Climate, species richness, and body size drive geographical variation in resource

specialization of herbivorous butterflies

Running title: Drivers of resource specialization

Ryosuke Nakadai[1,2*], Tommi Nyman[1,3], Koya Hashimoto[4], Takaya Iwasaki[5], Anu

Valtonen[1]

[1] Department of Environmental and Biological Sciences, Faculty of Science and

Forestry, University of Eastern Finland, Yliopistokatu 7, FI-80101 Joensuu, Finland

[2] Department of Ecosystem Studies, Graduate School of Agricultural and Life Sciences,

The University of Tokyo, 1-1-1 Yayoi, Bunkyo-ku, Tokyo 113-8657, Japan

[3] Department of Ecosystems in the Barents Region, Norwegian Institute of Bioeconomy

Research, Svanhovd 35, NO-9925, Svanvik, Norway.

[4] Department of Environmental Management, Faculty of Agriculture, Kindai University,

Nakamachi, 3327-204, Nara, Nara, 631-8505, Japan

[5] Department of Biological Sciences, Faculty of Science, Kanagawa University,

Tsuchiya 2946, Hiratsuka, Kanagawa 259-1293 Japan

[*] Correspondence: R. Nakadai

r.nakadai66@gmail.com

Number of words in the main text: 4850

Number of references: 76

Number of figures: 2

Number of tables: 3

Number of text boxes: 0

Acknowledgements

We are particularly grateful to local entomologists, and naturalists who accumulated the

background information on butterflies compiled for the dataset in this study. We also

thank Dr. Matthew Forister, who provided R code associated with the alpha shape

parameter. The Biodiversity Center of Japan and the Japanese Ministry of the

Environment kindly provided us with datasets on butterfly distributions. Dr. Yasuhiro

Sato gave us insightful comments for an early version of the manuscript. Financial

support was provided by the Japan Society for the Promotion of Science (grants

15J00601, 18J00093 to R.N.) and Academy of Finland (grant 324392 to A.V.).

Authorship

R.N. conceived the idea, designed the study, and analyzed the data; R.N. and T.N.

constructed the figures; K.H., R.N., T.I. constructed the butterfly dataset; R.N. and A.V.

wrote the first draft; all the authors significantly contributed to the final text.

Data accessibility statement

The calculated indices related to butterfly species and the environmental variables used

in this study for each 10-km grid cell are in Supplementary Table S7.

Abstract

Revealing drivers of variation in resource specialization is a long-standing goal in

ecological and evolutionary research. As a general prediction, the degree of resource

specialization increases towards lower latitudes. Although herbivorous insects are one

of the best-studied consumer groups, factors determining the degree of specialization on

large spatial scales are poorly understood. Herein, we focused on the fundamental host

breadth of 246 herbivorous butterfly species distributed across the Japanese archipelago.

Using Bayesian Structural Equation Modeling based on information of pooled

geographical occurrence and host use, we show that local butterfly communities tend to

become more specialized towards higher latitudes, a pattern that is opposite to

predictions from classical hypotheses. We also found that the pattern is mainly driven

by factors related to climate, butterfly diversity, and body size in each community. Our

results re-emphasize the importance of current climate as a regulating factor for

butterfly host breadth and morphology.

Keywords: Bayesian structural equation modeling, community assembly, continental

islands, host breadth, Pareto distribution, latitudinal gradient, macroecology, trait-based

approach

Introduction

Understanding the processes structuring communities across space and time is a central

subject in ecology (Cavender-Bares *et al.* 2009). Resource specialization is a major

factor shaping interspecific interactions and, therefore, community composition (Nylin

et al. 2017; Volf *et al.* 2017; Dyer & Forister 2018). Drivers of variation in the degree

of specialization has therefore been investigated intensively in the context of

community ecology (Novotny & Basset 2005; Forister *et al.* 2015). Such studies have

generally pointed out that species tend to be more specialized in the tropics than in the

temperate zone (MacArthur's latitude–niche breadth hypothesis; MacArthur 1972;

Vázquez & Stevens 2004; Dyer *et al.* 2007; reviewed by Dyer & Forister 2018). Using

a global dataset, Forister *et al.* (2015) addressed variation in resource specialization in

herbivorous insects along a geographical gradient, and showed that the mean and

variance of diet breadth in local communities indeed decreases toward the equator.

Resource specialization is driven by not only geographical and climatic gradients, but

also many other factors. Specifically, the higher number of species in the tropics (Loder

et al. 1998; Dyer & Forister 2018) could intensify interspecific competition ("species

packing"; Dobzhansky 1950; MacArthur 1972) and thereby favor specialization (Coley

& Kursar 2014). Also, the importance of body size and physiological constraints

imposed by climatic conditions are often argued (Bergman's rule; Bergmann 1947). For

example, there is evidence that average consumer body size, and its variation, increases

towards lower latitudes (Loder *et al.* 1998), although body size is generally thought to

be positively correlated with host breadth (Lindström *et al.* 1994; Pöyry *et al.* 2017).

However, inferring the drivers of specialization is complicated by the fact that

numerous potentially important factors change in parallel along the latitudinal and

climatic gradient (Loder *et al.* 1998).

On the other hand, some studies have found no difference in the degree of

specialization between temperate and tropical regions (e.g., Novotny *et al.* 2006), and

the hypothesis has even been called a "zombie idea" that "still wanders the world

feasting on scientists' brains" after having been killed by data and/or theory (Fox 2011;

Moles & Ollerton 2016). Thus far, most studies on variation in resource specialization

have relied on information on local communities. However, resource use within local

communities can be shaped by interspecific interactions (Connell 1980). Local

processes in community assembly (interspecific interactions), can produce "realized"

resource specialization, which could mask underlying fundamental resource

specialization. In this work, we aim to understand processes determining spatial

variation in "fundamental" resource specialization, which we defined as the host

breadth not limited by interspecific interactions at the same trophic level. More

specifically, we aim to reveal the drivers of geographical variation in fundamental

resource specialization through macroecological approaches.

Herein, we focused on angiosperm-feeding butterflies across the Japanese

archipelago to reveal the drivers of spatial variation in resource specialization. We

calculated species-specific fundamental host breadth based on information on both

pooled geographical occurrence and host-use records rather than on accumulation of

local, site-specific data on host use for each species. The latitudinal range of the

archipelago (22°N–45°N) comprises hemiboreal, temperate, and subtropical zones,

making it a useful system for assessing spatially continuous change in resource

specialization, i.e., not just providing a comparison between disconnected areas. In fact,

most previous studies have simply compared resource specialization between tropical

and temperate regions, which Dyer & Forister (2018) pointed out as a major

methodological problem. We focused on the latitudinal pattern and aimed to reveal

significant drivers of the level of specialization in regional species pools. As potential

drivers, we focused on geography, current climate, diversity and body size of butterflies

themselves, and their change along geographical gradients (Table 1). By using Bayesian

Structural Equation Modeling (Bayesian SEM), which has received increasing attention

in ecology and evolution (e.g., Arhonditsis *et al.* 2007; Read *et al.* 2018; reviewed in

Grace *et al.* 2012), we investigated the complicated relationships between these

variables and resource specialization in comprehensive models fitted for one index

reflecting the distribution of host breadths and two indices of phylogenetic host breadth

within each community.

