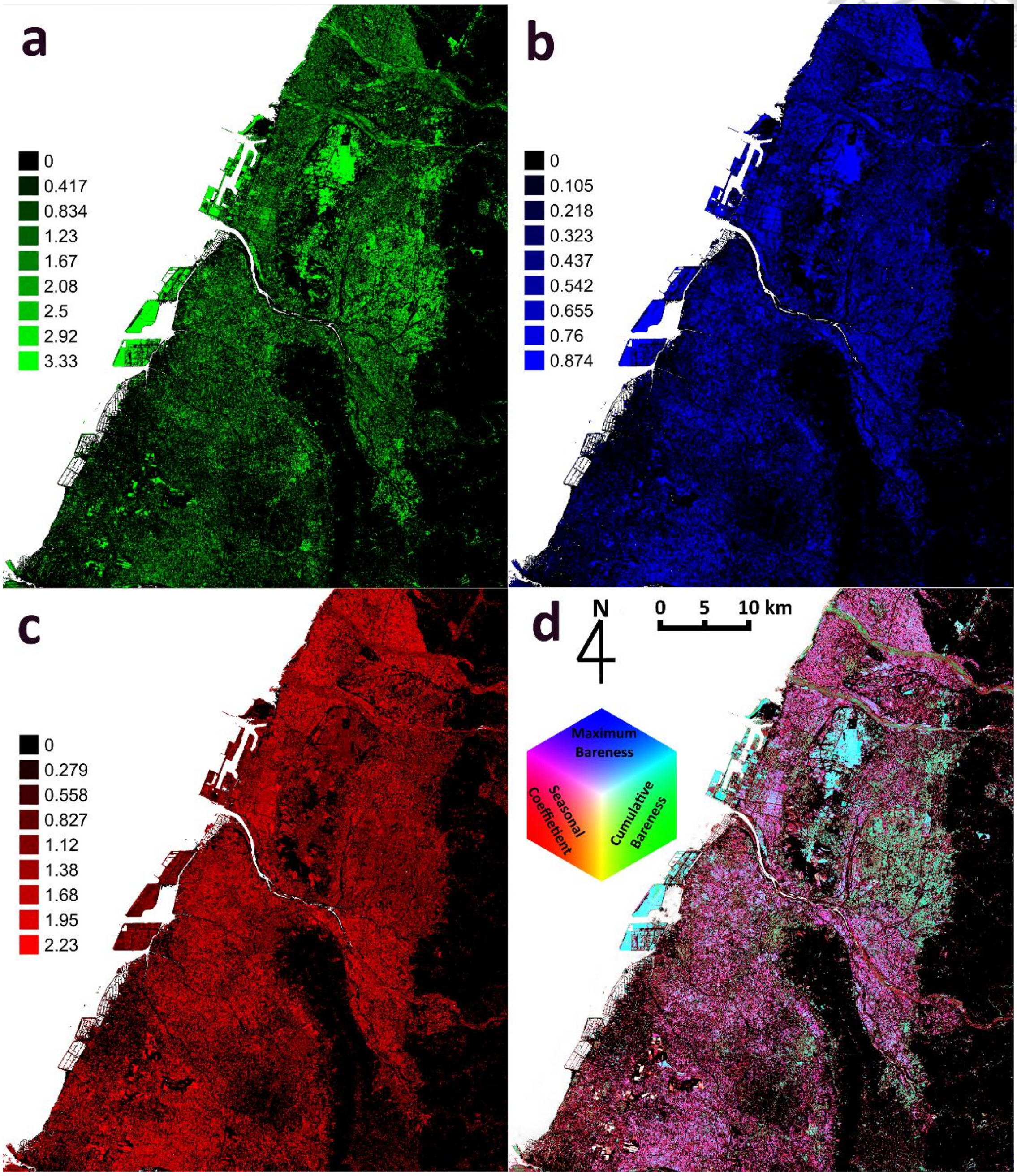

Figure 3 Dynamic Building/Bareness Indices (DBIs) of the study area derived by Enhance Build-up/Bareness Index. (a) cumulative DBI, (b) maximum DBI, (c) variation DBI, (d) combined DBIs were transformed into RGB color on the map (Red: Variation DBI; Green: Cumulative DBI; Blue: Maximum DBI)

Statistical analyses

All statistical works were done using R version 3.4.3. At all four sizes of sampling units, eight environmental factors were selected (Table 4), wood species richness, wood total basal area, herb species richness, and herb coverage were local vegetation factors (LV factors); and Cumulative DHI, Variation DHI, Cumulative DBI, and Variation DBI were remote sensing derived environmental factors (RS factors) (Table 4).

Matrix of spider family occupancy at each sampling sites (1 ha scale) was transformed into Ward's distance matrix, and went under unweighted pair-group method with arithmetic means (UPGMA) cluster analysis to group sampling sites based on spider family composition dissimilarity. Then, Kruskal-Wallis test and pair-wised Wilcoxon test (Bonferroni adjusted p-value) was adopted to test were RS factors different between different groups. Together with the results from pair-wised Wilcoxon test, RS factors preference of dominant spider families in each group and the significance of studying spider family composition through RS factors were tested by Bray-Curtis distance based Redundancy Analysis (RDA) and Monte Carlo permutation test.

Besides, in order to test if RS factors were suitable for explaining spider family composition differences between sampling sites (1 ha scale), the proportion of composition variances explained by RS factors and by LV factors through Bray-Curtis

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distance based RDA were compared. The same comparisons were also made at the 6.25, 25, 100 ha sampling unit size, and the sampling unit size which RS factors could explain the largest proportion of composition variances was considered as the proper spatial scale for studying spider family composition with RS factors.

On the other hand, to test the relationship between CHAO1 and RS factors among sampling sites (1 ha scale), and test did RS factors fit good models to CHAO1, negative binomial-based generalized linear models (GLM) were conducted between CHAO1 and each individual RS factor. Also, another two negative binomial-based GLM were conducted, one with both RS factors and LV factors while the other with RS factors only. The former was conducted in order to test could any RS factors still reach the 0.05 significance level when modeling CHAO1 with LV factors together. The latter was conducted for selecting the best-fitted model with highest AIC weight.

Besides, at sampling unit size larger than 1 ha, negative binomial-based generalized linear mixed models (GLMM) were conducted to model CHAO1 by RS factors (Table 1). Model AIC and AIC weight of all candidate models with different RS factors subset combinations were compared to select the best-fitted model for modeling CHAO1 at each spatial scale. Besides, I set the number of sampling site within a grid as a random factor to correct its effect on CHAO1. After all, model fitness of the best-fitted model at each scale was compared by pseudo R square (one minus ration between

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null deviance and residual deviance) between the predicted value generated from the model and CHAO1. The spatial scale that best-fitted model had the highest pseudo R square was considered the proper spatial scale of modeling CHAO1 by RS factors.

