

Effect of environmental factors at multiple landscape scales on bird community in riparian ecosystem at Mun-Chi River confluence, Thailand

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Abstract. Chaleekarn W, Duengkae P, Pongcharoen C, Sutummawong N, Nakmuenwai P, Siripin S, Chirachitmichi C, Kummo W, Paansri P, Suksavate W. 2022. Effect of environmental factors at multiple landscape scales on bird community in riparian ecosystem at Mun-Chi River confluence, Thailand. *Biodiversitas* 23: 5194-5204. Wetland and riparian ecosystem is an important migratory stopover for land and water birds in the East Asian - Australasian Flyway. Understanding relationship patterns between bird communities and environmental factors at multi-spatial scales within a landscape context could contribute to the conservation and management of bird biodiversity in wetland ecosystems. The landscape metrics index is critical in revealing the relationship between the composition of bird communities and habitats at both local and landscape scales. This study aims to determine the effect of the environmental factors at different designated spatial scales on the composition of local bird communities in terms of species and feeding guilds. Our study conducted a bird survey using 227-point transects along 40 tracks across different land cover types surrounding the Mun-Chi River confluence. Canonical correspondence analysis (CCA) was used to quantify the association between bird communities, represented by species and feeding guilds, and environmental factors with the integration of multilevel habitat metrics. From the results, the CCA showed patterns of the community-environmental association at multiple scales of patch, class, and landscape characteristics with the proportional explanation of 54% and 61.82% for the composition of species and feeding guilds, respectively. The results indicated the premise that the majority of bird species respond to the habitat at the local scale. Large forest patches can maintain migratory and resident bird species. Moreover, most avian groups were arranged primarily in a large forest core area, forest area, and Shrubland PA. The results confirmed existing information on feeding guilds. The prediction map of the principal component of avian species composition was created from the association with the drivers of land use, including crops, perennial farmland, and water body on the edge of forests. Therefore, wetland management must be done at both local and landscape scales to preserve suitable avian habitats.

Keywords: Bird community, feeding guilds, landscape metrics, multiple landscape scale, wetland

INTRODUCTION

Wetlands provide benefits to human society by provisioning, regulating, and supporting the ecosystem and cultural services (Barbier 2019); for example, wetlands help control floods by storing large amounts of water. The universal function of the wetland is the purification of water through storing nutrients and other pollutants in their soils and vegetation (Clarkson et al. 2013). Wetlands also act as carbon sinks which are important implications in the context of global climate change and the subsistence of biodiversity by providing habitat for many flora and fauna species, including birds. Birds play an essential role in maintaining the stability of the riparian ecosystem and are an obvious measure of environmental changes (Reid et al. 2013, Yuan et al. 2014). Due to the convenient acquisition of data on species and the abundance of birds with affirmed taxonomic identification, considerable study on bird communities has grown around the idea of environmental

indicators. However, bird populations recently declined due to the loss and degradation of habitat through land cover types and structural changes in the wetland landscape context (Marques et al. 2019). Therefore, understanding the response of the bird community composition to factors of the changing habitats is vital to the management and conservation of wetland landscape.

The patterns of relationships between bird communities and habitats are the key to gaining insight into bird species conservation and management problems of the riparian landscape. In the field of community ecology, it is a central issue to study the influence of environmental factors on the abundance and diversity of avian species (Dong et al. 2013; Hinojosa-Huerta et al. 2013). In previous studies, the relationship between the composition of avian communities and habitats was analyzed using various factors such as landscape structural metrics (Pearse et al. 2012; Yuan et al. 2014), small-scaled habitat (Ferenc et al. 2014; Wei et al. 2017), plant community structure (Jacobs et al. 2012; Wei

et al. 2017), human disturbance (Kang et al. 2015), and road (Polak et al. 2013; Kummoo et al. 2020). Furthermore, multispectral data of satellite imagery was also applied as a surrogate for phenology, amount, and distribution of vegetation which is essential in the studies of terrestrial ecosystems. The feasibility of including such data could be due to the solid association for distribution, population, and community dynamics of both plants and animals (Nieto et al. 2015; Leveau et al. 2018). The number of studies found strong relationships between bird diversity and indices of vegetation greenness, compositional heterogeneity, and vegetation structure based on remote sensing data (Culbert et al. 2012, Dronova et al. 2016). At multiple spatial scales, the composition and configuration of habitat covariates can affect ecological processes independently and interactively (Liu et al. 2017). Many studies focused on an intermediate scale with sample plots by considering habitat use as a hierarchical process that proceeds from large to narrow spatial scales. Every level of habitat use is important and could correspond to different behavioral processes such as territory selections and foraging strategies, which each one could have been differently affected by the various resolutions and extents (Yuan et al. 2014; Stralberg et al. 2018). The statistical model was required to quantify the magnitude and direction of relationships, and various constraint multivariate analytical methods are appropriate for this task. Canedoli et al. (2018) and Zhang et al. (2016) used redundancy analyses (RDA) to identify habitat factors that influence the diversity of avian species composition. In many studies, canonical correspondence analysis (CCA)

was used (Yuan et al. 2014; Wei et al. 2017; Habeeb et al. 2019; Weeks et al. 2020) to reveal the relationship between the composition of waterbirds and the characteristics of the riparian habitats.

Mun-Chi River is not only a habitat for resident birds but is also a migratory stopover for both land birds and water birds in the East Asian - Australasian Flyway. However, the factors influencing habitat use, assemblage, and community composition are relatively unknown regarding ecological patterns and processes. Therefore, the insight into landscape variables associated with the bird community is beneficial in the applications for the management, planning, and conservation of this terrestrial ecosystem. Thus, in this study, we hypothesized that the abundance of bird species and composition of species and feeding guilds would show variable patterns of multiscale influence by habitat factors at different designated scales. The multivariate canonical correspondence analysis (CCA) was used to quantify the relationships between environmental variables and the composition of avian communities in terms of both species and feeding guilds.

MATERIALS AND METHODS

Study area

The study site was located at the Mun-Chi River confluence, which was in the contact zone between Ubon Ratchathani and Si Sa Ket province, Thailand (approximately 15°10'58.31"N, 104°42'51.27"E) (Figure 1).