Materials and methods

Study area

The Japanese archipelago forms a long chain of continental islands lying off the eastern

coast of Asia, and is recognized as a hotspot of biodiversity (Mittermeier *et al.* 2011).

The mean temperatures of the coldest months range from –18.4 to 22.3 °C, mean

temperatures of the warmest months from 6.2 to 29.2 °C, and annual precipitation from

700.4 to 4477.2 mm (Fig. S1a, b: Japan Meteorological Agency, 1981–2010;

http://www.jma.go.jp/jma/indexe.html). Also, the Japan Sea side of the archipelago

typically receives more snow than does the Pacific Ocean side (Fig. S1c). The Japanese

archipelago belongs to a transient region between the Palaeotropical or Indo-Pacific and

the Holarctic regions (Cox 2001), and harbours relictual plants that were distributed

throughout a large portion of the Northern Hemisphere during much of the Tertiary

(Milne & Abbott 2002). Over 280 species of butterflies of five families are found in the

region (Shiro□zu 2006). With the exception of three lycaenid species, larvae of

Japanese butterfly species feed exclusively on plants (Honda 2005). The host plants are

diverse and include both dicot and monocot angiosperms as well as gymnosperms

(Saito *et al.* 2016).

Evaluation of butterfly host breadth and body size

Our analyses were based on butterfly census data, which includes records of 273

species/subspecies of butterflies from the entire Japanese archipelago, available on the

website of the Biodiversity Center of Japan, Ministry of the Environment

(http://www.biodic.go.jp/index_e.html), in grid cells of latitude 5 min and longitude 7.5

min (about 10 km × 10 km). For each species, the records were then used, in

conjunction with relevant climate data, to predict their potential distribution in Japan

using Maxent ver. 3.3.3e (Phillips *et al.* 2006; published in Nakadai *et al.* 2018; for

details see Supplementary text 1). As an exception, due to difficulties in estimating the

potential distribution by Maxent for rare species (Vaughan & Ormerod 2005; Breiner *et*

al. 2015), the presence records of eighteen butterfly species having four or fewer

records each were used as such for the following analyses.

Information on host plants of each studied butterfly species was compiled in order to

evaluate their diet breadth. The host plants of 278 butterfly species/subspecies (3,573

records in total, after excluding duplicates) were obtained from Saito *et al.* (2016). We

used adult forewing length as a proxy for body size of each butterfly species. The

forewing lengths of 284 species were derived from Shiro□zu (2006; earlier published in

Nakadai *et al.* 2018). For a total of 246 butterfly species, we were able to assemble data

on predicted distribution, host plants and body size. However, ten species were

excluded from the analyses, for the following reasons: First, the taxonomic status of

three species changed in the interval between the fourth and fifth biodiversity censuses

(Inomata 1990; Shirôzu 2006). Thus, we excluded these species because identifications

were unreliable. Second, we excluded three non-herbivorous and four

gymnosperm-feeding species (for details, see Table S1). After non-target species (those

with taxonomic changes and non-angiosperm feeders) were removed, the remaining

3,358 records of host plants were selected and converted to plant-genus resolution for

further analyses.

To describe the overall degree to which species are specialized to their hosts, for each

grid cell, we estimated the alpha parameter of the discrete truncated Pareto distribution

fitted to numbers of host genera for all butterfly species occurring within the cell

(Forister *et al.* 2015; Kozubowski *et al.* 2015). Higher values of the Pareto alpha

indicate higher incidence of species with relatively narrow host breadth in the

community.

For each cell, we also calculated the community mean and divergence (based on

Rao's Quadratic Entropy; RaoQ) for both phylogenetic host breadth and butterfly body

size by using the ade4 package (Chessel *et al.* 2013) in R (R Development Core Team

2017). The community mean indicates the dominant trait value within an assemblage

(Violle *et al.* 2007), while community divergence represents the degree of dissimilarity

between all possible pairs of species within the assemblage (Mouchet *et al.* 2010). To

describe the genus-level phylogenetic host breadth of butterfly species, we applied the

widely-used Faith's phylogenetic diversity index (cf., Davis *et al.* 2013). We calculated

this index with the R package picante (Kembel *et al.* 2010), based on a genus-level

angiosperm phylogeny derived from Zanne *et al.* (2014) using Phylomatic (Webb &

Donoghue 2005). The methods for estimating phylogenetic host breadth and the

distribution of host breadth follow Forister *et al.* (2015), which provides detailed

descriptions and statistical background.

To determine whether the observed mean and divergence of each trait in each grid

were greater or less than the values when drawing butterfly species at random from the

regional species pool, we calculated standardized effect sizes (SES) using two types of

null models (i.e., null model 1 and 2; for details Supplementary text 2). The

randomization procedures for both types of null models were repeated 1,000 times to

generate simulated datasets that were then used to compute cell-specific expected values

for mean and divergence of host breadth and body size. We calculated SES values for

each grid cell as the observed value minus the mean of the null distribution, with the

result divided by the standard deviation of the null distribution. Therefore, a negative

RaoQ value indicates that trait values within the cell are more similar than expected

based on the null model (i.e., convergence within the community), whereas a positive

value indicates that species in the assemblage are more dissimilar than expected (i.e.,

divergence within the community). In the main analysis, we used the datasets based on

the simpler null model 1, but re-fitted the final models using null model 2, to explore

the robustness of our results.

Climatic variables

We used annual mean temperature and precipitation at the 1-km grid scale from Mesh

Climate Data 2010 (Japan Meteorological Agency,

http://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-G02.html). We also included annual

maximum depth of snow cover (Mesh Climate Data 2010), and altitudinal data from the

National Land Numerical Information database (Geospatial Information Authority of

Japan). All of these variables were downloaded at the 1-km grid scale. Finally, for all

variables, we calculated averages at the 10-km grid scale using ArcGIS Pro ver. 2.3.3

software (Environmental Systems Resource Institute, Redlands, CA, USA).