Table 4 factors included in the analysis and their ecological meanings; EVI: Enhance Vegetation Index; EBBI: Enhanced Built-Up and Bareness Index; DHI: Dynamic Habitat Indices; DBI: Dynamic Building/Bareness Indices.

Type	**Factors**	**Calculation**	**Ecological meaning**
Local vegetation	Wood species richness	—	Horizontal vegetation structure
	Wood basal area	$\frac{\pi \times \left(\frac{\mathrm{DBH}}{2}\right)^2}{144}$	Vegetation abundance
	Herb species richness	—	Horizontal vegetation structure
	Herb coverage	—	Vegetation abundance
Remote sensing	Cumulative DHI	$\int_{2014\ \mathrm{Dec}}^{2013\ \mathrm{Dec}} \mathrm{EVI}$	Annual total productivity
	Variation DHI	$\frac{\partial(\mathrm{EVI})}{\mu(\mathrm{EVI})}$	Annual productivity variation
	Cumulative DBI	$\int_{2014\ \mathrm{Dec}}^{2013\ \mathrm{Dec}} \mathrm{EBBI}$	Annual total Building/Bareness
	Variation DBI	$\frac{\partial(\mathrm{EBBI})}{\mu(\mathrm{EBBI})}$	Annual Building/Bareness Variation

Results

Spider family composition differences in the subtropical urbanization landscape were mainly determined by the occupancy of four dominant spider families, which were wolf spiders (Lycosidae), sheet weaving spiders (Linyphiidae), goblin spiders (Oonopidae), and cobweb spiders (Theridiidae) (Figure 4). Based on the proportion of the occupancy of the four dominant spider families, sampling sites were divided into five groups: wolf spiders dominance (occupancy>0.5), sheet weaving spiders dominance, goblin spiders dominance, cobweb spiders dominance, and complex community which included other 23 spider families with low species richness and abundance (Figure 4).

Remote sensing derived environmental factors (RS factors) at sampling sites in different groups were significantly different (Figure 5). Thus, habitat preferences of these dominance spider families could be stated by the RS factors (Figure 6). Wolf spiders preferred habitats which had high but unstable annual productivity and low but also unstable annual building/bareness (Figure 6). Sheet weaving spiders, on the other hand, preferred habitats which had high and stable annual productivity and low and also stable annual building/bareness (Figure 6). Goblin spiders and cobweb spiders, however, preferred similar habitats which had low and unstable annual productivity

doi:10.6342/NTU201902479

while had high and unstable annual building/bareness (Figure 6). Beside the four dominant families, most of the less-abundant spider families were recorded in habitats which had low but stable annual productivity and medium but stable annual building/bareness.

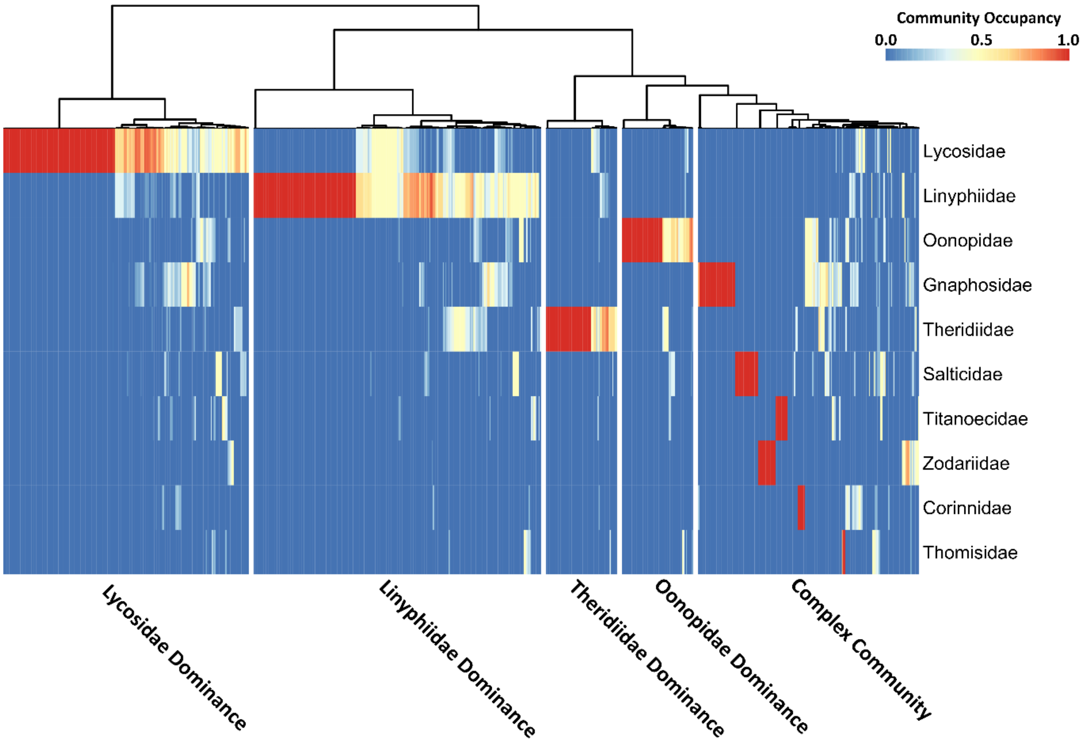

Figure 4 Sampling sites occupied by Lycosidae, Linyphiidae, Theridiidae, and Oonopidae had higher spider family composition dissimilarity and thus were divided from other sampling sites into four unique groups through unweighted pair-group method with arithmetic means (UPGMA) cluster analysis. Note: figure here only presents families with abundance over 30 individuals. Other 17 Families with abundance less than 30 individuals were all belonged to the complex community in the

cluster analysis.