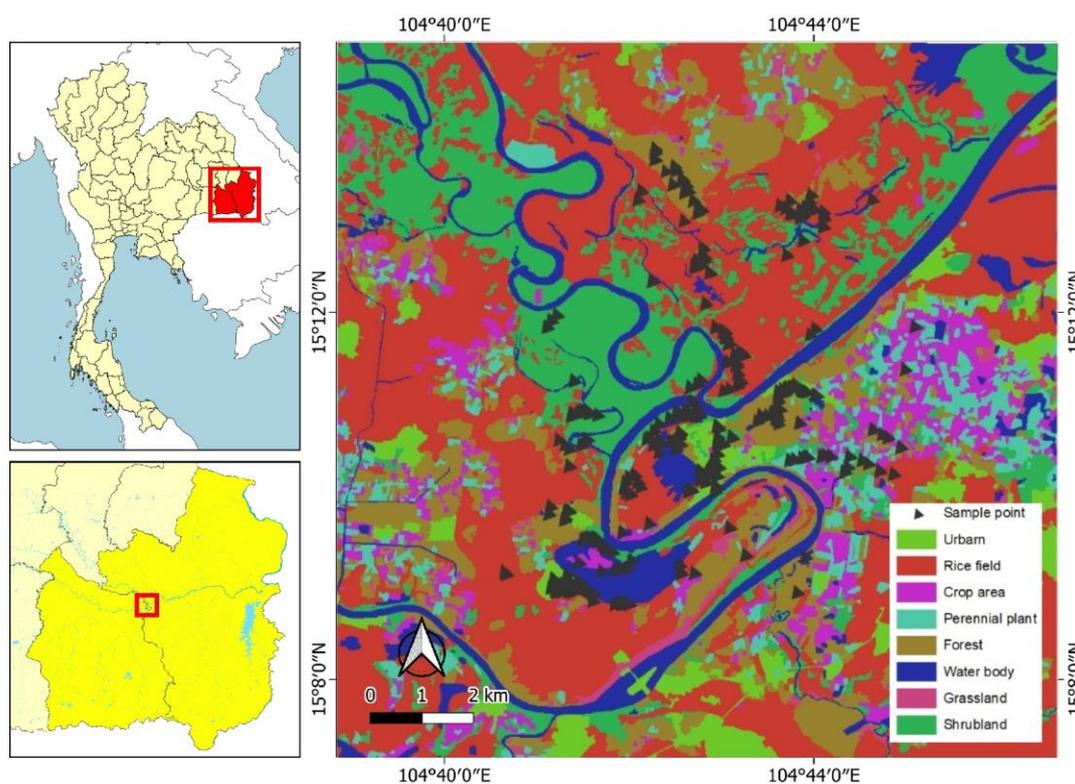


Figure 1. Map of study area, Mun-Chi River confluence wetland landscape (Dash frame), between Ubon Ratchathani and Si Sa Ket province, Thailand. The location of sample sites was indicated by triangular symbol. The sampling of bird species composition by point-count survey was conducted from August 2018 to July 2019

Mun-Chi River confluence was listed as one of 48 registered wetlands designated by Ministry of Natural Resources and Environment (Office of Environmental Policy and Planning 1999). Most of the area within Mun-Chi River confluence is relatively flat, so it has been widely affected by the flood caused by overflowed runoff from Mun and Chi rivers. The influence of water regimes brings on the seasonal fluctuation of the unique local environment and provides a widely eco-environmental niche for various flora and fauna. The 103,000-ha study area was delineated by a radius of 5 km from the centroid of the river confluence (Figure 1). Landcover data of the study area provided by the Land Development Department indicated that the majority, 91.5%, of the total area belongs to rice fields. The forest area encompasses 3 percent of the study area, while the water body and cropland cover 4.5 (4556 ha) and 0.3 (348 ha) percent of the study area, respectively.

Data collection

Bird survey

Based on landcover data, we determined the study area from 8 classes of habitat types. The land cover types were grouped into 8 classes: water body, rice field, urban, crop area, perennial plant, forest, grassland, and shrub land (Table 1). The spatial depiction of habitats within a 5 km radius from the center of confluence is shown in Figure 1. Bird surveys were carried out monthly between August 2018 to July 2019 using a point count survey along the defined transect lines designed to cross different habitat types. This approach is appropriate for bird census in open areas such as wetlands, coastlines and urban areas (Dronova et al. 2016). Point transects at 227 locations were conducted along 40 tracks across different land cover types. The survey was conducted at 06.00-10:00 and 15.00-18.00, the most active time for birds. All individual birds were directly observed and recorded in 10 minutes of the survey period, by both direct and indirect methods, within a 50 m radius from the survey point, while the flyover was excluded from the analysis.

Multiple-scaled environmental variables

Numerous researches on bird communities revealed that environmental factors are essential to the habitat use of birds. However, different habitat scales are essential for birds' distribution and species composition. In this study, we determined the variables at different scales to investigate the environmental-bird relationship. Different spatial levels of environmental covariates that could have direct or indirect effects on individual bird species or feeding guilds of birds were measured (Ding et al. 2019). Then, the three different spatial scales composed of 100 m, 500 m, and 1000 m were determined by parameterizing the habitat-species relationship at 30 m resolution. The habitat variables related to the vegetation index were applied using remotely sensed data, Normalized Difference Vegetation Index (NDVI), from the data acquired in mid-July 2018. NDVI is an index derived by dividing the difference between the near-infrared and red bands' reflectance measurements by their sum (Wu et al. 2014). Normalize

Difference Water Index (NDWI) was also used to quantify the water features by efficiently suppressing built-up land, vegetation, and soil noise. All satellite imagery data of Landsat 8 were derived from the Earth Explorer website (<https://earthexplorer.usgs.gov>). The multispectral covariates were also calculated for the multilevel buffer at each grid.

To investigate the effects of landscape composition and configuration on bird community, we used the *landscapemetrics* package in R, which provides FRAGSTATS-style metrics at patch, class, and landscape levels (Kupfer 2012; McGarigal et al. 2012; Hesselbarth et al. 2019). Such metrics could be calculated across classes that cover whole study landscapes, such as the diversity of patch types, average patch size, degree of clumping, etc. In this study, six metrics were considered as habitat factors composed of core area index (CAI), patch area (PA), total class area (CA), mean patch area (AREA MN), forest patch cohesion index (COHESION), and patch density (PD) (Table 2). The buffering scales were also calculated for each landscape matrix covariate, except the Forest Patch Cohesion Index. Moving window analysis was used in calculating landscape metrics, as McGarigal (2015) described.

Multivariate analysis of environment variables and bird community

To understand the bird-environment relationship, Canonical correspondence analysis (CCA) was used to quantify the constrained ordination by identifying the relevant parameters that influence the abundance of bird species within the community (Braak 1986). The exceedingly common species that were >90 sampling points of sample points were excluded from the analysis because the abundance-based analysis of such species could exhibit an obscure or unassociated pattern with an underlying environmental gradient and tend to obscure community patterns. Also, all species found in less than 5 percent (<18 sampling point) of the total sample points were eliminated from consideration. After CCA analyses, variance inflation factors (VIF) were applied to identify collinearity among explanatory variables. The model selection was made by calculating VIF values for all explanatory variables, then removing the variables whose VIF were <20. ANOVA-like permutation tests were performed to assess the explanation of variation. The prediction of CCA axis values to project the modeled community composition in a landscape context using the selected CCA model and the landscape covariates. All the analyses were carried out in R program (R Core Team, 2020), and all of the ordination base data analysis was done using the *vegan* package (Oksanen 2010).

RESULTS AND DISCUSSION

Results

From August 2018 to July 2019, there were 4944 observed birds composed of 119 species, consisting of 74 resident species, 28 non-breeding visitors, and 17 resident

and non-breeding visitor populations seasonal status information is based on the Bird Conservation Society of Thailand. Only 43 species were found consistently enough to be allowed for the analysis (Table 3). All species were grouped into thirteen feeding guilds, including terrestrial insectivore-frugivore (TIF), arboreal insectivore-frugivore (AIF), foliage-gleaning insectivore (FGI), terrestrial

insectivore-faunivore (TIV), diurnal or nocturnal raptor (R), sallying insectivore (SaI), sweeping insectivore (SwI), terrestrial insectivore (TI), insectivore-nectarivore (IN), terrestrial frugivore (TF) and arboreal frugivore (AF) based on Round et al. (2011) and Siri et al. (2019). Two groups of water birds re composed of duck, grebe, heron, egret, and openbill, based on Ntiamoa-Baidu et al. (1998).