Driver analysis for host breadth and body size

To reveal the drivers of resource specialization, we compiled two Bayesian SEMs in

which (1) the alpha parameter of the discrete truncated Pareto distribution and (2) the

two indices of phylogenetic host breadth were explained by butterfly species richness,

two indices of body size (i.e., mean and divergence) and six environmental factors. In

this study, the highest correlation ($r = -0.901$) occurred between the alpha parameter of

the discrete truncated Pareto distribution and the mean of phylogenetic host breadth

(Table S6), so we separated those two models to reduce the risk of multicollinearity

problems. The environmental factors included as explanatory variables were latitude

and elevation as geographical factors, and annual precipitation, mean temperature and

annual maximum depth of snow cover as climatic factors. Although climatic and

geographical factors are correlated (Table S6), including both of these correlated

variables may be informative (see justification with respect to multicollinearity in

Supplementary text 3). For example, there is a strong negative correlation between

latitude and annual mean temperature, but the ingredient of the partial effect of latitude

may include other ecological factors that were not considered in this study, such as

variation in day length and length of active season. Prior to analyses, two types of grid

cells were excluded from the dataset: (1) cells with $p < 0.05$ according to a chi-square

goodness-of-fit test contrasting observed values of the host breadth distribution to the

expectation from the fitted discrete truncated Pareto distribution, and (2) cells with

fewer than twenty butterfly species. These cells (N = 1,291 and N = 1,209, respectively:

N = 2,069 in total) were excluded because their values were considered less reliable and

due to difficulties in correctly estimating alpha of the discrete truncated Pareto

distribution (Forister *et al.* 2015; see Supplementary text 5). Regarding the second

criterion, we also repeated the analysis with the minimum number of species set to ten

or thirty, to check the robustness of the main results.

We fitted the full Bayesian structural equation models in Mplus version 8.4 (Muthén

& Muthén 1998-2017). We evaluated model fit based on a Bayesian variant of root

mean square error of approximation (BRMSEA), the Bayesian comparative fit index

(BCFI), and the Bayesian Tuchr—Lewis index (BTLI) (Hoofs *et al.* 2018,

Garnier-Villarreal & Jorgensen 2019, Asparouhov & Muthén 2019; for details see

Supplementary text 4). Hoofs *et al.* (2018) suggested cutoff values for the lower (<0.05)

and upper limit (<0.08) in the 90% posterior probability interval of the BRMSEA as a

valid criterion for good model fit, and Asparouhov & Muthén (2019) proposed three

possible conclusions: the fit index is inconclusive (lower limit <0.06< upper limit), the

index suggests that the model fits reasonably well (both lower and upper limits <0.06),

and the fit index suggests poor fit between model and data (0.06 < both lower and upper

limits). For BCFI and BTLI, Asparouhov & Muthén (2019) suggested similar criteria,

but so that the cuttoff values need to be beyond 0.95 for adequate fit.

After fitting the full model, we trimmed non-significant paths from the model until

only significant paths remained (Kline *et al.* 2011). Also, we explored the robustness of

the results of the main analysis by re-fitting the final models for each response variable

using datasets of observed distributions instead of fundamental distributions estimated

by Maxent, null model 2, and the aforementioned two minimum numbers of butterfly

species (i.e., ten and thirty) within each grid cell.

Results

Across the Japanese archipelago, butterfly species richness increased towards lower latitudes (south) and higher elevations, and both mean and divergence of butterfly body size increased toward lower latitudes (Fig. 1). Pareto alpha, which indicates the degree of concentration of species having narrower host breadth, increased towards higher latitudes (north), and phylogenetic host breadth mean and divergence decreased towards higher latitudes (Table S6).

Of the total of 4673 grid cells of the Japanese archipelago, 2542 passed our filtering criteria and were included in the Bayesian SEM models (Tables 2, 3). Both final models satisfied the criteria of good fit measured by BRMSEA, BCFI and BLTI. Four of the 33 paths in the model of the Pareto alpha and five of the 42 paths in the model of phylogenetic host breadth were non-significant and therefore removed during the processes of model simplification (Tables 2, 3).

Of the many factors affecting host breadth, annual mean temperature was most strongly associated with host breadth in both SEM models (Tables 2, 3, Fig. 2). Specifically, communities with low concentration of narrower host breadth species (i.e., having low pareto alpha) as well as high community-level phylogenetic host breadth mean and divergence increased along with annual mean temperature (Tables 2, 3, Fig. 2). There were negative correlations between Pareto alpha and mean and divergence of body size (Table 2, Fig. 2a). Also, there was a positive correlation between phylogenetic host breadth mean and body size mean; phylogenetic host breadth mean and body size divergence; and phylogenetic host breadth divergence and body size divergence (Table 3, Fig. 2b).

Butterfly species richness was driven by annual precipitation, annual maximum depth of snow cover, latitude, and elevation. Based on standardized estimates, elevation was

the strongest (positive) driver of butterfly species richness, while latitude was the

second most effective (negative) predictor (Table 2, 3).

Mean of butterfly body size was strongly driven by annual mean temperature

(positively) and latitude (negatively), while the effects of annual precipitation, annual

maximum depth of snow cover and butterfly species richness were relatively weak

(Tables 2, 3, Fig. 2). Butterfly body size divergence was driven by latitude, annual mean

temperature, annual precipitation, and butterfly species richness. Of these, latitude

strongly and negatively influenced body size divergence (Tables 2, 3, Fig. 2).

Furthermore, there was a positive correlation between butterfly body size mean and

divergence (Table 2, 3, Fig. 2).

The significances and the strengths of major paths that were associated with host

breadth and butterfly body size were consistent when re-running the final models with

datasets of observed distributions (Table S3), null model 2 (Table S4), and the two

alternative criteria for minimum number of butterfly species per grid cell (Table S5).

Discussion

Latitudinal pattern of fundamental host breadth is opposite to classical understanding

One of the most widespread assumptions in ecology is the increase in degree of

resource specialization towards lower latitudes (i.e., towards the tropics) (Moles &

Ollerton 2016; Dyer & Forister 2018). By contrast, our results show that the host

breadth of butterfly communities becomes more specialized towards higher latitudes

(i.e., towards the north) across the Japanese archipelago. Our finding therefore

apparently contradicts the widespread assumption of how species accumulate to local

communities. According to our results, host breadth of butterfly communities was most

strongly associated with climatic factors (i.e., annual mean temperature, annual

precipitation, annual maximum depth of snow cover), a geographic factor (latitude), and

butterfly species richness. Specifically, the mean and divergence of host breadth of

butterfly communities were higher where temperatures were higher. Furthermore, grid

cells having high butterfly diversity showed broader and more divergent host breadths.

The trend of broader and more divergent host breadths within communities towards

lower latitudes could be produced by relaxing of physiological constraints by increasing

the amount of energy, thus reducing the relative importance of abiotic environmental

filters and allowing for wider variation in niches (Park 1949, Fisher 1960). Read *et al.*

(2018) suggested that relaxing of physiological constraints together with stronger biotic

interactions among species towards the tropics leads to increased resource specialization,

which is opposite to our finding. We note that the existence of strong interspecific

resource competition among herbivorous insects, causing niche partitioning, has been

generally questioned (Lawton & Strong 1981; Strong *et al.* 1984; Nakadai & Kawakita

2017). In fact, Nakadai *et al.* (2018) showed that butterfly species pairs that use similar

host-plant taxa tend to overlap in their distribution across the Japanese archipelago.

Evidently, the relaxation of abiotic regulation towards lower latitudes allows the

occurrence of butterfly species having broader host breadths because of the weak

influence of interspecific competition.