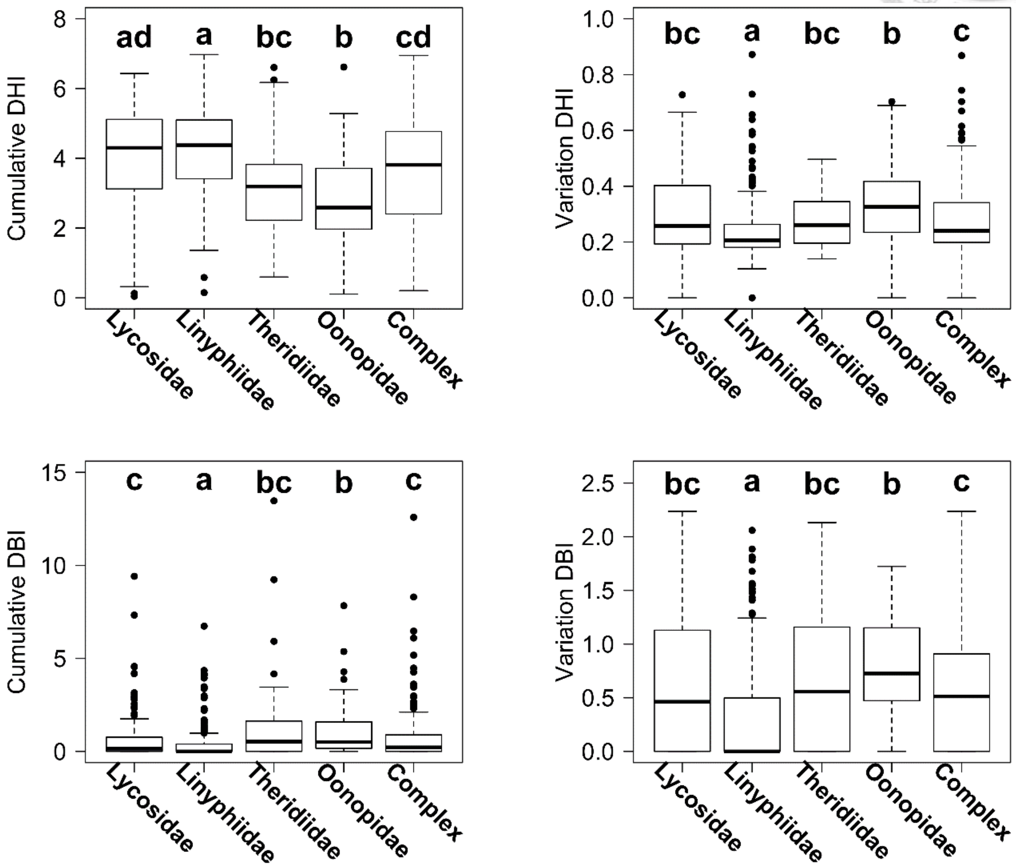

Figure 5 Kruskal-Wallis test and pair wised Wilcoxon test indicated that sampling sites dominant by wolf spiders had high cumulative Dynamic Habitat Index (DHI), Variation DHI, and Variation Dynamic Building/Bareness Index (DBI) while had low Cumulative DBI. Sampling sites dominant by sheet weaving spiders, on the other hand, had high cumulative DHI while had low Cumulative DBI, Variation DHI, and Variation DBI. No statistical significance (Bonferroni adjusted p-value >0.05) between RS factors at sampling sites dominant by cobweb spiders and goblin spiders, they both had low cumulative DHI while had high Cumulative DBI, Variation DHI, and Variation DBI.

Upper boundaries of the rectangles: 25th percentiles; lower boundaries of the rectangles: 75th percentiles; horizontal bars: median; dotted vertical bars: upper and lower distribution limits. DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index.

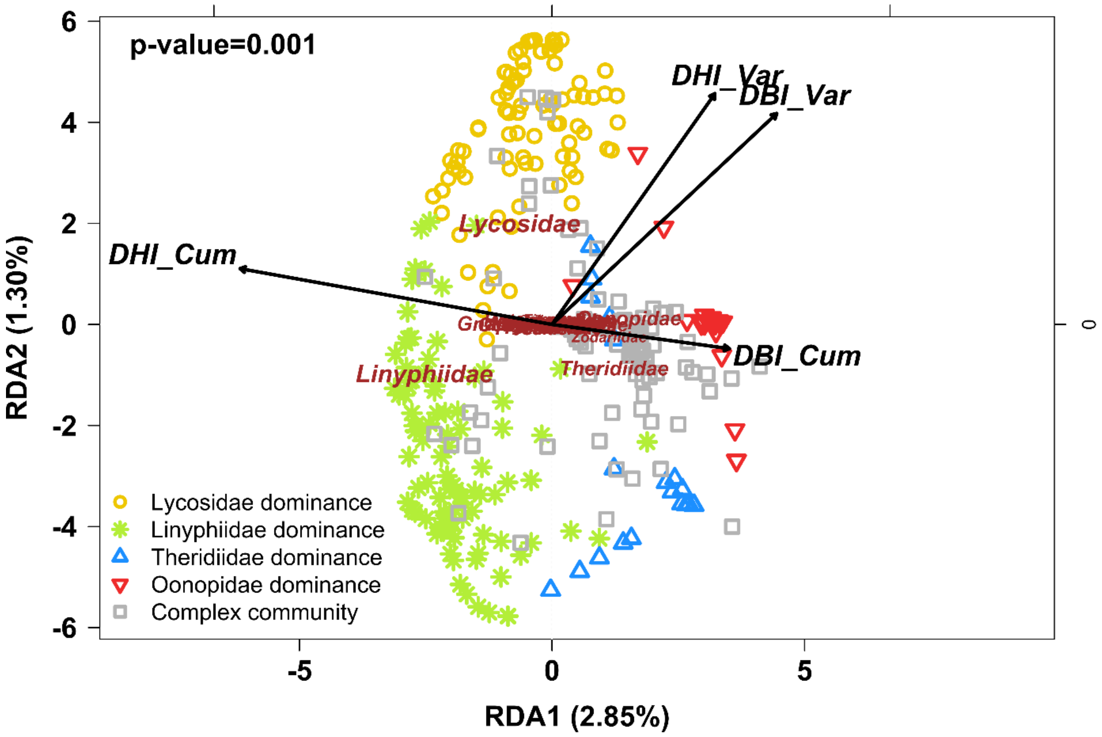

Figure 6 relationship between remote sensing derived environmental factors and sampling site with different spider family composition. DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index; Cum: cumulative; Var: variation.

RS factors could serve as significant constrained factors in explaining spider family composition variances and could explain variances which LV factors could not explain (Figure 7). Further, among the variances explained by both types of factors (5.91% of the total variances), larger proportion of variances were explained by RS factors than LV factors did (RS factors: 41%; LV factors: 35%; both: 24%) (Figure 7). Also, the proportion of spider family composition variances explained by RS factors increased about 10% from 1 ha spatial scale to 25 ha spatial scale while declining at the spatial scale larger than 25 ha spatial scale (25 ha: 53%; 100 ha: 50%) (Figure 8). Therefore, 25 ha spatial scale was the proper scale for using RS factors on explaining spider family composition.

