REPORT

Ecological dissimilarity among land-use/land-cover types improves a heterogeneity index for predicting biodiversity in agricultural landscapes

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Abstract Land-use/land-cover heterogeneity is among the most important factors influencing biodiversity in agricultural landscapes and is the key to the conservation of multi-habitat dwellers that use both terrestrial and aquatic habitats. Heterogeneity indices based on land-use/land-cover maps typically do not integrate ecological dissimilarity between land-use/land-cover types. Here, we applied the concept of functional diversity to an existing land-use/land-cover diversity index (Satoyama index) to incorporate ecological dissimilarity and proposed a new index called the dissimilarity-based Satoyama index (DSI). Using Japan as a case study, we calculated the DSI for three land-use/land-cover maps with different spatial resolutions and derived similarity information from normalized difference vegetation index values. The DSI showed better performance in the prediction of Japanese damselfly species richness than that of the existing index, and a higher correlation between the index and species richness was obtained for higher resolution maps. Thus, our approach to improve the land-use/land-cover diversity index holds promise for future development and can be effective for conservation and monitoring efforts.

Keywords Damselfly · NDVI · Proper conditional autoregressive model · Remote sensing · Satoyama

INTRODUCTION

The quantification and evaluation of the biodiversity status of agricultural landscapes are key elements of wildlife conservation (Billeter et al. 2008; Firbank et al. 2008) because farming is a dominant form of land management globally; croplands occupy approximately 38% of the Earth's ice-free terrestrial surfaces (Foley et al. 2011). While intensive agriculture is often treated as a strong driver of biodiversity loss (Millennium Ecosystem Assessment 2005), farming with low-intensity and/or traditional management protocols contributes substantially to wildlife conservation by various mechanisms, such as promoting the persistence of species that are disturbance dependent or require multiple habitats (Katoh et al. 2009; Kadoya and Washitani 2011; Lomba et al. 2014; Queiroz et al. 2014). There are increasing efforts to monitor ecologically important practices and habitats in farmland-dominated landscapes both spatially and temporally (Lomba et al. 2014) as well as ongoing discussions on how to maintain a balance between biodiversity conservation and agricultural production (e.g., Fischer et al. 2008), which influences the structural/functional features of agricultural landscapes. Thus, spatially explicit mapping of such information is a potentially powerful tool for decision-making and resource allocation in biodiversity conservation (Lomba et al. 2014).

Heterogeneity is among the most useful indicators of landscape biodiversity status because environmental variability in space and time provides suitable environmental conditions and/or refuge from adverse conditions for various species (Benton et al. 2003; Stein et al. 2014). Indeed, environmental heterogeneity is generally positively correlated with biodiversity (Atauri and de Lucio 2001; Kadoya and Washitani 2011; Stein et al. 2014). In addition, heterogeneity

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is a conspicuous characteristic of traditional agricultural landscapes, which are typically considered sustainable socio-ecological systems (Kadoya and Washitani 2011).

Furthermore, heterogeneous agricultural landscapes are particularly important for species that require multiple habitats to complete their life histories. In particular, many multi-habitat dwellers that use both aquatic and terrestrial ecosystems, such as frogs, dragonflies, and some birds, are endangered (Rodrigues et al. 2006; Kadoya et al. 2009; Katoh et al. 2009). Therefore, the quantification of environmental heterogeneity in agricultural landscapes is important to characterize and assess the status of habitats relevant to these species.

Many indices are used to quantify landscape heterogeneity (Stein et al. 2014). Typical indices include the number of land-use/land-cover types and/or semi-natural habitats per unit area (Atauri and de Lucio 2001; Moser et al. 2002; Honnay et al. 2003; Jeanneret et al. 2003; Billeter et al. 2008), diversity indices (Honnay et al. 2003; Schindler et al. 2008; Gottschalk et al. 2010; Gil-Tena et al. 2015), and evenness indices (Honnay et al. 2003; Schindler et al. 2008). To describe heterogeneity in an agricultural landscape, the Satoyama index (SI) has been proposed (Kadoya and Washitani 2011). The SI is estimated by weighting the Simpson's diversity index by the overall proportions of natural and semi-natural land-use/land-cover types, thereby taking into account the ecological contribution of these areas to agricultural landscapes. The SI can be readily calculated from land-use/land-cover maps; the values are positively correlated with the distributions of diverse multi-habitat dwellers in temperate zones in the Japanese archipelago and high values have been obtained in highly biodiverse agricultural areas globally (Kadoya and Washitani 2011).