Along the focal latitudinal and climatic gradients, many other variables than host

breadth also change jointly or independently (e.g., both body size and diversity of

butterflies). Teasing apart the directionality of causalities among these patterns

constitute long-standing subjects in ecology (Wasserman & Mitter 1978; Loder *et al.*

1998). Consistent with previous studies on plant-feeding insects (Brown and Maurer

1989; Pöyry *et al.* 2017), we found a strong positive relationship between body size and

host breadth. Lindström *et al.* (1994) argued that larger body size in Lepidoptera allows

a larger "home range", and, thus, encounters with a wider range of host plants, but also

requires more energy which is easier to acquire if the species is a broad generalist. In

our dataset, both mean and divergence of body size increased toward lower latitudes

and higher temperatures (Tables 2, 3). Such a pattern of increasingly smaller body sizes

towards higher latitudes is called a converse Bergmann cline (although most

interspecific studies on insects have found no clines; Shelomi 2012). The southward

increases in both mean and divergence of body size are also consistent with the

hypothesis based on relaxing physiological constraints (Table 1). Furthermore, mean

body size positively correlated with mean phylogenetic host breadth. Increasing mean

body size within a community could therefore be one of the enhancers of the diet

generalization in the communities of herbivorous insects (Table 1). Towards higher

latitudes or elevations, increasingly shorter growing seasons also limit the duration of

the larval stage, which would restrict the distributions of large-bodied or

slow-developing insects (Blanckenhorn & Demont 2004; Shelomi 2012). For example,

Zeuss *et al.* (2017) found that among European lepidopteran species, average body size

and the average number of generations per year decreases with latitude.

Methodological considerations

In order to elucidate the detailed drivers of host breadth in Japanese butterflies, we

attempted to include as many factors as possible in our analyses, but our results also

reveal several important limitations of current methods that need to be addressed in

future studies. The largest difference from previous studies concerns the properties of

the herbivore community dataset. The analyses of Forister *et al.* (2015) and many others

(e.g., Novotny *et al.* 2006) have been based on direct observations of local insect–plant

associations in communities. By contrast, our 'species-pool' approach based on

modeled distributions can stack the distributions also of some species pairs that would

typically not occur at the same site at the same time due to, for example, phenological

niche division. In our analyses, we did not focus on phenological patterns along the

latitudinal gradient, because our main focus was on "fundamental" patterns on a large

spatial scale. Differences in the results between previous studies and our results could

partly reflect the phenology and the length of active time for butterfly species.

In addition, we mainly focused on the transient region between the hemiboreal and

subtropical zones, so the pattern found cannot necessarily directly be generalized to

global scale. Regional studies focusing on narrower latitudinal gradients should

consider geohistorical effects (e.g., where the region was colonized by species at

different times or where the hotspots of endemism are located). However, most of the

butterfly species of the Japanese archipelago are not endemics, but rather

widely-distributed species shared with the Eurasian continent. This is largely explained

by the fact that the Japanese archipelago was repeatedly connected with the continent by

land bridges throughout glacial episodes of the Pliocene and Pleistocene periods,

allowing for butterfly dispersal (details reviewed in Tojo *et al.* 2017). On the other hand,

detailed regional studies have the advantage that it is possible to extensively correct

information on host use. Previous studies have suggested that sampling effort directly

affects the inferred degree of host specialization (Dixon *et al.* 1987), but such effects are

difficult if not impossible to address in large-scale meta-analyses.

Unfortunately, we were not able to directly study the effect of regional plant diversity

on the geographic distribution of resource specialization. In general, however, the

proportion of rare plant species increases towards the tropics (e.g., Ulrich *et al.* 2016),

possibly due to negatively density-dependent survival (Janzen–Connell hypothesis;

Janzen 1970). Such a process was suggested as a fundamental explanation for the

opposed latitudinal pattern (i.e., more generalists toward lower latitudes) of resource

specialization found in the simulation study by Forister & Jenkins (2017). Specifically,

a high proportion of rare plants would favor the evolution of broader host breadth in

insects, meaning that the mean and divergence of host breadth would increase toward

lower latitudes (Ghazoul & Sheil 2010). However, even if the evenness of plant

abundance would drive resource specialization, such patterns should be driven by

resource biomass in a strict sense, but data on available plant biomass were lacking in

our and previous studies. Therefore, studies focusing on the biomass of available

alternative resources are needed in the future, in order to reveal more detailed effects of

floral composition on herbivore host breadth.

Historical and evolutionary perspectives

We did not address evolutionary processes in this study, because phylogenetic

information on all the studied butterfly species was not available. However, our findings

should be generalizable to other regions and broader spatial patterns by including

evolutionary processes. For example, we could expand the recently proposed

evolutionary ideas on species association dynamics proposed by Nylin *et al.* (2017) and

the oscillation hypothesis proposed by Janz *et al.* (2001, 2006), which espcially focused

on speciation and species distributions, into specific ideas from spatial perspectives, by

adding a latitudinal direction to the oscillation dynamics. The oscillation hypothesis

proposed by Janz *et al.* (2001, 2006) postulates that, over time, herbivorous insect

lineages oscillate between a generalist state, during which they may expand their

geographical ranges, and various specialist states presenting opportunities for local

adaptation of individual populations; speciation occurs after host specialization. To

explore this issue further, we plotted minimum and maximum values of phylogenetic

host breadth and body size within butterfly communities against latitude (Fig. S3), and

confirmed that the ranges of these trait values become increasingly narrow toward

higher latitudes. If physical constraints on host breadth and/or body size in insect

herbivores exist (Fig. S3), very large or very small butterfly species should have

difficulties in extending their distribution ranges from the south to the north, and

therefore such large or small species could be filtered out. Our finding is consistent with

the proposal of Fisher (1960), who argued that the stable climate in the tropics allowed

for a wider range of morphological and physiological adaptations than in the temperate

region. On the other hand, the spread of butterfly species with broader host breadth

from south to north might be hindered by biogeographic limitations (Kimura 2004;

Hirao *et al*. 2015). Therefore, we propose a novel prediction: butterfly species having a

wide host breadth could have more likely expanded their distribution to south, and

specialized and diversified there via oscillation processes, and only descendant species

with narrower host breadth could return in the northward direction. Although

biogeographic limitations and abiotic variables (e.g., temperature, precipitation, and

snow) are important determinants of butterfly distributions, our above predictions

would provide further insight into the importance of geographical and morphological

constraints for species association dynamics and the oscillation hypothesis. These also

provide a possibility to cross with other general ecological rules like Rapoport's rule

(Rapoport 1982), which is related to latitudinal distribution range and global history that

dramatically have changed the species distributions (Nyman *et al.* 2012).

Conclusions

Butterfly communities became more specialized in their host use towards higher

latitudes (i.e., towards the north) across the Japanese archipelago, a pattern that is

opposite to predictions from classical hypotheses. Our results clearly revealed not only

how the variation in resource specialization is distributed, but also the potential

influence of physiological constraints resulting from variation in body size along the

same geographical gradient. Since Ehrlich & Raven (1964), coevolutionary interactions

between plants and herbivores have been considered the main determinant of host

breadth. However, our results re-emphasize the importance of current climate as a

regulating factor for butterfly host breadth and morphology (Fisher 1960). Future

studies should explore how latitudinal gradients in butterfly and plant phylodiversity

and evenness of resources modify host breadth at a global scale. As the number of

related variables would necessarily increase, the analyses would become more complex,

which would make finding simple answers more difficult. However, it should be

remembered that ecosystems are not simple, and novel analytical approaches such as

using Bayesian structural equation modeling provide a way for accepting the

complexity of nature. This should be one of the starting points when striving to

understand hidden eco-evolutionary patterns and processes driving the origin and

maintenance of biological diversity.