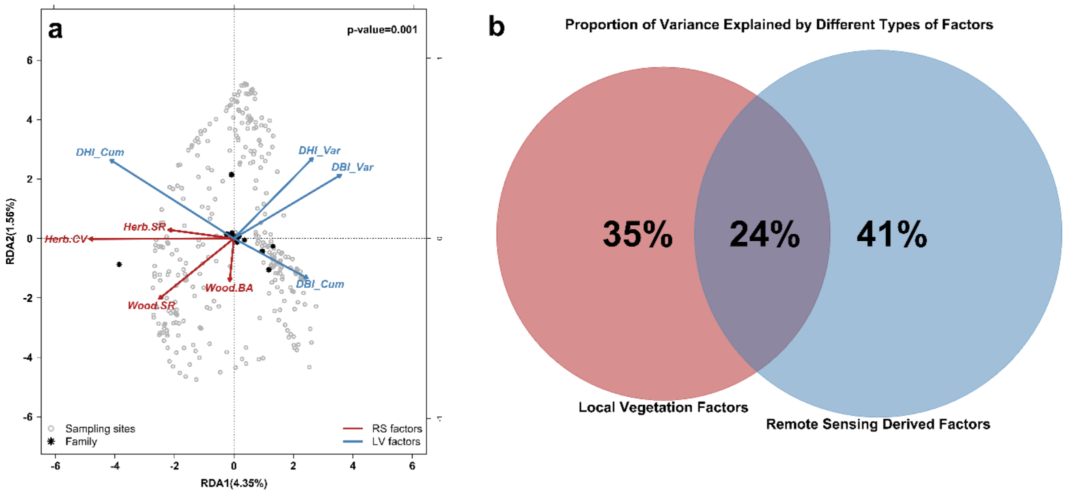

Figure 7 Comparison between the proportion of the spider family composition variances explained by remote sensing derived environmental factors (RS factors) and local vegetation factors (LV factors). (a) RS factors and LV factors could explain different parts of the spider family composition variances and together explained 5.91%

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of total variances. (b) RS factors could explain more variance (blue circle) than local vegetation factors did (red circle). SR: species richness; BA: basal area; CV: coverage; DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index.

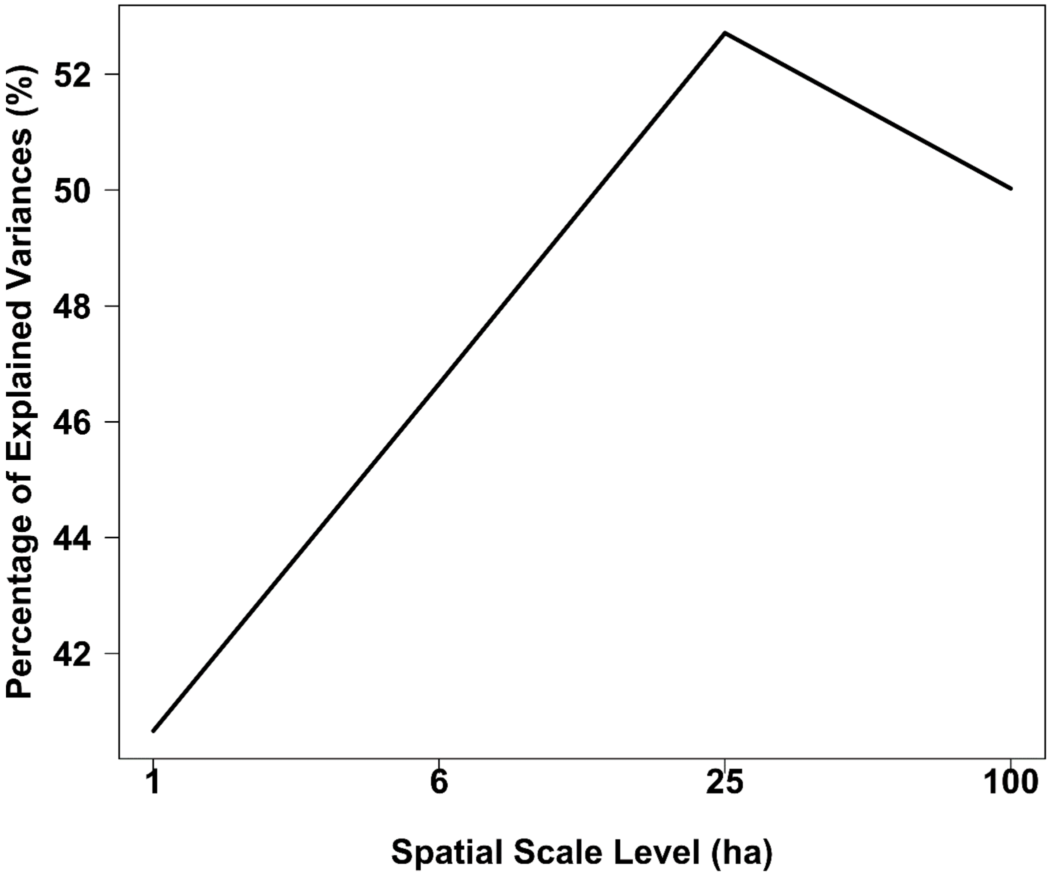

Figure 8 The proportion of the spider family composition variances explained by remote sensing derived environmental factors at 1, 6, 25, and 100 ha sampling unit size. At 25 ha spatial scale, remote sensing derived environmental factors explain the largest percentage of spider family composition variances.

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Estimated spider species richness (CHAO1) was higher in habitats which had high annual productivity while lower in habitat with high productivity variation, high annual building/bareness, and high building/bareness variation and all four RS factors were significantly correlated to CHAO1 (Table 5). Besides, although the model with local vegetation factors (LV factors) added fitted CHAO1 better (AIC with LV factor: 3887.3; AIC without LV factor: 3982.7), RS factors could still found significantly correlated to CHAO1, especially Cumulative DHI (Table 6).

Table 5 Correlation relationship and model AIC between estimated spider species richness and each remote sensing derived environmental factors at 1 ha sampling unit size. “***”: p-value<0.001; “**”: p-value<0.01; DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index.

Factor	**Trend**	**Significance**	**AIC**
Cumulative DHI	+	***	3985
Variation DHI	–	***	4129
Cumulative DBI	–	**	4166
Variation DBI	–	***	4133

doi:10.6342/NTU201902479

Table 6 Correlation relationship between estimated spider species richness and both remote sensing derived environmental factors and local vegetation factors. “***”: p-value<0.001; SR: species richness; BA: basal area; CV: coverage; DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index.