Table 1. The land use types and area for bird habitats

Type	Description	Area (ha)
Water body	Inland water and river with a depth of 2 m or more. The wider the water surface, the greater the likelihood that birds will recognize these areas as a habitat.	1897
Rice field	Land where rice is planted for food production. Grains produced in this area are food resources for resident and migratory birds.	7885
Urban	Land where human activity is constantly present. These areas comprise residential areas, industrial areas, transportation areas.	1268
Crop area	Land where agricultural crops in short harvesting cycles.	1196
Perennial plant	Land where planted in long rotation crop. Including orchard, Eucalyptus, and rubber plantation.	1102
Forest area	Land where trees are collectively growing. Broadleaf forests, coniferous forests and mixed forests can be used as breeding grounds and roosting areas for migratory birds.	2759
Grassland	Land covered with herbaceous plants. Migratory birds use grasslands as roosting areas and breeding grounds.	353
Shrubland	Land were occupied by smaller plant than trees. Most of the forests in this area are flood plain forest.	3119

Table 2. Independent variables describe and buffer area at 227 sample points in Mun-Chi River Confluence, Thailand

Environmental variable	Equation	Abbreviation	Buffer
MNDWI	$(\text{Green} - \text{SWIR}) / (\text{Green} + \text{SWIR})$	MNDWI	100, 500 and 1000
NDVI	$(\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$	NDVI	100, 500 and 1000
Distance to water	-	D _{water}	-
Distance to urban	-	D _{urban}	-
Patch metrics			
Core area index	$\frac{a_{ij}^c}{a_{ij}} (100)$	CAI	100, 500 and 1000
Patch area	-	PA	100, 500 and 1000
Class metrics			
Total class area	$\sum_{j=1}^n a_{ij} \left(\frac{1}{10,000} \right)$	CA	100, 500 and 1000
Mean patch area	$\frac{\sum_{j=1}^n X_{ij}}{n_i}$	MN	100, 500 and 1000
Edge Density	$\frac{\sum_{k=1}^{m'} e_{ik}}{A} (10,000)$	ED	100, 500 and 1000
Forest connectivity	$\left[1 - \frac{\sum_{j=1}^n P_{ij}^*}{\sum_{j=1}^n P_{ij}^*} \right] \cdot \left[1 - \frac{1}{\sqrt{Z}} \right]^{-1} \cdot (100)$	FC	-
Landscape metrics			
Patch density	$\frac{n_i}{A} (10,000)(100)$	PD	100, 500 and 1000

Table 3. List of bird species and their guilds used to CCA biplot analyses.

Species code	Scientific name	Common name	Feeding guild	Axis I	Axis II	Axis III
ACRGRA	<i>Acridotheres grandis</i>	White-vented Myna	TIF	0.297	-0.406	0.386
ACRTRI	<i>Acridotheres tristis</i>	Common Myna	TIF	0.182	0.060	0.077
ANAOSC	<i>Anastomus oscitans</i>	Asian Openbill	Hérons	-0.046	-0.826	1.861
ANTRUF	<i>Anthus rufulus</i>	Paddyfield Pipit	TI	-0.095	-0.247	0.136
ARDBAC	<i>Ardeola bacchus</i>	Chinese Pond Heron	Hérons	-0.712	0.184	0.175
ARTFUS	<i>Artamus fuscus</i>	Ashy Woodswallow	SwI	0.514	-0.336	0.812
CENSIN	<i>Centropus sinensis</i>	Greater Coucal	TI	-1.326	0.308	-0.315
CINJUG	<i>Cinnyris jugularis</i>	Olive-backed Sunbird	IN	-0.746	0.338	-0.233
CISJUN	<i>Cisticola juncidis</i>	Zitting Cisticola	SaI	0.313	-0.267	0.717
COLLIV	<i>Columba livia</i>	Rock Pigeon	TF	0.648	0.765	0.230
CORLEV	<i>Corvus leuallantii</i>	Eastern Jungle Crow	FGI	-0.859	0.478	0.717
CULCEY	<i>Culicicapa ceylonensis</i>	Grey-headed Canary-flycatcher	SaI	-1.869	0.195	0.291
CYOHAI	<i>Cyornis hainanus</i>	Hainan Blue Flycatcher	SaI	-1.819	0.710	1.076
CYPBAL	<i>Cypsiurus balaisensis</i>	Asian Palm Swift	SwI	-0.137	-0.038	-0.219
DENJAV	<i>Dendrocygna javanica</i>	Lesser Whistling Duck	Duck	-0.537	-0.301	-0.822
DICCRU	<i>Dicaeum cruentatum</i>	Scarlet-backed Flowerpecker	AF	-0.798	0.264	-0.102
DICLEU	<i>Dicrurus leucophaeus</i>	Ashy Drongo	SaI	-1.591	0.347	0.496
DICMAC	<i>Dicrurus macrocercus</i>	Black Drongo	SaI	-0.118	-0.570	0.799
EGRGAR	<i>Egretta garzetta</i>	Little Egret	Hérons	0.134	-0.417	0.645
EUDSCO	<i>Eudynamis scolopaceus</i>	Asian Koel	AIF	-1.618	0.262	0.129
FICALB	<i>Ficedula albicilla</i>	Taiga Flycatcher	SaI	-0.585	-0.232	0.312
GLACUC	<i>Glaucidium cuculoides</i>	Asian Barred Owlet	R	-1.409	0.364	-0.589
GRANIG	<i>Gracupica nigricollis</i>	Black-collared Myna	TIF	-0.568	-0.699	-0.463
HALIND	<i>Haliastur indus</i>	Brahminy Kite	R	-0.848	-0.552	0.101
HIRRUS	<i>Hirundo rustica</i>	Barn Swallow	SwI	0.390	-0.780	0.966
HYPAZU	<i>Hypothymis azurea</i>	Black-naped Monarch	SaI	-1.654	0.473	0.233
IXOCIN	<i>Ixobrychus cinnamomeus</i>	Cinnamon Bittern	Hérons	0.004	-0.727	0.090
LANCRI	<i>Lanius cristatus</i>	Brown Shrike	TIV	-0.207	-0.412	0.122
LONPUN	<i>Lonchura punctulata</i>	Scaly-breasted Munia	AF	0.341	-0.334	0.382
LONSTR	<i>Lonchura striata</i>	White-rumped Munia	AF	0.327	-0.691	-1.048
MERORI	<i>Merops orientalis</i>	Green Bee-eater	SaI	-0.040	-0.085	-0.126
ORTSUT	<i>Orthotomus sutorius</i>	Common Tailorbird	FGI	-0.840	0.398	-0.183
PASDOM	<i>Passer domesticus</i>	House Sparrow	TIF	0.623	0.483	0.265
PASMON	<i>Passer montanus</i>	Eurasian Tree Sparrow	TIF	0.710	1.065	-0.323
PHATRI	<i>Phaenicophaeus tristis</i>	Green-billed Malkoha	FGI	-1.331	0.729	0.113
PROPHI	<i>Ploceus philippinus</i>	Baya Weaver	TIF	0.190	-1.003	-0.936
PRIINO	<i>Prinia inornata</i>	Plain Prinia	FGI	-0.552	-0.632	-0.697
PSILIN	<i>Psilopogon lineatus</i>	Lineated Barbet	AIF	-2.346	0.756	-0.397
PYCCON	<i>Pycnonotus conradi</i>	Streak-eared Bulbul	AIF	-1.215	0.339	0.123
RHIJAV	<i>Rhipidura javanica</i>	Malaysian Pied Fantail	SaI	-1.062	0.409	0.596
SAXCAP	<i>Saxicola caprata</i>	Pied Bushchat	SaI	-0.060	-0.244	0.070
SAXMAU	<i>Saxicola maurus</i>	Eastern Stonechat	SaI	-0.033	-0.529	0.121
STRTRA	<i>Streptopelia tranquebarica</i>	Red Collared Dove	TF	-0.036	0.007	-0.361

Species-environment relationship

The model can explain 54% of the variation in species composition from the CCA. The eigenvalues of the three axes were 0.696, 0.671 and 0.630, respectively. To alleviate the effect of collinearity, the variables were selected following Braak and Smilauer (1998) by removing variables with VIF above 20 from the model. This resulted in the optimal CCA model in the species-environment biplot (Figure 2). From the selected model based on VIF, CCA can explain 19.5% of the constrained proportion. The eigenvalues of the first three canonical axes were 0.4768, 0.4249, and 0.3335, respectively. Monte Carlo permutation was conducted to test for all canonical axes, and the results were highly significant (P-value <0.001). Species-environment correlations of the first three axes were

83.3%, 76.5%, and 69.9%, respectively. In this dataset, the cumulative explanatory proportion of the first three axes was 17.61%, 33.31%, and 45.63%, respectively. The relationships between community composition and environmental variables were depicted by a joint biplot of bird species CCA scores to environmental variables. The length and magnitude of the arrow indicate the correlation and relative importance of habitat variables on the composition of bird species.