References

Arhonditsis, G.B., Stow, C.A., Paerl, H.W., Valdes-Weaver, L.M., Steinberg, L.J. &

Reckhow, K.H. (2007). Delineation of the role of nutrient dynamics and

hydrologic forcing on phytoplankton patterns along a freshwater-marine

continuum. *Ecol. Modell.*, 208, 230–246.

Asparouhov, T. & Muthén, B. (2019). Advances in Bayesian model fit evaluation for

structural equation models. http://www.statmodel.com/download/BayesFit.pdf

Blanckenhorn, W.U., & Demont, M. (2004). Bergmann and converse Bergmann

latitudinal clines in arthropods: two ends of a continuum? *Integr Comp Biol.* 44,

413–424.

Breiner, F. T., Guisan, A., Bergamini, A., & Nobis, M. P. (2015). Overcoming

limitations of modelling rare species by using ensembles of small models. *Methods

Ecol. Evol.*, 6, 1210-1218.

Brown, J. H., & Maurer, B. A. (1989). Macroecology: the division of food and space

among species on continents. *Science,* 243, 1145-1150.

Cavender-Bares, J., Kozak, K.H., Fine, P.V.A. & Kembel, S.W. (2009). The merging of

community ecology and phylogenetic biology. *Ecol. Lett.*, 12, 693–715.

Chessel, D., Dufour, A.-B. & Dray, S. (2018). CRAN R package ade4. Analysis of

ecological data, version 1.7–13. R Foundation for Statistical Computing, Vienna.

https://cran.r-project.org/web/packages/ade4/.

Connell, J.H. (1980). Diversity and the Coevolution of Competitors, or the Ghost of

Competition Past. *Oikos*, 35, 131–138.

Coley, P. D., & Kursar, T. A. (2014). On tropical forests and their pests. *Science*, 343,
35-36.

Cox, B. (2001). The biogeographic regions reconsidered. *J. Biogeogr.*, 28, 511–523.

Currie, D. J., Mittelbach, G. G., Cornell, H. V., Field, R., Guégan, J. F., Hawkins, B. A.
et al. (2004). Predictions and tests of climate-based hypotheses of broad-scale
variation in taxonomic richness. *Ecol. Lett.*, 7, 1121-1134.

Davis, R.B., Õunap, E., Javoiš, J., Gerhold, P. & Tammaru, T. (2013). Degree of
specialization is related to body size in herbivorous insects: a phylogenetic
confirmation. *Evolution*, 67, 583–589.

Dixon, A. F. G., Kindlmann, P., Leps, J., & Holman, J. (1987). Why there are so few
species of aphids, especially in the tropics. *Am. Nat.*, 129, 580-592.

Dobzhansky, T. (1950). Evolution in the tropics. *Am. Sci.*, 38, 209-221.

Dyer, L.A. & Forister, M.L. (2018). Challenges and advances in the study of latitudinal
gradients in multitrophic interactions, with a focus on consumer specialization.
Curr. Opin. Insect Sci., 1–9.

Dyer, L. A., Singer, M. S., Lill, J. T., Stireman, J. O., Gentry, G. L., Marquis, R. J. *et al.*
(2007). Host specificity of Lepidoptera in tropical and temperate forests. *Nature*,
448, 696.

Ehrlich, P.R. & Raven, P.H. (1964). Butterflies and plants: A study in coevolution.
Evolution, 18, 586.

Fischer, A. G. (1960). Latitudinal variations in organic diversity. *Evolution*, 14, 64-81.

Forister, M.L. & Jenkins, S.H. (2017). A neutral model for the evolution of diet breadth.
Am. Nat., 190, E40–E54.

Forister, M.L., Novotny, V., Panorska, A.K., Baje, L., Basset, Y. & Butterill, P.T.
(2015). The global distribution of diet breadth in insect herbivores. *Proc. Natl.*
Acad. Sci. USA, 112, 442–447.

Fox, J. W. 2011. Zombie ideas in ecology.

"https://dynamicecology.wordpress.com/2011/06/17/zombie-ideas-in-ecology/".

Garnier-Villarreal, M., & Jorgensen, T.D. (2019). Adapting fit indices for Bayesian

structural equation modeling: Comparison to maximum likelihood. *Psychol*

methods.

Gaston, K.J, Blackburn, T.M., & Lawton J.H. (1997). Interspecific abundance-range

size relationships: an appraisal of mechanisms. *J. Anim. Ecol.* 66:579–601.

Ghazoul, J., & Sheil, D. (2010). Tropical rain forest ecology, diversity, and

conservation. Oxford University Press, Oxford.

Grace, J.B., Schoolmaster, D.R., Guntenspergen, G.R., Little, A.M., Mitchell, B.R.,

Miller, K.M. *et al.* (2012). Guidelines for a graph-theoretic implementation of

structural equation modeling. *Ecosphere*, 3: 1–44.

Gutiérrez, D. (2009). Butterfly richness patterns and gradients. Ecology of butterflies in

Europe (ed. by J. Settele, T. Shreeve, M. Konvicka and H. van Dyck), pp. 250–280.

Cambridge University Press, Cambridge.

Hutchinson, G.E., & MacArthur, R.H. (1959). A theoretical ecological model of size

distributions among species of animals. *Am. Nat.*, 93, 117-125.

Hawkins, B.A., Rueda, M., Rangel, T.F., Field, R., & Diniz-Filho, J.A.F. (2014).

Community phylogenetics at the biogeographical scale: cold tolerance, niche

conservatism and the structure of North American forests. *J. Biogeogr.*, 41, 23-38.

Hirao, T., Kubota, Y. & Murakami, M. (2015). Geographical patterns of butterfly

species diversity in the subtropical Ryukyu Islands: the importance of a

unidirectional filter between two source islands. *J. Biogeogr.*, 42, 1418–1430.

Hoofs, H., van de Schoot, R., Jansen, N.W.H. & Kant, Ij. (2018). Evaluating Model Fit

in bayesian confirmatory factor analysis with large samples: Simulation study

introducing the BRMSEA. *Educ. Psychol. Meas.*, 78, 537–568.

Honda K (2005). Larval feeding habit and host selection. In: Honda K, Kato Y (eds)

Biology of butterflies. University of Tokyo Press, Tokyo, pp 255–301 (in

Japanese)

Inomata T (1990). Keys to the Japanese butterflies in natural color. Hokuryukan, Tokyo

(In Japanese)

Janz, N., Nyblom, K. & Nylin, S. (2001). Evolutionary dynamics of host-plant

specialization: a case study of the tribe Nymphalini. *Evolution*, 55, 783–796.