Factor type	**Factor**	**Trend**	**Significance**
Local vegetation	Wood SR	+	***
	Wood BA	+	
	Herb SR	+	***
	Herb CV	+	***
Remote sensing	Cumulative DHI	+	***
	Variation DHI	–	
	Cumulative DBI	+	
	Variation DBI	–	
	AIC	3887.3	

RS factors subsets significantly correlated to CHAO1 at 1, 6.25, and 25 ha sampling unit size (Table 7). The best-fitted model at 1 ha spatial scale consisted of Cumulative DHI and Variation DBI (Weight AIC: 0.383), the former was positively

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correlated to CHAO1 while the latter was negatively correlated to CHAO1 (Table 7). At 6.25 ha spatial scale, Cumulative DHI was the significant factor which positively correlated to CHO1 and fitted CHAO1 better than other candidate models did at the same spatial scale (AIC weight: 0.267) (Table 7). On the other hand, The best-fitted model at 25 ha spatial scale consisted of Cumulative DHI and Variation DHI (Weight AIC: 0.339), the former was positively correlated to CHAO1 while the latter was negatively correlated to CHAO1 (Table 7). At 100 ha spatial scale, the model with Cumulative DHI alone fitted CHAO1 better than other candidate models did at the same scale. However, Cumulative DHI did not reach the 0.05 significance level (Table 7).

Further, model fitness of the best-fitted model at each spatial scale was different, it increased from 1 ha to 100 ha spatial scale (Pseudo R square at 1 ha: 0.103; 6.25 ha: 0.506; 25 ha: 0.595; 100 ha: 0.622) (Figure 9). However, the increasing trends of the model fitness declined at sampling unit size greater than 6.25 ha (Figure 9). After all, considered both model fitness and factor significance of the best-fitted model at each spatial scale, sampling unit size between 6.25 and 25 ha were the proper sampling unit size for modeling CHAO1 by RS factors, and Cumulative DHI could serve as an important RS factor.

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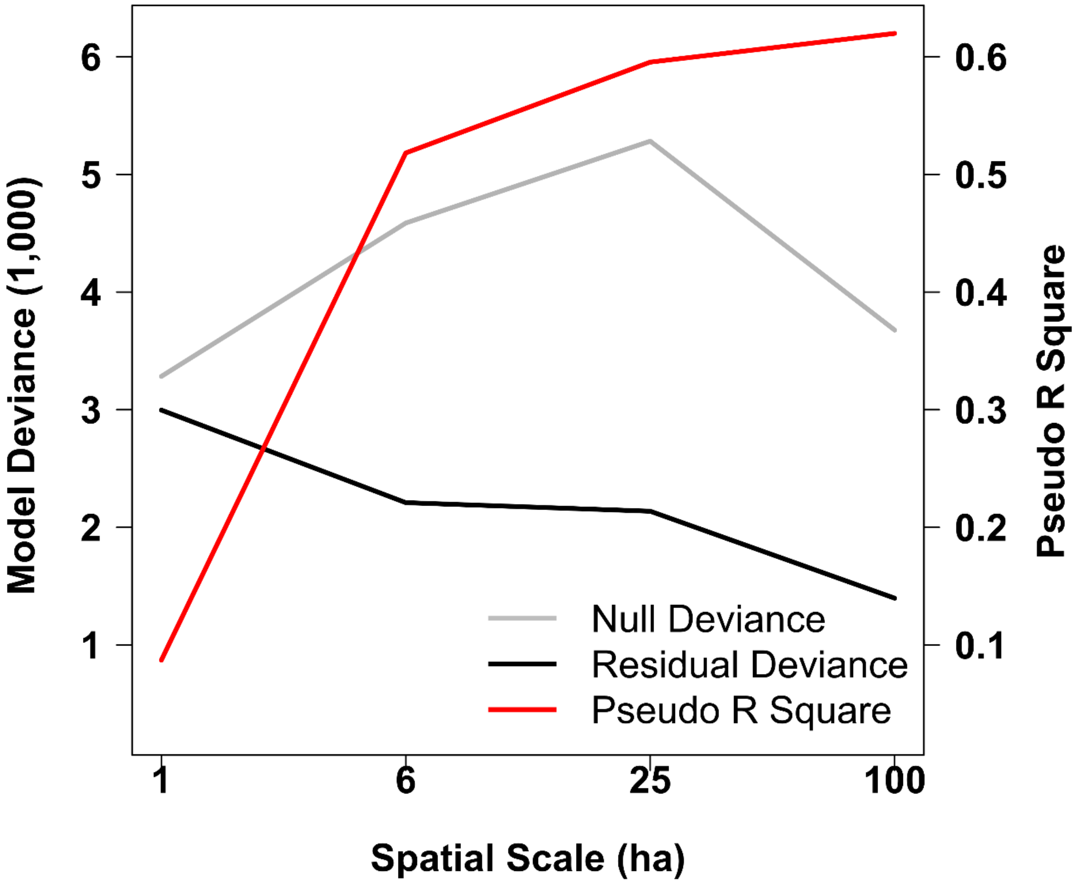

Figure 9 Model fitness measured by model deviance and pseudo R square of the best-fitted model at 1, 6.25, 25, and 100 ha sampling unit size. The increasing trend of the model fitness declined at sampling unit size greater than 6.25 ha.

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Table 7 Best-fitted model when modeling estimated spider species richness by remote sensing derived environmental factors at 1 ha, 6.25 ha, 25 ha, and 100 ha sampling unit size. "***": p-value<0.001; "**": p-value<0.01; "*": p-value<0.05; "**NS**": p-value>0.05; DHI: Dynamic Habitat Index; DBI: Dynamic Building/Bareness Index.

Factor	1 ha		6.25 ha		25 ha		100 ha	
	Trends	Significance	Trends	Significance	Trends	Significance	Trends	Significance
Cumulative DHI	+	***	+	***	+	**	+	**NS**
Variation DHI					-	*		
Cumulative DBI								
Variation DBI	–	**						
Weight(AIC)	0.383		0.267		0.339		0.143	

Discussion

Results of this study suggest spider communities in the subtropical urbanization landscape were mainly dominated by wolf spiders, sheet weaving spiders, cobweb spiders, and goblin spiders. RS factors could significantly explain the composition variances and define the habitat preferences of each dominant spider family. Besides, RS factors could explain the largest proportion of spider family composition variances at the 25 ha spatial scale. On the other hand, RS factors were found significantly correlated to CHAO1, and only Cumulative DHI was positively correlated to CHAO1. Also, the model with Cumulative DHI and Variation DHI fitted CHAO1 the best at the spatial scales between 6.25 to 25 ha.

Relationship between animal composition assemblage and nature resources is thought to be driven by two mechanisms, inter-species competition, and environmental filtering (Andrew *et al.*, 2012; Nakadai *et al.*, 2018). In habitats which are lack of resources, the effect of environmental filtering is usually larger than competition and only a few species/taxa of animal can survive become dominant (Andrew *et al.*, 2012). Therefore, the present study speculates that the differences in ground-dwelling spider composition in the present study may also be driven by environmental filtering due to low and unstable productivity in urban areas and its surrounding landscapes. Similar

doi:10.6342/NTU201902479

result has been also reported in other invertebrates like butterflies (Andrew *et al.*, 2012).