For CCA I axis, Rice field CAI100 (0.211) and Rice field MN1000 (0.184) showed less positive values in this axis. On the other hand, Forest CAI100 (-0.635) had the most negative correlation, followed by Forest PA (-0.626), Shrubland CAI100 (-0.392), and Shrubland PA (-0.362), and Shrubland CAI1000 (-0.35). These variables were

present in negative correlation in this axis. In the second axis (CCAII), Rice field CAI100 (-0.663) had the highest negative correlation, followed by Forest CAI1000 (-0.383), while Rice field MN1000 (0.359) and Rice field CAI100 (0.326) had a positive correlation with this axis. Rice field MN1000 (0.359) and Rice field CAI100 (0.326) showed a positive correlation in the third CCA axis. This axis shows the negative correlation Forest CAI1000 (-0.383) and Water body PA500 (-0.239). For the relationships between the composition of bird species and CCA axes, the results showed the three species which had the most positive correlation with axis CCAI, consisting of Eurasian Tree Sparrow (*Passer montanus*, 0.710), Rock Pigeon (*Columba livia*, 0.648), and House Sparrow (*Passer domesticus*, 0.623). Species that had the most negative association with axis CCAI was Lineated Barbet (*Psilopogon lineatus*, -2.346), Grey-headed Canary-flycatcher (*Culicicapa ceylonensis*, -1.869), and Hainan Blue Flycatcher (*Cyornis hainanus*, -1.819). For the axis CCAII, the most positive associated species were Eurasian Tree Sparrow (1.065) and Rock Pigeon (0.765), while the most negative species were Lineated Barbet (0.756), Baya Weaver (*Ploceus philippinus*, -1.003) Asian Openbill (*Anastomus oscitans*, -0.826), and Barn Swallow (*Hirundo rustica*, -0.780). In the third axis, CCA III, the results showed Asian Openbill (1.861), Hainan Blue Flycatcher (1.016), Barn Swallow (0.966) had a positive correlation, while White-rumped Munia (*Lonchura striata*, -1.048), Baya Weaver (-0.936), and Lesser Whistling Duck (*Dendrocygna javanica*, -0.882) had a negative correlation. Species composition scores in each axis were shown in Figure 5.

The ordination biplot showed a well-spread distribution of relations between species and habitat variables (Figure 2). The habitat covariates, Rice field CAI100, Forest CAI100, and Forest PA, were the most critical landscape structure variables, followed by shrubland CAI100, Shrubland PA, Shrubland CAI1000, and Shrubland

MN1000. On the other hand, Water body CAI100, Water body ED and perennial plant CAI100 had relatively low relations to bird species composition. A longer arrow in the diagram indicated a strong effect of Rice field CAI100, and the distance from the marked position for each species showed a correlation with the covariates. The results showed the solid projected relationship of Baya Weaver, White-rumped Munia, Asian Openbill, Barn Swallow, and Cinnamon Bittern (*Ixobrychus cinnamomeus*) to the Rice field CAI100. The projected distance between Black Drongo (*Dicrurus macrocercus*), Eastern Stonechat (*Saxicola maurus*), Little Egret (*Egretta garzetta*), and White-vented Myna (*Acridotheres grandis*) was short but was located in the positive side.

Feeding guild-environment relationship

We choose the same data in the species-environment relationship to determine the feeding groups' compositions. Avian species were aggregated into 5 feeding guilds and 2 groups of water birds. Then the CCA was applied to the data together with the same multiscale environmental dataset as before (Figure 3). The full model on feeding guilds proportionally explained 61.82% of the variation in bird species composition with eigenvalues of 0.5554, 0.5162, and 0.4019 for the first three CCA axes. Highly correlated variables with VIF greater than 20 were excluded from the model. From the selected model, the total inertia had 23.12% explanatory proportion of the variation in the composition of feed guilds. The eigenvalues of the first three canonical axes were 0.355, 0.230 and 0.160, respectively. The guilds-environment correlations were 76.0%, 60.71%, and 54.49%, for three axes, respectively, while the cumulative proportion was 31.71%, 51.43%, and 65.49% for each canonical axis, respectively. Monte Carlo permutation tests for all canonical axes were highly significant ($P < 0.001$).

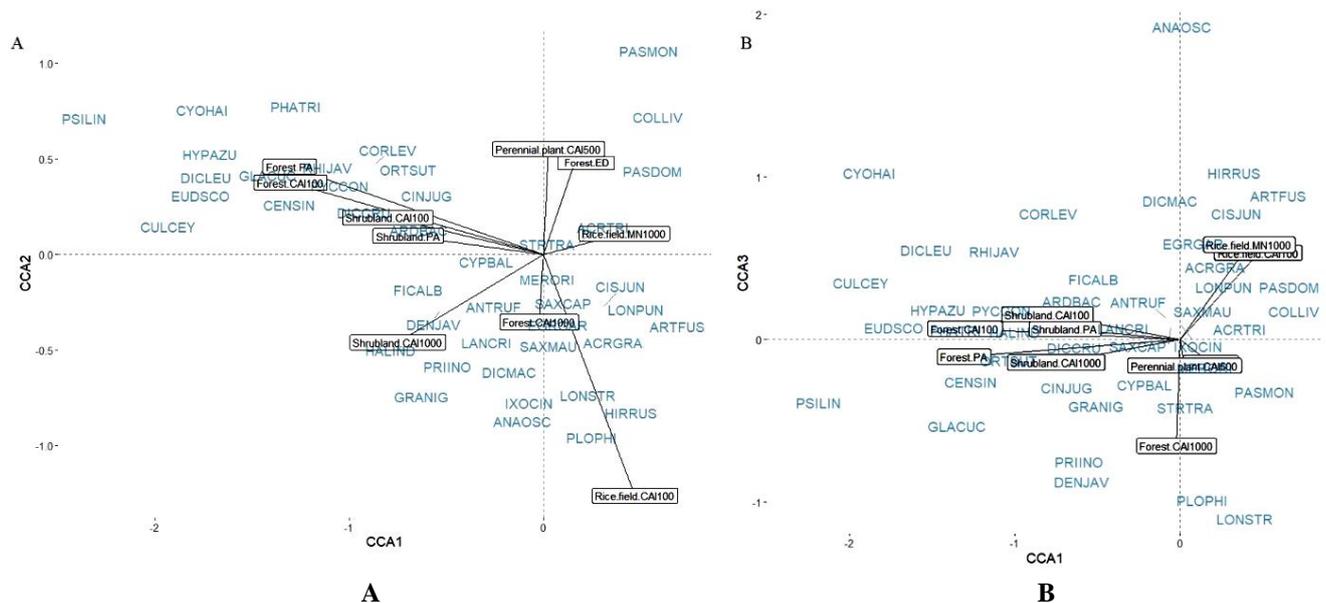


Figure 2. CCA biplot of species distribution and environmental factors in Mun-Chi River confluence between CCA I and CCA II (A) and CCA I and CCA III (B). Environmental variables were represented by lines with arrows