Janz, N., Nylin, S. & Wahlberg, N. (2006). Diversity begets diversity: host expansions

and the diversification of plant-feeding insects. *BMC Evol. Biol.*, 6, 4.

Kimura, M.T. (2004). Cold and heat tolerance of drosophilid flies with reference to their

latitudinal distributions. *Oecologia*, 140, 442–449.

Kline R. B., (2011). Principles and practice of structural equation modeling, The uilford

Press, New York, NY, USA, 3rd edition.

Kozubowski, T.J., Panorska, A.K. & Forister, M.L. A discrete truncated Pareto

distribution. *Stat. Methodol.*, 26, 135–150.

Lawton JH, Strong DR (1981). Community patterns and competition in folivorous

insects. *Am. Nat.* 118, 317–338

Lindström, J., Kaila, L., & Niemelä, P. (1994). Polyphagy and adult body size in

geometrid moths. *Oecologia*, 98, 130-132.

Loder, N., Gaston, K.J. & Warren, P.H. (1998). Body size and feeding specificity :

macrolepidoptera in Britain.

MacArthur, R. H. (1972). Geographical ecology: Patterns in the distribution of species

Princeton University Press, Princeton.

Milne, R.I. & Abbott, R.J. (2002). The origin and evolution of tertiary relict floras. *Adv.*

Bot. Res., 38, 281–314.

Mittermeier R.A., Turner W.R., Larsen F.W., Brooks T.M., Gascon C. (2011). Global

biodiversity conservation: the critical role of hotspots. In: Zachos FE, Habel JC

(eds) Biodiversity hotspots. Springer, Berlin, pp 3–22

Moles, A.T. & Ollerton, J. (2016). Is the notion that species interactions are stronger

and more specialized in the tropics a zombie idea? Biotropica, 48, 141–145.

Mouchet, M.A., Villéger, S., Mason, N.W.H. & Mouillot, D. (2010). Functional

diversity measures: An overview of their redundancy and their ability to

discriminate community assembly rules. *Funct. Ecol.*, 24, 867–876.

Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus user's guide. eighth edition. Los

Angeles, CA

Nakadai, R., Hashimoto, K., Iwasaki, T. & Sato, Y. (2018). Geographical co-occurrence

of butterfly species: the importance of niche filtering by host plant species.

Oecologia, 186, 995-1005.

Nakadai R, Kawakita A (2017). Patterns of temporal and enemy niche use by a

community of leaf cone moths (*Caloptilia*) coexisting on maples (*Acer*) as revealed

by metabarcoding. *Mol. Ecol.,* 26, 3309–3319

Novotny V. & Basset Y. (2005). Host specificity of insect herbivores in tropical forests.

Proc. Roy. Soc. B., 272, 1083-1090.

Novotny V., Drozd P., Miller SE., Kulfan M., Janda M, Basset Y. *et al.* (2006). Why

are there so many species of herbivorous insects in tropical rainforests? *Science*

313, 1115-1118.

Nylin, S., Agosta, S., Bensch, S., Boeger, W.A., Braga, M.P., *et al.* (2017). Embracing

colonizations: A new paradigm for species association dynamics. *Trends Ecol.*

Evol., 33, 4–14.

Nyman T, Linder HP, Peña C, Malm T & Wahlberg N (2012). Climate-driven diversity

dynamics in plants and plant-feeding insects. *Ecol. Lett.* 15: 889–898

Owens, H., Lewis, D., Dupuis, J., Clamens, A., Sperling, F., Kawahara, A., *et al.* (2017).

The latitudinal diversity gradient in New World swallowtail butterflies is caused by

contrasting patterns of out-of- and into-the-tropics dispersal. *Glob. Ecol. Biogeogr.*,

1447–1458.

Kembel, S.W., Cowan, P.D., Helmus, M.R., Cornwell, W.K., Morlon, H., Ackerly, D.

D. *et al.* (2010). Picante: R tools for integrating phylogenies and ecology.

Bioinformatics, 26, 1463-1464.

Park, O. (1949). Application of the converse Bergmann principle to the carabid beetle,

Dicaelus purpuratus. *Physiol. Zool.*, 22, 359–372.

Phillips, S.J., Anderson, R.P. & Schapire, R.E. (2006). Maximum entropy modeling of

species geographic distributions. *Ecol. Modell.*, 190, 231–259.

Pöyry J, Carvalheiro LG, Heikkinen RK, Kuhn I, Kuussaari M, Schweiger O *et al.*

(2017). The effects of soil eutrophication propagate to higher trophic levels Global

Ecol. Biogeogr., 26, 18–30

Rapoport, E. H. (1982). Areography. Geographical strategies of species. Pergamon

Press, Oxford, UK.

R Development Core Team (2017). R: a language and environment for statistical

computing. R Foundation for Statistical Computing, Vienna, Austria.

http://www.R-project.org/.

Read, Q.D., Grady, J.M., Zarnetske, P.L., Record, S., Baiser, B., Belmaker, J., *et al.*

(2018). Among-species overlap in rodent body size distributions predicts species

richness along a temperature gradient. *Ecography.*, 41, 1718–1727.

Romero, G.Q., Gonçalves-Souza, T., Kratina, P., Marino, N.A., Petry, W.K.,

Sobral-Souza, T., *et al.* (2018). Global predation pressure redistribution under

future climate change. Nature Climate Change, 8, 1087.

Saito, M.U., Jinbo, U., Yago, M., Kurashima, O. & Ito, M. (2016). Larval host records
of butterflies in Japan. *Ecol. Res.*, 31, 491–491.

Scriber, J.M. (2010). Integrating ancient patterns and current dynamics of insect-plant
interactions: Taxonomic and geographic variation in herbivore specialization.
Insect Sci., 17, 471–507.

Shiro□zu, T. (2006). The butterflies of Japan in color. Gakken Holdings, Tokyo (In
Japanese)

Strong, D.R., Lawton, J.H., & Southwood, S.R. (1984). Insects on plants. Community
patterns and mechanisms. Harvard University Press, Cambridge

Shelomi, M. (2012). Where are we now? Bergmann's rule sensu lato in insects. *Am.*
Nat., 180, 511-519.

Sutton, S.L., & Collins, N.M. (1991). Insects and tropical forest conservation. The
conservation of insects and their habitats, 405-424. Academic Press

Tojo, K., Sekiné, K., Takenaka, M., Isaka, Y., Komaki, S., Suzuki, T., *et al.* (2017).
Species diversity of insects in Japan: their origins and diversification processes.
Entomol. Sci., 20, 357-381.

Ulrich, W., Kusumoto, B., Shiono, T., & Kubota, Y. (2016). Climatic and geographic
correlates of global forest tree species–abundance distributions and community
evenness. *J. Vege Sci*, 27: 295-305.

Vaughan, I.P., & Ormerod, S.J. (2005). The continuing challenges of testing species
distribution models. *J. Appl. Ecol.*, 42, 720-730.