The main differences which cause those dominant spider families preferred different habitats shall be their foraging behavior and morphological traits. Most of the sheet weaving spiders are web builders in small to medium size, which weaves 2-dimensional sheet web and can hunt for their prey efficiently and control most of the agricultural pests (Uetz *et al.*, 1999; Cardoso *et al.*, 2011; Yin *et al.*, 2011). However, web building is also a foraging strategy which costs a lot of energy (Uetz *et al.*, 1999; Cardoso *et al.*, 2011). Also, sheet weaving spiders need to anchor their web to vegetation (Cardoso *et al.*, 2011). Therefore, based on the special needs and high energy cost of web building, sheet weaving spiders need habitats with high and stable year-round productivity. Therefore, sheet weaving spiders can serve as a good environmental indicator on monitoring urban greenness due to their habitat preference.

Wolf spiders are ground wandering spiders in medium to large size (Uetz *et al.*, 1999; Cardoso *et al.*, 2011), they prefer habitat with higher productivity to support the high energy cost caused by their larger body. However, rather than hunting by web in a specific spot, wolf spiders have good mobility, which makes them able to travel for a distance for hunting (Uetz *et al.*, 1999; Cardoso *et al.*, 2011). Their mobility also gives them flexibility when facing disturbance (Yu *et al.*, 2002). which may make them possible to dwell in habitats with unstable productivity, such as paddy fields and

doi:10.6342/NTU201902479

wetlands.

Goblin spiders are small-sized ground wandering spiders smaller than wolf spiders do (Cardoso *et al.*, 2011). Therefore, the energy cost of goblin spiders are low. Further, the exoskeleton in some of the goblin spiders is thickened and skeletonized (Simon, 1890). Altogether, goblin spiders can endure small and dry habitats in the highly urbanized area such as small vegetated patches or street trees on asphalt and concrete.

Like sheet weaving spiders, most of the cobweb spiders are also web builders in small to medium size, while they weave a 3-dimensional irregular web for catching preys (Uetz *et al.*, 1999; Cardoso *et al.*, 2011). However, cobweb spiders have been reported as edge or urban species in several cases (Miyashita *et al.*,1998; Magura *et al.*, 2010). They can anchor their web on artificial structures and forage on the sufficient insects lured by human activities such as street lights (Magura *et al.*, 2010).

Overall, although spiders are small invertebrate predators, the correlation relationships between CHAO1 and DHIs are the same to those in vertebrates and herbivorous invertebrates, such as birds (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Hobi *et al.*, 2017) and butterflies (Andrew *et al.*, 2012). Therefore, ground-dwelling spiders in subtropical urbanization landscape follow habitat productivity hypotheses. However, the hypothesis was not supported in spiders in temperate floodplains landscapes (Lafage *et al.*, 2014) although two landscape types

doi:10.6342/NTU201902479

share similar EVI value (maximum about 0.5). Possible reason for this finding is these two studies were conducted at different spatial scales, size of the study area in Lafage *et al.* (2014) was 7.4 ha while that is the present study could up to more than 1000 ha. Habitat productivity hypothesis is more likely to be agreed at regional scale (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Birkhofer and Wolters, 2012; Michaud *et al.*, 2014; Suttidate, 2016; Hobi *et al.*, 2017; Khlifa *et al.*, 2017). Besides, the RS factors in the present study not just contain vegetation indices, but also building indices. However, like the previous study (Shih, 2017), building indices cannot serve as factors which are as good as vegetation indices when modeling species richness.

RS factors could explain more variance to both CHAO1 and spider family composition, and agree with the results reported in previous studies, which stated that productivity related factors are more significant at regional scale (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Birkhofer and Wolters, 2012; Michaud *et al.*, 2014; Suttidate, 2016; Hobi *et al.*, 2017; Khlifa *et al.*, 2017). However, the best spatial scale, which RS factors could explain the largest proportion of both CHAO1 and spider family composition variances, in the present study was larger than 4.84 ha (220 m^2) suggested by De Mas *et al.* (2009). Main reason for this difference may be the area ratio of different land covers in the study area. Study area of De Mas *et al.* (2009) was located in mountains (altitude range: 800 m–2500 m), which were landscapes with

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complex land covers with various vegetation types at different altitudes (Lasseur *et al.*, 2018). On the other hand, land covers in the urbanization landscape in the present study were simpler than those in mountains, and land cover of most of the sampling sites in the present study was large-sized paddies and urban areas. Therefore, large-sized sampling grids in landscapes with complex land covers may mix multiple land covers with different spider composition and obscure the relationships of RS factors with spider species richness and family composition. Overall, the present study suggests that sampling unit with its size between 6.25 to 25 ha is the best when studying both spider species and family composition in subtropical urbanization landscape.

Although DHIs was designed to describe vegetation phenology (Berry *et al.*, 2007), the present study found they can also be used in describing urbanized land cover types. Parks and school (green area) are land cover which had high cumulative DHI, high minimum DHI, and low variation DHI; paddies, on the other hand, had high cumulative DHI, low minimum DHI, and high variation DHI while urbanized area had low cumulative, minimum, and variation DHI. However, land covers with high minimum DHI, but low cumulative and variation DHI, which usually represent temperate grass land in previous studies (Coops *et al.*, 2009a; Coops *et al.*, 2009b; Coops *et al.*, 2009c; Andrew *et al.*, 2012), cannot be found in the study areas and thus cause strong collinearity between cumulative and minimum DHI. Therefore, the present

doi:10.6342/NTU201902479

study suggests that when studying species diversity in tropical or subtropical landscapes minimum DHI can be skipped, and represented by cumulative DHI, which contains more temporal information of primary productivity.

The spider distribution data set in the present study was previously used in a study (Huang *et al.*, 2015) examing relationship between spider species richness and other environmental index, Biotope Area Factor (BAF), which is defined as ratios of ecologically effective land covers (e.g. green areas) among landscapes (Butchar *et al.*, 2010). BAF has been a commonly used index in urban planning in Europe, and is derived by scoring every surface material at sampling sites mainly based on their water permeability (e.g. 5 points for soil while 1 point for asphalt) (Huang *et al.*, 2015). However, BAF do not present any significant relationship to neither spider, nor plant species richness (Huang *et al.*, 2015). Therefore, the present study suggests that indices of habitat productivity shall also be considered when using BAF or other similar indices.