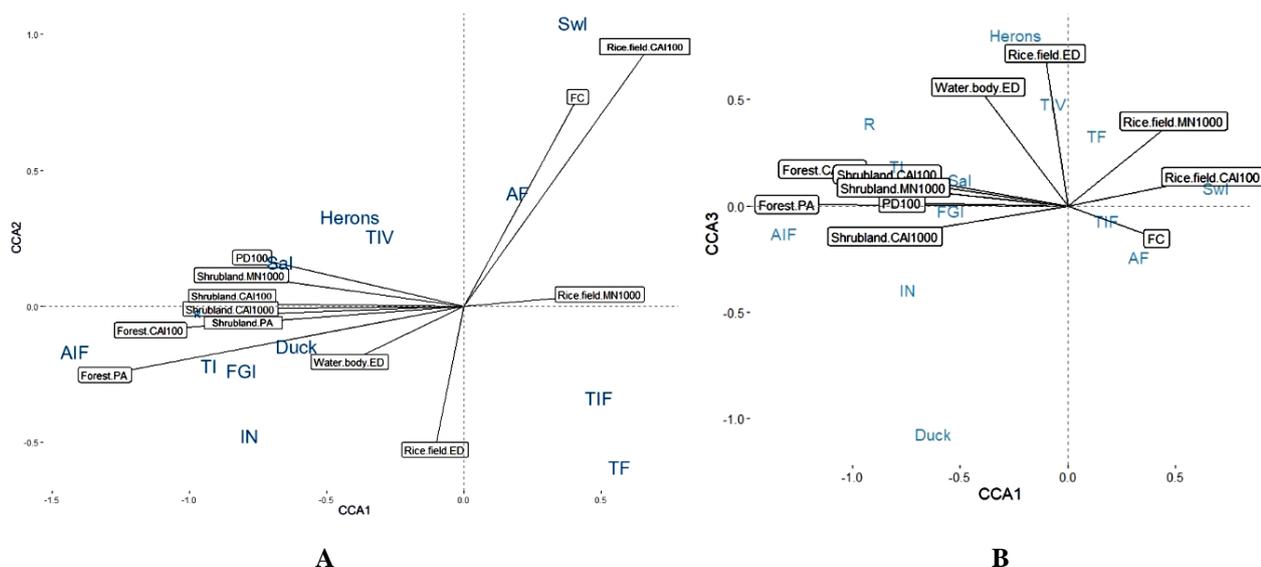


Figure 3. CCA biplot between CCA I and CCA II (A) and CCA I and CCA III (B) of feeding guild distribution and environmental factors in Mun-Chi River confluence

The correlation between habitat variables and bird-feeding guilds is explained in three canonical axes. The negative correlation with the CCA1 axis was Rice field CAI100 (0.255) and Rice field MN1000 (0.198). Forest PA (-0.580) and Forest CAI100 (-0.520) had the highest negative correlation with this axis again. Rice field CAI100 (0.575) and FC (0.462) showed a positive correlation, and the negative correlation Dwater (-0.298), Rice field ED (-0.270) and Perennial plant CAI500 (-0.269) were shown in the second axis. In the last axis, Rice field ED (0.451) and Water body ED (0.373) had a positive correlation. On the other hand, Water body PA500 (-0.279) and Forest CAI1000 (-0.272) showed a positive correlation. From the feeding guilds dataset, sweeping insectivore (SwI, 0.5202), terrestrial insectivore-faunivore (TIF, 0.4069) and terrestrial frugivore (TF, 0.3361) showed negative arboreal insectivore-frugivore (AIF, -1.5026), terrestrial insectivore (TI, -0.8819), and diurnal or nocturnal raptor (R, -0.8669). The second axis, sweeping insectivore (SwI, 0.93542), arboreal frugivore (AF, 0.93542), and Herons (0.24928) were the highest positive value. The negative feeding guild group includes terrestrial frugivore (TF, -0.86772), insectivore-nectarivore (IN, -0.37268), and terrestrial insectivore-frugivore (TIF, -0.31668). In the last axis, terrestrial frugivore (TF, 0.66080), Heron (0.57634), and sweeping insectivore (SwI, 0.53688) again show positive and arboreal frugivore (AF, -0.64380), Duck (-0.55730) and insectivore-nectarivore (IN, -0.28030) show negative values, respectively. Species scores of feeding guilds in each axis were shown in Figure 6.

According to the feeding guild dataset, the variables of small spatial scale were again the most important in the diagram, particularly Forest PA, Shrubland PA, and Rice field CAI100, followed by medium scale (100 m) radius and the large scale (1000m radius). Most avian groups were arranged primarily on a Forest CAI 100, Forest PA, Shrubland PA, and Shrubland ED. For example, the

individual group confirmed existing natural history information. Such as terrestrial insectivores (TI) and arboreal insectivores-frugivores, which feed in the forest at Mun-Chi River confluence, occurred on Forest CAI 100 and Forest PA.

Prediction of CCA scores at the landscape level

From the selected CCA models, the prediction of site scores was applied to the whole landscape. The site scores were predicted using the linear combination of habitat covariates from the selected CCA model to generate a predicted map for all three canonical axes, each represented as a map (Figure 4). The prediction map based on the first canonical axis showed areas with negative values associated with water sources, crops, and perennial plant areas. The minimum axis I had smaller than other axes, and the minimum value of this axis is -91.3, the maximum is 0.783, and the mean is -8.877. On the other hand, crop area showed positive values on the second canonical axis. The water sources were associated with negative values on this second axis. The summary of this axis represents the minimum, maximum, and mean -80.127, 90.931, and -2.314, respectively. The summary of the last axis represents the minimum, maximum, and mean -56.94, 151.70, and 1.196. The summary of all three axes is shown in Table 4.

Table 4. Summary of predicted CCA maps

CCA Axes	Axis I	Axis II	Axis III
Minimum	-91.297	-80.127	-56.940
Maximum	0.783	90.931	151.704
Mean	-8.877	-2.314	1.196
Standard deviation	10.845	11.158	12.892

Discussion

Bird-environmental variables relationship

Even though the explanatory variables at the scale of the sampling site were highly associated with species composition, the spatial relationship with the surrounding landscape context should not be neglected. Both landscape structure metrics and remote sensed indices were used to model the bird-environment relationship at multiscale by the mean of buffering distance. Based on the results of this study, both on-site variables and the buffered at 100 meters scale were able to describe the response of both the species

and the feeding guild to the spatial variation of the habitat factors. This result was not unexpected, and numerous studies found clear that many birds respond to local scale habitat variables when they are selected for breeding habitat (Chang et al. 2017; Yu et al. 2019). In our study area, most bird species are small, which may utilize a narrowly specific habitat in a small area, such as Hainan Blue Flycatcher, Black-napped Monarch, Grey-headed Canary-flycatcher, Pied Fantail, Common tailorbird, Scarlet-backed Flowerpecker, and Olive-backed Sunbird.

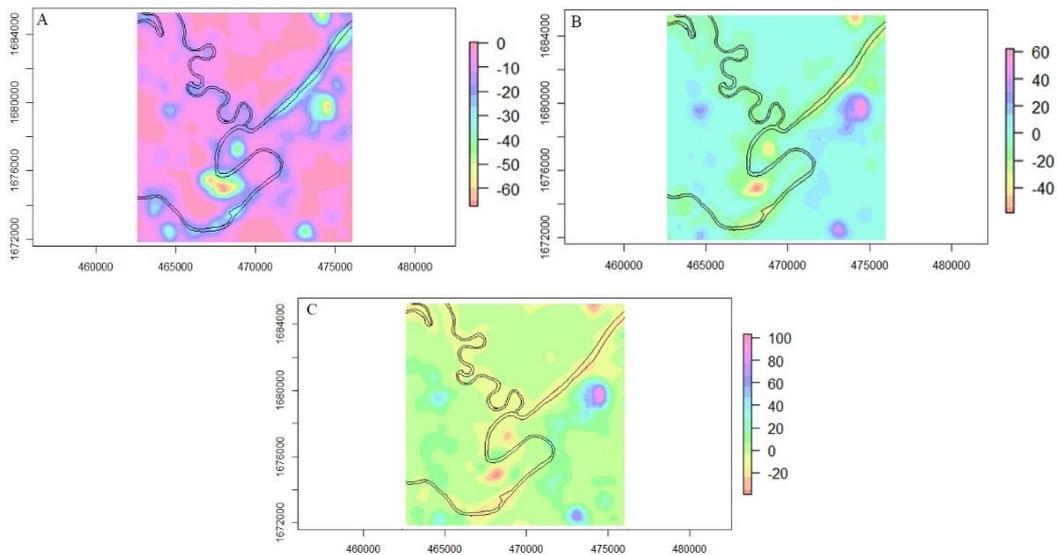


Figure 4. CCA predict map of Mun-Chi River confluence study area. Map CCA I was represented in A, Map CCA II represent B, Map CCA III represent C, respectively