Vázquez, D.P., & Stevens, R.D. (2004). The latitudinal gradient in niche breadth:
concepts and evidence. *Am. Nat.*, 164(1), E1-E19.

Violle, C., Navas, M.-L., Vile, D., Kazakou, E., Fortunel, C., Hummel, I., *et al.* (2007).
Let the concept of trait be functional! *Oikos*, 116, 882–892.

Volf, M., Pyszko, P., Abe, T., Libra, M., Kotásková, N., Šigut, M., *et al.* (2017).

Phylogenetic composition of host plant communities drives plant-herbivore food

web structure. *J. Anim. Ecol.*, 86, 556–565.

Wasserman, S.S., & Mitter, C. (1978). The relationship of body size to breadth of diet

in some Lepidoptera. *Ecol. Entomol.*, 3, 155-160.

Webb, C.O. & Donoghue, M.J. (2005). Phylomatic: tree assembly for applied

phylogenetics. *Mol. Ecol. Notes*, 5, 181–183.

Zanne, A.E., Tank, D.C., Cornwell, W.K., Eastman, J.M., Smith, S.A., FitzJohn, R.G.,

et al. (2014). Corrigendum: Three keys to the radiation of angiosperms into

freezing environments. *Nature*, 514, 394–394.

Zeuss, D., Brunzel, S., & Brandl, R., (2017). Environmental drivers of voltinism and

body size in insect assemblages across Europe *Glob. Ecol. Biogeogr.*, 26, 154-165

Figure legends

Figure 1 Patterns of (a) butterfly species richness based on stacked predicted species

distribution data (Nakadai et al. 2018), (b) butterfly body size mean, (c) body size

divergence, (d) alpha parameter of the discrete truncated Pareto distribution, (e)

phylogenetic host breadth mean, and (f) phylogenetic host breadth divergence across the

Japanese archipelago. Only grids that satisfied the criteria (see text) are shown in (d),

(e), and (f). Values except (a) represent standardized effect sizes (SES) estimated based

on null model 1.

Figure 2 Path diagrams of the Bayesian SEMs explaining host-breadth parameters.

Parameter estimates are shown in Tables 2, 3, and Table S2. Red arrows indicate

positive effects or correlations, and blue arrows indicate negative ones. Dashed lines

indicate paths removed through the modification process in the analysis. The

abbreviations indicate LAT: Latitude, ELV: Elevation, AP: Annual precipitation, AMT:

Annual mean temperature, SNW: annual maximum depths of snow cover, BSR:

Butterfly species richness, BSM: Body size mean, BSD Body size divergence, PAL:

The alpha parameter of the discrete truncated Pareto distribution, PHBM: Phylogenetic

host breadth mean, and PHBD: Phylogenetic host breadth divergence.

Figure 1

Figure 2

Table 1 Hypothetical paths from previous studies, which are considered in this study

Hypothetical path				References
Response	Predictor		Explanation	
Climate	Geography	(a)	Temperature, precipitation, and snow change along latitude and elevation gradients (+/–).	Romero *et al.* 2018
Butterfly diversity	Geography	(b)	Butterfly diversity changes along latitude (+/–) and elevation (+/–).	Sutton & Collins 1991, Gutiérrez 2009, Owens et al. 2017
Butterfly diversity	Climate	(c)	Butterfly diversity change along climatic conditions (+/–).	Currie et al. 2004, Owens et al. 2017
Butterfly body size	Geography	(d)	Butterfly body size changes along latitudes and elevations (+/–).	Bergmann 1947; Park 1949; Fisher *et al.* 1960
Butterfly body size	Climate	(e)	Butterfly body size and divergence change along with climatic conditions (+/–)	Bergmann 1947; Park 1949; Zeuss *et al.* 2017
Butterfly body size	Butterfly diversity	(f)	Body size increases toward regions that have lower butterfly diversity (+)	Hutchinson & MacArthur 1959
Host	Geography	(g)	Mean and divergence of host breadth decreases towards lower	Scriber 1995;

breadth				latitudes (–)	Forister *et al.* 2015
Host breadth	Climate		(h)	Mean and divergence of host breadth decrease towards regions that have higher amount of energy (+)	Schemske *et al.* 2009; Read *et al.* 2018 Dobzhansky 1950 ;
Host breadth	Butterfly diversity		(i)	Higher butterfly diversity intensifies competition and as consequence the host breadths become more narrow (–).	MacArthur 1972; Coley & Kursar 2014
Host breadth	Butterfly body size	*	(j)	There is a positive correlation between host breadth and butterfly body size (possibly related to effectiveness of resource exploitation) (+)	Brown & Maurer 1989; Lindström 1994; Gaston *et al.* 1997; Davis *et al.* 2013

The asterisk indicates a correlational relationship

We also hypothesized a correlation within each factor (e.g., mean and divergence of body size)

Table 2 The final Bayesian structural equation model (SEM) focusing on the alpha

parameter of the discrete truncated Pareto distribution fitted to butterfly host breadth.

The abbreviations indicate LAT: Latitude, ELV: Elevation, AP: Annual precipitation,

AMT: Annual mean temperature, SNW: annual maximum depth of snow cover, BSR:

Butterfly species richness, BSM: Body size mean, BSD: Body size divergence, PAL:

The alpha parameter of the discrete truncated Pareto distribution.

| | | | | 95% C.I. | | |
| | | | | Lower | Upper | |
	Response	Explanation	Estimate	2.5%	2.5%	Significance
Causal effect	AMT	LAT	-0.836	-0.846	-0.826	*
		ELV	-0.525	-0.541	-0.510	*
	AP	LAT	-0.549	-0.574	-0.523	*
		ELV	0.305	0.276	0.333	*
	SNW	LAT	0.470	0.440	0.499	*
		ELV	0.339	0.307	0.370	*
	BSR	AMT	–	–	–	
		AP	-0.191	-0.230	-0.151	*
		SNW	-0.220	-0.257	-0.182	*
		LAT	-0.316	-0.359	-0.273	*
		ELV	0.646	0.618	0.673	*
	BSM	AMT	0.397	0.351	0.443	*
		AP	0.238	0.210	0.266	*
		SNW	-0.180	-0.206	-0.153	*
		LAT	-0.274	-0.328	-0.220	*
		ELV	–	–	–	
		BSR	-0.135	-0.160	-0.109	*
	BSD	AMT	–	–	–	
		AP	0.305	0.279	0.329	*
		SNW	-0.213	-0.237	-0.189	*
		LAT	-0.548	-0.575	-0.521	*
		ELV	-0.281	-0.306	-0.257	*
		BSR	-0.230	-0.253	-0.206	*

	PAL	AMT	-0.885	-0.943	-0.826	*
		AP	-0.263	-0.298	-0.229	*
		SNW	0.160	0.127	0.193	*
		LAT	-0.405	-0.476	-0.336	*
		ELV	–	–	–	
		BSR	-0.257	-0.288	-0.225	*
Co-variate	PAL	BSM	-0.212	-0.249	-0.175	*
		BSD	-0.287	-0.323	-0.251	*
	BSM	BSD	0.729	0.711	0.747	*
	AMP	SNW	0.335	0.299	0.369	*

	Model fit (N=2542)	
	Lower 5.0%	Upper 5.0%
BRMSEA	0.045	0.062 †
BCFI	0.997	0.999 ††
BTLI	0.987	0.993 ††
BIC	95188.085	

† Satisfied only the criteria of good model fit of BRMSEA (Lower 5.0% <0.05, Upper

5.0% < 0.08: Hoof et al. 2018).