Previous studies indicated that proper managements in urban green areas, such as parks, are critical to spider conservation (Buchholz *et al.*, 2018; Lowe *et al.*, 2018). However, the present study showed that not just green areas, but also small vegetated patches and even street trees can serve as important habitats to many different spider families. In Taiwan, these small habitats have often undergone pesticide and herbicide

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usage in order to keep the urban clean and green. Although the target of pesticide and herbicide are not spiders, the toxic chemicals can still be consumed by spiders through bioconcentration effect (Girard *et al.*, 2011; Gill & Garg, 2014; Maurya & Malik, 2016) and lead to their death by harming their nerve systems (Samu &Vollrath, 1992). Therefore, beside the effect of low productivity, the use of toxic chemical may also be one of the main cause of low spider species richness and abundance in highly urbanized area.

The present study offers methods of modeling the spatial distribution of small carnivorous invertebrate species richness in the urbanization landscape by a very large scale monitoring scheme and remote sensing data. In conservation works, the present study suggests that maintaining high and stable habitat productivity, such as parks or school campuses, can help maintain high spider species richness. On the other hand, reduce the amount of pesticide and herbicide usage on street trees and small vegetated patches in highly urbanized areas, can also help on increasing urban spider species richness and abundance.

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Appendix

Appendix 1 patches selected in Global Research & Education on Environment and Society project, with their land use types, location, size, and number of the sampling site within the patches

Patch	Land use type	Longitude	Latitude	Area (ha)	N.O. of sampling sites
Asia University	School	120.68679	24.04707	22.467	10
Central Taiwan University	School	120.73565	24.17269	8.7826	8
Chaoyang University	School	120.71499	24.06876	13.6063	15
Fengchia University	School	120.64839	24.18003	16.3076	5
Lingtung University	School	120.60317	24.13496	23.7684	14

doi:10.6342/NTU201902479

National Chunghsing University	School	120.67435	24.12022	77.3713	25
Providence University	School	120.58049	24.22726	30.684	14
Tunghai University	School	120.60583	24.17948	146.7321	90
Baguashan Ecological Park	Park	120.54961	24.07911	23.4942	13
Dakeng Hiking Trails 5–1	Park	120.79879	24.18933	9.8464	7
Dakeng Hiking Trails 9–1	Park	120.73399	24.18392	9.5526	7
Zhongzheng Park	Park	120.68271	24.15678	7.4833	5
Zhongzheng Park to Botanical Garden	Park	120.67397	24.15736	2.1287	5

doi:10.6342/NTU201902479

National Chunghsing University to TongFeng Park	Park	120.67682	24.12332	9.5247	7
Chunghsing Lake	Park	120.67361	24.12146	14.446	7
Wenxin Forest Park	Park	120.64509	24.14533	9.2492	9
Taichung Park	Park	120.6843	24.14456	11.7203	10
Taichung Metropolitan Park	Park	120.59777	24.20805	80.6893	44
Tianzhong Forest Park	Park	120.61419	23.85108	10.6881	8
Baguashan Hiking Trail	Park	120.62907	23.94077	11.9573	9
Dongguang Parkway	Park	120.69596	24.13301	8.8288	9
Tongfeng Park	Park	120.68768	24.12492	7.9526	10
Tunghai Lake	Park	120.61052	24.18196	32.1284	45

Houli Huatian Pinbu Park	Park	120.70395	24.28785	25.8899	15
Nanliao Hiking Trail C	Park	120.55736	24.1767	43.6381	11
Miaoli Hakka Culture Park	Park	120.8319	24.25774	7.851	7
Maple Garden	Park	120.63906	24.16724	3.1828	4
National Taiwan Museum of Fine Arts to Chonglun Park	Park	120.66285	24.13633	3.0585	5
National Taiwan Museum of Fine Arts	Park	120.66391	24.14129	10.2192	7
Yuanlin Sports Park	Park	120.61871	23.94035	10.3926	6
Calligraphy Greenway	Park	120.66427	24.14854	10.9955	9

doi:10.6342/NTU201902479

Jiankang Park	Park	120.6684	24.12017	6.1097	10
Chonglun Park	Park	120.65944	24.1326	4.9772	5
Huludun Park	Park	120.71001	24.25613	9.1855	12
Xingjin Road	Park	120.69319	24.15583	2.786	5
Fengle Sculpture Park	Park	120.64263	24.1308	6.6701	10
Tiehchen Mountain Park	Park	120.64818	24.35952	22.885	15
Tiehchen Mountain Hiking Trail	Park	120.64458	24.36079	2.3307	7
Daan Estuary	Wetland	120.60441	24.405	593.9413	71
Dadu Estuary	Wetland	120.49665	24.20142	1721.9119	132
Zhuoshui Estuary	Wetland	120.28422	23.8608	1238.7935	198
Gaomei Wetland	Wetland	120.557	24.32648	925.9667	73
Daja Youth Industrail Area	Industrail	120.65202	24.40391	230.9493	20

Daja Urban Planning Industrail Area	Industrail	120.62248	24.35208	62.5621	9
Dali Industrail Area	Industrail	120.71651	24.10173	78.0242	10
Central Taiwan Science Area (Houli)	Industrail	120.61706	24.20905	389.161	20
Central Taiwan Science Area	Industrail	120.72835	24.31847	139.9395	48
Taichung Industrail Area	Industrail	120.60453	24.17208	114.9126	11
Nangang Industrial Area	Industrail	120.65934	23.92336	190.8234	26
Shengang Industrial Area	Industrail	120.70363	24.27812	50.0358	6

Changhua Costal Industrail Area (Lukang)	Industrail	120.40946	24.07782	218.3041	28
Changhua Costal Industrail Area (Xianxi)	Industrail	120.42686	24.13196	274.7659	37
Taichung Harbor Related Industrail Area	Industrail	120.52321	24.23468	279.5736	39

Appendix 2 Morphological species list of the present study. Male and female were treated as different morphological species; odd coding numbers were for male while even coding numbers were for female. THU: Tunghai University.

Family	THU Morphological species code	Abundance
Agelenidae	Age-001	1
Amaurobiidae	Ama-001	7
Amaurobiidae	Ama-002	1
Anyphaenidae	Any-001	1
Caponiidae	Cap-001	1
Caponiidae	Cap-002	1
Clubionidae	Clu-002	1
Clubionidae	Clu-003	1
Clubionidae	Clu-005	1
Clubionidae	Clu-009	2
Corinnidae	Cor-001	11
Corinnidae	Cor-002	7
Corinnidae	Cor-003	3

doi:10.6342/NTU201902479

Corinnidae	Cor-004	1
Corinnidae	Cor-005	3
Corinnidae	Cor-007	5
Ctenidae	Cte-001	1
Ctenidae	Cte-002	1
Dictynidae	Dic-001	1
Dictynidae	Dic-002	1
Gnaphosidae	Gna-001	3
Gnaphosidae	Gna-002	15
Gnaphosidae	Gna-003	34
Gnaphosidae	Gna-004	20
Gnaphosidae	Gna-005	19
Gnaphosidae	Gna-006	12
Gnaphosidae	Gna-007	10
Gnaphosidae	Gna-008	4
Gnaphosidae	Gna-009	4
Gnaphosidae	Gna-010	6
Gnaphosidae	Gna-011	3