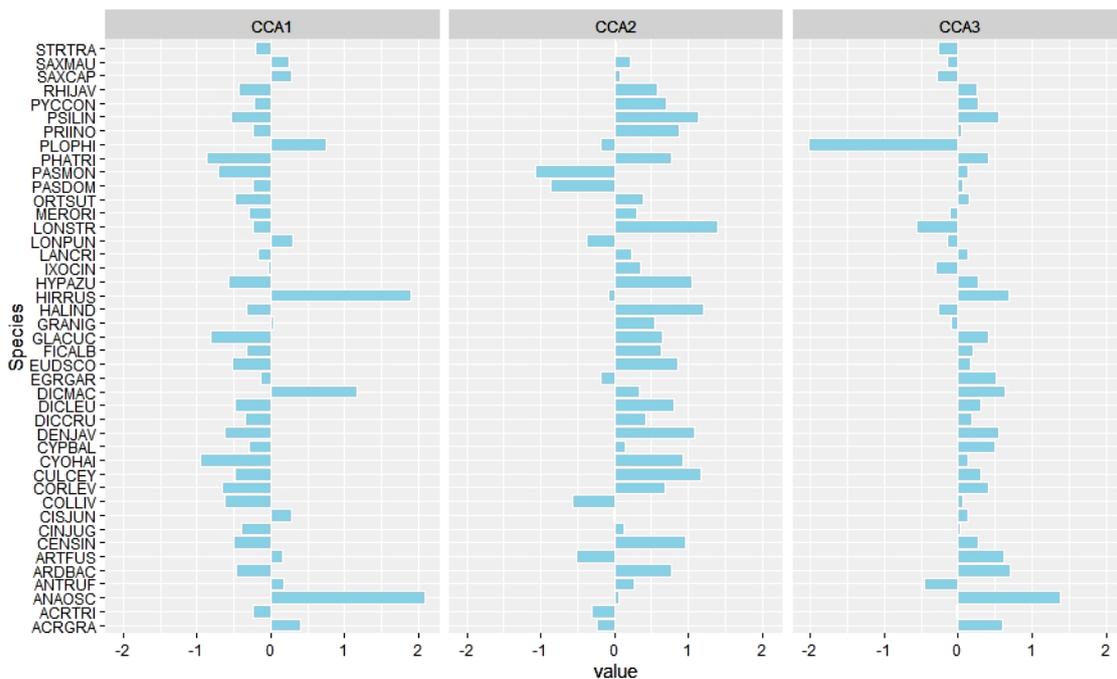


Figure 5. Species score of 43 species datasets

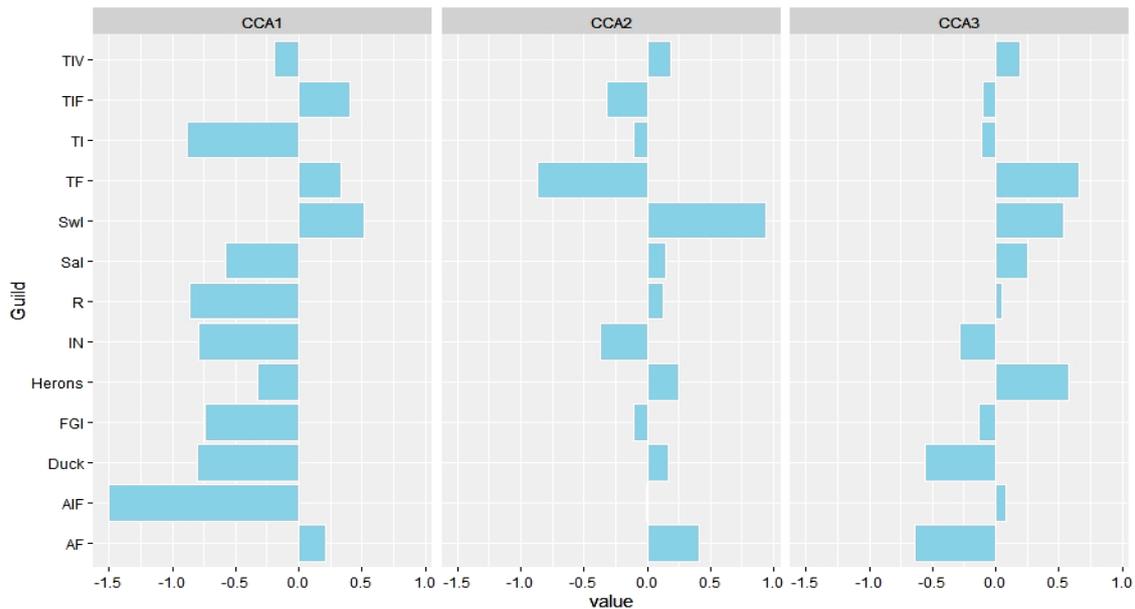


Figure 6. Species score of 13 feeding guild datasets

Similarly, patch metrics strongly project in both bird species and feeding guilds. These variables may be primary habitat determinants for the composition of bird communities in the vicinity of Mun-Chi River confluence. Some of the patch-size related factors, for example, forest core and patch area; and rice field core area, had more influence than other variables. Another example is Lineated Barbet (PSILIN); the species prefers forest habitats and fed on fruits of many plant species. This species scored high on forest patch area (Forest PA) and forest core area index (Forest CAI100) but low score on rice field core area index (Rice field CAI100). These factors tend to cause an impact in the same way on most of bird species. The habitats influences on species composition of birds, as the stable ecological condition, is usually related to size and position within the patch; for instance, the diversity of plant species in large forest patches leads to the high diversity of other organisms and resources that could provide shelter or food for both migratory and endemic birds. Kim et al. (2018) suggested that a large patch should be preserved so that various migratory bird species can rest during the passage, which is consistent with our research.

Furthermore, forest patches can maintain the species richness and functional diversity of birds in the landscape (Kang et al. 2015; Pratumtong et al. 2019). Rice field is a long-established land use that mainly comprises the whole landscape of Mun Chi River confluence. Some birds take the rice field habitat for nesting, such as Baya Weaver, Yellow-breasted Bunting (this species has been cut out of the model), and other migratory species. The robustness of vegetative habitat structure, as represented by NDVI, is often correlated to abundance and species richness, as described by previous studies (Webb et al. 2010; Kang et al. 2015). Dissimilarly, in our study, such remotely sensed vegetative index was neither included in the selected model for both species and feeding guild. This may be because the

metrics of landscape structure based on multiple landcover types are more responsive to the diverse ecological niche of avian species than the vegetation.

For class metric variables, total class area (CA) and mean patch area (MN) were omitted from the CCA model based on VIF. The correlation of Edge Density (ED) was low ($VIF < 20$) because they scantily explain species and functional group composition in CCA. Likewise, at the 500-m buffering scale, most of the VIF was greater than 20, so there were only 3 covariates left for this scale, composed of Perennial plant CAI500, Water body PA500 and Crop PA500. However, they cannot describe species composition and feeding guild well. On the other hand, the mean patch area (MN) buffered at 1000m showed partly informative in gradient analysis of both species and feeding guilds composition of the community. In the feeding guild dataset, sallying insectivore (Sal) was strongly related to the Shrubland MN1000 variable. In coarse-scale descriptors are full of environmental variance that affects habitat use, but they influence general distribution patterns and perhaps even specific habitat affinities. The migrant sallying insectivore was frequent in the canopy and chaired in both areas between the orchard and the forest patch (Round et al. 2006). In our study area, most of these areas are flood plain forests which is the area with a dense canopy.