†† Satisfied the criteria of good model fit of BRMSEA (both Lower 5.0% and Upper

5.0% <0.06: Asparouhov & Muthén 2019), BCFI and BTLI (both Lower 5.0% and

Upper 5.0% >0.95: Asparouhov & Muthén 2019).

*Credible interval (C.I.) did not overlap zero

–Paths trimmed through model modification (The original full model is in Table S2)

Table 3 Results of the Bayesian structural equation model (SEM) focusing on mean and

divergence (RaoQ) of phylogenetic host breadth. The abbreviations indicate LAT:

Latitude, ELV: Elevation, AP: Annual precipitation, AMT: Annual mean temperature,

SNW: annual maximum depth of snow cover, BSR: Butterfly species richness, BSM:

Body size mean, BSD: Body size divergence, PHBM: Phylogenetic host breadth mean,

and PHBD: Phylogenetic host breadth divergence.

| | | | | 95% C.I. | | |
| | | | | Lower | Upper | |
	Response	Explanation	Estimate	2.5%	2.5%	Significance
Causal effect	AMT	LAT	-0.836	-0.846	-0.826	*
		ELV	-0.525	-0.541	-0.509	*
	AP	LAT	-0.549	-0.574	-0.523	*
		ELV	0.305	0.275	0.334	*
	SNW	LAT	0.470	0.440	0.499	*
		ELV	0.339	0.307	0.370	*
	BSR	AMT	–	–	–	
		AP	-0.191	-0.231	-0.151	*
		SNW	-0.220	-0.258	-0.181	*
		LAT	-0.316	-0.360	-0.272	*
		ELV	0.646	0.618	0.673	*
	BSM	AMT	0.395	0.349	0.441	*
		AP	0.238	0.210	0.266	*
		SNW	-0.180	-0.207	-0.154	*
		LAT	-0.275	-0.330	-0.221	*
		ELV	–	–	–	
		BSR	-0.135	-0.161	-0.109	*
	BSD	AMT	–	–	–	
		AP	0.304	0.279	0.329	*
		SNW	-0.214	-0.237	-0.190	*
		LAT	-0.549	-0.576	-0.521	*
		ELV	-0.280	-0.304	-0.256	*
		BSR	-0.230	-0.254	-0.207	*

			Estimate	Lower	Upper	
	PHBM	AMT	0.823	0.762	0.882	*
		AP	0.265	0.230	0.300	*
		SNW	-0.243	-0.277	-0.210	*
		LAT	0.471	0.399	0.542	*
		ELV	–	–	–	
		BSR	0.381	0.349	0.413	*
	PHBD	AMT	0.881	0.813	0.951	*
		AP	0.324	0.284	0.363	*
		SNW	-0.042	-0.081	-0.004	*
		LAT	0.645	0.563	0.728	*
		ELV	–	–	–	
		BSR	0.558	0.523	0.593	*
Co-variate	PHBM	BSM	0.245	0.207	0.282	*
		BSD	0.332	0.297	0.366	*
		PHBD	0.855	0.844	0.865	*
	PHBD	BSM	0.128	0.089	0.167	*
		BSD	0.195	0.157	0.232	*
	BSM	BSD	0.729	0.71	0.747	*
	AMP	SNW	0.335	0.301	0.369	*

	Model fit (N=2542)	
	Lower 5.0%	Upper 5.0%
BRMSEA	0.043	0.060 †
BCFI	0.998	0.999 ††
BTLI	0.987	0.993 ††
BIC	102244.105	

† Satisfied only the criteria of good model fit of BRMSEA (Lower 5.0% <0.05, Upper 5.0% < 0.08: Hoof et al. 2018).

†† Satisfied the criteria of good model fit of BRMSEA (both Lower 5.0% and Upper 5.0% <0.06: Asparouhov & Muthén 2019), BCFI and BTLI (both Lower 5.0% and Upper 5.0% >0.95; Asparouhov & Muthén 2019).

*Credible interval (C.I.) did not overlap zero

–Paths trimmed through model modification (The original full model is in Table S2)

Appendix

Figure S1 Geographical patterns of climatic variables and elevation. (a) annual mean

temperature, (b) annual precipitation, (c) annual maximum depth of snow cover, (d)

elevation.

Figure S2 Latitudinal patterns in (a) phylogenetic host breadth minimum (r=–0.014,

p<0.001), (b) phylogenetic host breadth maximum (r= –0.059, p<0.001), (c) body size

minimum (r= –0.130, p<0.001), and (d) body size maximum (r= 0.071, p<0.001).

Values represent standardized effect sizes (SES) estimated based on null model 1

Figure S3 Latitudinal patterns in (a) alpha parameter of the discrete truncated Pareto

distribution by using predicted occurrence data (r= 0.020, p<0.001), (b) alpha parameter

of the discrete truncated Pareto distribution by using observed occurrence data (r= 0.008,

p<0.001). Values represent non-standardized trends which are comparative with

Forister et al. (2015).

Figure S4 The relationships between body size and diet breadth across Japanese

butterfly species. There were no significant correlations ((a) r=–0.021, p=0.745; (b)

r=–0.071, p= 0.268).

Table S1. The Japanese butterfly species analyzed in the present study.

Table S2 Comparison between the results based on the full model and final model for

(a) discrete truncated Pareto alpha and (b) phylogenetic host breadth.

Table S3 Comparison between the results based on predicted and observed distribution

datasets for (a) discrete truncated Pareto alpha and (b) phylogenetic host breadth. The

model structures are as in Tables 2, 3.

Table S4 Comparison between the results based on null model 1 and null model 2 for

(a) discrete truncated Pareto alpha and (b) phylogenetic host breadth. The model

structures are as in Tables 2, 3.

Table S5 Comparison between the results based on different criteria of minimum

butterfly species richness for (a) discrete truncated Pareto alpha and (b) phylogenetic

host breadth. The model structures are as in Tables 2, 3.

Table S6 The correlations among the environmental variables and the calculated

indices.

Table S7 The environmental variables and the calculated indices that were used in this

study for all 10-km grids.

Supplementary text 1 Detailed description of butterfly distribution data.

Supplementary text 2 Detailed description of null models.

Supplementary text 3 Treatment of multicollinearity problems in Structural Equation

Modeling.

Supplementary text 4 Detailed explanation of Bayesian SEM.

Supplementary text 5 Sampling size dependency in the chi-square test.

(a) Alpha parameter of discrete truncated Pareto distribution

(b) Phylogenetic host breadth mean and divergence