Gnaphosidae	Gna-012	2
Gnaphosidae	Gna-013	2
Gnaphosidae	Gna-014	3
Gnaphosidae	Gna-015	2
Gnaphosidae	Gna-016	1
Gnaphosidae	Gna-017	5
Gnaphosidae	Gna-019	1
Gnaphosidae	Gna-021	4
Gnaphosidae	Gna-023	13
Gnaphosidae	Gna-025	1
Gnaphosidae	Gna-027	1
Gnaphosidae	Gna-033	1
Gnaphosidae	Gna-037	1
Hahniidae	Hah-001	3
Hahniidae	Hah-002	1
Linyphiidae	Lin-00	1
Linyphiidae	Lin-004	3
Linyphiidae	Lin-006	31

doi:10.6342/NTU201902479

Linyphiidae	Lin-008	40
Linyphiidae	Lin-009	1
Linyphiidae	Lin-010	9
Linyphiidae	Lin-011	14
Linyphiidae	Lin-012	5
Linyphiidae	Lin-013	146
Linyphiidae	Lin-014	8
Linyphiidae	Lin-015	66
Linyphiidae	Lin-016	8
Linyphiidae	Lin-017	61
Linyphiidae	Lin-018	1
Linyphiidae	Lin-019	18
Linyphiidae	Lin-020	1
Linyphiidae	Lin-021	16
Linyphiidae	Lin-022	15
Linyphiidae	Lin-023	2
Linyphiidae	Lin-024	1
Linyphiidae	Lin-025	59

Linyphiidae	Lin-026	2
Linyphiidae	Lin-027	17
Linyphiidae	Lin-028	9
Linyphiidae	Lin-029	6
Linyphiidae	Lin-030	2
Linyphiidae	Lin-031	26
Linyphiidae	Lin-032	2
Linyphiidae	Lin-033	7
Linyphiidae	Lin-035	1
Linyphiidae	Lin-036	1
Linyphiidae	Lin-037	6
Linyphiidae	Lin-039	2
Linyphiidae	Lin-041	6
Linyphiidae	Lin-042	1
Linyphiidae	Lin-043	1
Linyphiidae	Lin-045	1
Linyphiidae	Lin-053	1
Linyphiidae	Lin-064	1

doi:10.6342/NTU201902479

Linyphiidae	Lin-075	1
Linyphiidae	Lin-077	2
Liocranidae	Lio-001	1
Liocranidae	Lio-003	7
Liocranidae	Lio-004	1
Liocranidae	Lio-aa	2
Lycosidae	Lyc-001	200
Lycosidae	Lyc-002	29
Lycosidae	Lyc-002a	5
Lycosidae	Lyc-003	72
Lycosidae	Lyc-004	32
Lycosidae	Lyc-005	39
Lycosidae	Lyc-006	19
Lycosidae	Lyc-007	39
Lycosidae	Lyc-008	11
Lycosidae	Lyc-009	23
Lycosidae	Lyc-010	19
Lycosidae	Lyc-011	7

doi:10.6342/NTU201902479

Lycosidae	Lyc-012	14
Lycosidae	Lyc-013	13
Lycosidae	Lyc-014	4
Lycosidae	Lyc-015	4
Lycosidae	Lyc-016	22
Lycosidae	Lyc-017	33
Lycosidae	Lyc-018	4
Lycosidae	Lyc-019	10
Lycosidae	Lyc-020	3
Lycosidae	Lyc-021	1
Lycosidae	Lyc-022	1
Lycosidae	Lyc-023	3
Lycosidae	Lyc-024	1
Lycosidae	Lyc-025	4
Lycosidae	Lyc-026	4
Lycosidae	Lyc-030	2
Lycosidae	Lyc-033	1
Lycosidae	Lyc-036	1

doi:10.6342/NTU201902479

Miturgidae	Mit-001	1
Mysmenidae	Mys	1
Mysmenidae	Mys-001	1
Oonopidae	Oon-001	1
Oonopidae	Oon-002	21
Oonopidae	Oon-003	23
Oonopidae	Oon-004	24
Oonopidae	Oon-005	2
Oonopidae	Oon-006	25
Oonopidae	Oon-007	11
Oonopidae	Oon-008	3
Oonopidae	Oon-009	6
Oonopidae	Oon-011	1
Oonopidae	Oon-013	33
Oonopidae	Oon-014	6
Oonopidae	Oon-015	4
Oonopidae	Oon-016	2
Oonopidae	Oon-017	15

doi:10.6342/NTU201902479

Oonopidae	Oon-018	1
Oonopidae	Oon-019	1
Oonopidae	Oon-021	2
Oonopidae	Oon-023	1
Oxyopidae	Oxy-003	1
Pisauridae	Pis-001	2
Pisauridae	Pis-002	1
Salticidae	Sal-001	3
Salticidae	Sal-002	1
Salticidae	Sal-003	3
Salticidae	Sal-004	2
Salticidae	Sal-009	13
Salticidae	Sal-010	2
Salticidae	Sal-011	2
Salticidae	Sal-013	1
Salticidae	Sal-015	4
Salticidae	Sal-017	1
Salticidae	Sal-030	3

doi:10.6342/NTU201902479

Salticidae	Sal-032	1
Salticidae	Sal-036	2
Scytodidae	Scy-001	3
Segestriidae	Seg-001	7
Tetragnathidae	Tet-002	1
Theridiidae	The-001	1
Theridiidae	The-002	3
Theridiidae	The-004	3
Theridiidae	The-007	1
Theridiidae	The-012	1
Theridiidae	The-019	3
Theridiidae	The-021	2
Theridiidae	The-033	1
Theridiidae	The-035	1
Theridiidae	The-036	1
Theridiidae	The-039	3
Theridiidae	The-041	8
Theridiidae	The-101	5

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Theridiidae	The-102	17
Theridiidae	The-103	6
Theridiidae	The-105	1
Thomisidae	Tho-001	1
Thomisidae	Tho-003	2
Thomisidae	Tho-007	1
Thomisidae	Tho-008	1
Thomisidae	Tho-009	2
Thomisidae	Tho-010	1
Thomisidae	Tho-011	7
Titanoecidae	Tit-001	44
Titanoecidae	Tit-002	5
Zodariidae	Zod-001	6
Zodariidae	Zod-002	9
Zodariidae	Zod-003	6
Zodariidae	Zod-004	4
Zodariidae	Zod-005	2
Zodariidae	Zod-006	4

Zodariidae	Zod-007	2
Zodariidae	Zod-009	1
Unknown	UN-001	2