The Mun-Chi River confluence has been regarded as having been used by humans for hundreds of years and has undergone a long transformation. Therefore, some birds have adapted to this wide range of uses. In the landscape metric variables, patch density (PD) showed a weak response in both species community and feeding guild. That indicated most birds are associated with a less fragmented landscape. Patch density is a factor describing the proportion covered by different patches in the landscape. In contrast, species that respond positively to

patch density have various land use patches. For example, from the species dataset, the projection of Lesser Whistling Duck, Taiga Flycatcher, Brahminy Kite, Black-collared Myna, and Plain Prinia was positively associated with patch density in our study.

The physical factors have a significant influence on bird community compositions. Moreover, the difference in the cover canopy natural forest is high biodiversity of birds in the ecosystem (Siri et al. 2019). So forest areas are diverse on the canopy and can maintain a wide range of bird groups. In our study, arboreal insectivore-frugivore (AIF), terrestrial insectivore (TI), and foliage-gleaning insectivore (FGI) need structural complex canopy for different behaviors and niche. The relationship between landscape composition and configuration in the dimension of bird were clarified by the number of proportions constrained. The proportion of constrained in canonical correspondence analysis was explained by the feeding guild rather than the bird community. Show that functional groups may be necessary in ecological assessment because they reduce the complexity implicit in detailed consideration of individual species while avoiding the use of oversimplified indices such as total species richness. Furthermore, feeding guilds related to habitat use provide a good link between overall trends in bird biodiversity and land cover/use.

Prediction

Most values in map CCA1 are closer to zero. An interesting remark in the prediction map shows areas of large water bodies that mix in with crop and perennial plants are associated with a negative value. This landcover factor also negatively affected the values of the second canonical axis. It is undeniable that humidity affects the appearance of birds at the Mun-Chi River confluence. Baya Weaver, Scaly-breasted Munia, Rock Pigeon, Eurasian Tree Sparrow, and House Sparrow usually use rice paddies proximate to the rivers. These birds are grain eaters, which is consistent with the off-season rice paddy field where grain food sources are farmed throughout the year. Mix in crop and Perennial plant areas bordered by forests not far from water sources are often associated with many bird species. Hainan Blue Flycatcher, Green-billed Malkoha, and Lineated Barbet often use interface between forests and orchards. Not only does the Lesser Whistling Duck need of water body to dabbling, but it also takes the vegetation cover for shelter. On the other hand, agricultural areas far from water sources have a lower relationship with bird species. Although there is a large concentration of bird occurrence in agricultural areas, the reduction, degradation, or fragmentation of natural habitat areas should not be overlooked. So, careful planning on land development and conservation could facilitate in the persistence of not only bird species but also other groups of animals and plant species. The Mun-Chi River confluence is considered East Asian-Australasian Flyway migratory stopovers. Therefore, local management of wetlands will bring a balance between biodiversity and human habitation surrounding the wetland. Landscape management of wetlands should have a clear goal that will lead to success. Many researchers have suggested that management of the area must be considered

based on the properties of the organisms of concern to succeed in developing a comprehensive conservation strategy (Fairbairn and Dinsmore 2001; Grand and Cushman 2003).

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REFERENCES

- Barbier EB. 2019. The value of coastal wetland ecosystem services. In: Perillo GME, Wolanski E, Cahoon DR, Hopkinson CS (eds). *Coastal Wetlands*. Elsevier, Netherlands.
- Braak CJF. 1986. Canonical correspondence analysis: A new eigenvector technique for multivariate direct gradient analysis. *Ecology* 67 (5): 1167-1179. DOI: 10.2307/1938672.
- Braak CJF, Smilauer P. 1998. *CANOCO Reference Manual and User's Guide to Canoco for Windows: Software for Canonical Community Ordination*. Centre for Biometry, Wageningen.
- Canedoli C, Manenti, R, Padoa-Schioppa E. 2018. Birds biodiversity in urban and periurban forests: environmental determinants at local and landscape scales. *Urban Ecosyst* 21 (4): 779-793. DOI: 10.1007/s11252-018-0757-7.
- Chang CR, Chien HF, Shiu HJ, Ko CJ, Lee PF. 2017. Multiscale heterogeneity within and beyond Taipei city greenspaces and their relationship with avian biodiversity. *Landsc Urban Plan* 157: 138-150. DOI: 10.1016/j.landurbplan.2016.05.028.
- Clarkson BR, Ausseil AGE, Gerbeaux P. 2013. Wetland ecosystem services. In: Dymond JR (eds). *Ecosystem Services in New Zealand: Conditions and Trends*. Manaaki Whenua Press, Lincoln.
- Culbert PD, Radeloff VC, St-Louis V, Flather CH, Rittenhouse CD, Albright TP, Pidgeon AM. 2012. Modeling broad-scale patterns of avian species richness across the Midwestern United States with measures of satellite image texture. *Remote Sens Environ* 118: 140-150. DOI: 10.1016/j.rse.2011.11.004.
- Ding Z, Liang J, Hu Y, Zhou Z, Sun H, Liu L, Liu H, Hu H, Si X. 2019. Different responses of avian feeding guilds to spatial and environmental factors across an elevation gradient in the central Himalaya. *Ecol Evol* 9 (7): 4116-4128. DOI: 10.1002/ece3.5040.
- Dong Z, Wang Z, Liu D, Li, L, Ren C, Tang X, Jia M, Liu C. 2013. Assessment of habitat suitability for waterbirds in the West Songnen Plain, China, using remote sensing and GIS. *Ecol Eng* 55: 94-100. DOI: 10.1016/j.ecoleng.2013.02.006.
- Dronova I, Beissinger SR, Burnham JW, Gong P. 2016. Landscape-level associations of wintering waterbird diversity and abundance from remotely sensed wetland characteristics of poyang lake. *Remote Sens* 8 (6): 1-22. DOI: 10.3390/rs8060462.
- Fairbairn SE, Dinsmore JJ. 2001. Local and landscape-level influences on wetland bird communities of the prairie pothole region of Iowa, USA. *Wetlands* 21 (1): 41-47. DOI: 10.1672/0277-5212(2001)021[0041:LALLIO]2.0.CO;2.
- Ferenc M, Sedláček O, Fuchs R. 2014. How to improve urban greenspace for woodland birds: Site and local-scale determinants of bird species richness. *Urban Ecosyst* 17 (2): 625-640. DOI: 10.1007/s11252-013-0328-x.
- Grand J, Cushman SA. 2003. A multi-scale analysis of species-environment relationships: Breeding birds in a pitch pine-scrub oak

- (*Pinus rigida-Quercus ilicifolia*) community. *Biol Conserv* 112 (3): 307-317. DOI: 10.1016/S0006-3207(02)00323-3.
- Habeeb MK, Hussain NA, Jaleel SAA. 2019. Effect of biotic and abiotic factors on the composition of wader birds assemblage (Charadriiformes and ciconiiformes) at shatt Al-Arab estuary. Iraq. NW Arabian gulf. *Plant Archives* 19: 1123-1130.
- Hesselbarth MHK, Sciaini M, With KA, Wiegand K, Nowosad J. 2019. landscapemetrics: An open-source R tool to calculate landscape metrics. *Ecography* 42 (10): 1648-1657. DOI: 10.1111/ecog.04617.
- Hinojosa-Huerta O, Guzmán-Olachea R, Butrón-Méndez J, Butrón-Rodríguez JJ, Calvo-Fonseca A. 2013. Status of marsh birds in the wetlands of the Colorado River delta, México. *Ecol Engg* 59: 7-17. DOI: 10.1016/j.ecoleng.2013.04.058.
- Jacobs RB, Thompson III FR, Koford RR, La Sorte FA, Woodward HD, Fitzgerald JA. 2012. Habitat and landscape effects on abundance of Missouri's grassland birds. *J Wildl Manag* 76 (2): 372-381. DOI: 10.1002/jwmg.264.
- Kang W, Minor ES, Park CR, Lee D. 2015. Effects of habitat structure, human disturbance, and habitat connectivity on urban forest bird communities. *Urban Ecosyst* 18 (3): 857-870. DOI: 10.1007/s11252-014-0433-5.
- Kim M, Choi YE, Chon J. 2018. Key coastal landscape structures for resilient coastal green infrastructure to enhance the abundance of migratory birds on the Yellow Sea. *Environ Pollut* 243: 1617-1628. DOI: 10.1016/j.envpol.2018.08.081.
- Kummoo W, Teampanpong J, Utsa P, Paansri P, Suksavate W, Duengkae P, Prompat S. 2020. Impact of highway on vertebrate roadkill in Nam Nao National Park, Thailand. *Biodiversitas* 21: 5540-5549. DOI: 10.13057/biodiv/d211163.
- Kupfer JA. 2012. Landscape ecology and biogeography: Rethinking landscape metrics in a post-FRAGSTATS landscape. *Prog Phys Geogr: Earth Environ* 36 (3): 400-420. DOI: 10.1177/0309133312439594.
- Leveau LM, Isla FI, Bellocoq MI. 2018. Predicting the seasonal dynamics of bird communities along an urban-rural gradient using NDVI. *Landsc Urban Plan* 177: 103-113. DOI: 10.1016/j.landurbplan.2018.04.007.
- Liu Z, Zhang C, Xu H, Ma X, Shi Z, Yin J. 2017. A facile method synthesizing hydrogel using Hybranched Polyether Amine (hPEA) as Cointiator and Crosslinker. *Macromol Chem Phys* 218 (21): 1-77. DOI: 10.1002/macp.201700251.
- Marques A, Martins IS, Kastner T, Plutzer C, Theurl MC, Eisenmenger N, Huijbregts MAJ, Wood R, Stadler K, Bruckner M, Canelas J, Hilbers, JP, Tukker A, Erb K, Pereira HM. 2019. Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nat Ecol Evol* 3 (4): 628-637. DOI: 10.1038/s41559-019-0824-3.
- McGarigal K. 2015. FRAGSTATS Help. University of Massachusetts, Amherst, MA, USA.
- McGarigal K, Cushman SA, Ene E. 2012. Spatial pattern analysis program for categorical and continuous maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst. FRAGSTATS v4. See <http://www.umass.edu/Landeco/Research/Fragstats/Fragstatshtml>.
- Nieto S, Flombaum P, Garbulsky MF. 2015. Can temporal and spatial NDVI predict regional bird-species richness. *Glob Ecol Conserv* 3: 729-735. DOI: 10.1016/j.gecco.2015.03.005.
- Ntiama-Baidu Y, Piersma T, Wiersma P, Poot, M, Battley P, Gordon C. 1998. Water depth selection, daily feeding routines and diets of waterbirds in coastal lagoons in Ghana. *Ibis* 140 (1): 89-103. DOI: 10.1111/j.1474-919x.1998.tb04545.x.
- Office of Environmental Policy and Planning. 1999. An Inventory of Wetlands of International and National Importance in Thailand. Ministry of Science, Technology and Environment, Thailand.
- Oksanen J. 2010. Multivariate analysis of ecological communities. *Trends Ecol Evol* 3 (5): 121. DOI: 10.1016/0169-5347(88)90124-3.
- Pearse AT, Kaminski RM, Reinecke KJ, Dinsmore SJ. 2012. Local and landscape associations between wintering dabbling ducks and wetland complexes in Mississippi. *Wetlands* 32 (5): 859-869. DOI: 10.1007/s13157-012-0317-5.
- Polak M, Wiącek J, Kucharczyk M, Orzechowski R. 2013. The effect of road traffic on a breeding community of woodland birds. *Eur J For Res* 132 (5): 931-941. DOI: 10.1007/s10342-013-0732-z.
- Pratumtong D, Gale GA, Duengkae P, Pongpattananurak N. 2019. The Influence of Environmental Variables on Bird Communities in Tropical Seasonal Forests, Western Thailand. FAO, Rome.
- R Core Team. 2020. R: A Language and Environment for Statistical Computing. <https://www.r-project.org/>.
- Reid JRW, Colloff MJ, Arthur AD, McGinness HM. 2013. Influence of catchment condition and water resource development on waterbird assemblages in the Murray-Darling Basin, Australia. *Biol Conserv* 165: 25-34. DOI: 10.1016/j.biocon.2013.05.009.
- Round PD, Gale GA, Brockelman WY. 2006. A comparison of bird communities in mixed fruit orchards and natural forest at Khao Luang, southern Thailand. *Biodivers Conserv* 15 (9): 2873-2891. DOI: 10.1007/s10531-005-2006-7.
- Round PD, Pierce AJ, Sankamethawee W, Gale GA. 2011. The Avifauna of the Mo Singto Forest Dynamics. *Nat Hist Bull Siam Soc* 57: 57-80.
- Siri S, Ponpituk Y, Safoowong M, Marod D, Duengkae P. 2019. The natural forest gaps maintenance diversity of understory birds in Mae Sa-Kog Ma Biosphere Reserve, northern Thailand. *Biodiversitas* 20: 181-189. DOI: 10.13057/biodiv/d200121.
- Stralberg D, Carroll C, Pedlar JH, Wilsey CB, McKenney DW, Nielsen SE. 2018. Macrorefugia for North American trees and songbirds: Climatic limiting factors and multi-scale topographic influences. *Glob Ecol Biogeogr* 27 (6): 690-703. DOI: 10.1111/geb.12731.
- Webb EB, Smith LM, Vrtiska MP, Lagrange TG. 2010. Effects of local and landscape variables on wetland bird habitat use during migration through the rainwater Basin. *J Wildl Manag* 74 (1): 109-119. DOI: 10.2193/2008-577.
- Weeks BC, Naeem S, Winger BM, Cracraft J. 2020. The relationship between morphology and behavior in mixed-species flocks of island birds. *Ecol Evol* 10 (19): 10593-10606. DOI: 10.1002/ece3.6714.
- Wei P, Zan Q, Tam NFY, Shin PKS, Cheung G, Li M. 2017. Impact of habitat management on waterbirds in a degraded coastal wetland. *Mar Pollut Bull* 124 (2): 645-652. DOI: 10.1016/j.marpolbul.2017.02.068.
- Wu X, Lv M, Jin Z, Michishita R, Chen J, Tian H, Tu X, Zhao H, Niu Z, Chen X, Yue T, Xu B. 2014. Normalized difference vegetation index dynamic and spatiotemporal distribution of migratory birds in the Poyang Lake wetland, China. *Ecol Indic* 47: 219-230. DOI: 10.1016/j.ecolind.2014.01.041.
- Yu C, Ngoprasert D, Round PD, Pierce AJ, Savini T, Gale GA. 2019. Roost selection of the endangered Spotted Greenshank (*Tringa guttifer*) in critical habitat in the Inner Gulf of Thailand. *Avian Research* 10 (1): 1-10. DOI: 10.1186/s40657-019-0148-7.
- Yuan Y, Zeng G, Liang J, Li X, Li Z, Zhang C, Huang L, Lai X, Lu L, Wu H, Yu X. 2014. Effects of landscape structure, habitat and human disturbance on birds: A case study in East Dongting Lake wetland. *Ecol Eng* 67: 67-75. DOI: 10.1016/j.ecoleng.2014.03.012.
- Zhang C, Yuan Y, Zeng G, Liang J, Guo S, Huang L, Hua S, Wu H, Zhu Y, An H, Zhang L. 2016. Influence of hydrological regime and climatic factor on waterbird abundance in Dongting Lake Wetland, China: Implications for biological conservation. *Ecol Eng* 90: 473-481. DOI: 10.1016/j.ecoleng.2016.01.076.