Nevertheless, the correlation between SI and biodiversity may be insufficient in agricultural landscapes. In particular, SI does not adequately account for the “ecological dissimilarity” between land-use/land-cover categories (note that “ecological dissimilarity” in this study is defined as the dissimilarity of physical and chemical properties that affect a focal component of biodiversity). For example, heterogeneity based on Simpson's diversity index for a landscape consisting of 40% cropland, 30% wetland, and 30% broadleaf forest is lower than that of a landscape consisting of 40% cropland, 20% tall grass vegetation, 20% short grass vegetation, and 20% tall forb vegetation. That is, a landscape consisting of only grassland and cropland is mathematically more heterogeneous than a landscape that includes wetlands and forests. This can lead to a low correlation between estimated heterogeneity and species that use both aquatic and terrestrial ecosystems. Re-categorization of land types is a potential solution, but this process treats “similar” land-use/land-cover types as a single landscape element, and important information for some

species may be lost. The measure used to define “similar” is also ambiguous.

Accordingly, a more objective, quantitative method for incorporating ecological dissimilarity is needed. This may be particularly important for paddy field environments, which are dominant agricultural ecosystems in Asia. As an aquatic ecosystem, paddy fields have more important functions for the conservation of multi-habitat dwellers, such as dragonflies, amphibians, and some birds (Katoh et al. 2009; Kadoya and Washitani 2011), than drier farmlands. However, the ecological uniqueness of the paddy field as an inland water ecosystem has not been adequately evaluated at the landscape scale (Kadoya and Washitani 2011; Yoshioka et al. 2013).

Ecological dissimilarity can be incorporated by applying metrics of functional diversity (Botta-Dukát 2005; Pavoine and Dolédec 2005; Ricotta and Szeidl 2006). That is, incorporating not only the richness and evenness of land-use/land-cover types, but also weighting them by ecological dissimilarity, in the same way that the richness and evenness of each species are weighted by the dissimilarity of functional traits to calculate functional diversity, should lead to an improved representation of landscape heterogeneity. Such an index may better reflect the differences among combinations of land-use/cover types from the viewpoint of focal multi-habitat dwellers.

In this study, we proposed a simple, comprehensive index to quantify land-use/land-cover heterogeneity at the regional and/or national scales. By incorporating dissimilarity between land-use/land-cover types, we hypothesize that the proposed index is more closely associated with the diversity of multi-habitat dwellers in agricultural landscapes. To demonstrate its applicability, we calculated the dissimilarity-based heterogeneity index using remote-sensing data and estimated its power to explain the distribution of damselflies in Japan. Our focus on the national scale was relevant to Japanese international commitments related to the conservation of biodiversity. Japan is an ideal study region because (i) its ecosystems are highly diverse, with marked spatial variation in environments and a broad geographical span from boreal to subtropical regions of East Asia (JWRC 2010), and (ii) the high prevalence of paddy field agriculture is expected to clearly demonstrate the effects of incorporating ecological differences between terrestrial and aquatic ecosystems on index performance.

MATERIALS AND METHODS

Concept and protocol for the DSI approach

A schematic diagram of the procedure used to generate the dissimilarity-based Satoyama index (DSI) is summarized

and compared to those of the MSI (a modified SI) described by Yoshioka et al. (2013). Note that MSI differs from SI in that each land-use/land-cover cell, rather than each landscape, has a heterogeneity value to depict high-resolution maps. First, base maps containing important land-use/land-cover information that may reflect the biodiversity status of the target region were needed. Base maps with ecologically relevant information (e.g., discrimination of water-flooded paddy fields and other croplands) were especially relevant. The following step was critical for our approach: quantification of dissimilarity between land-use/land-cover types defined by the base maps in a manner that was as objective and ecologically meaningful as possible. The land-use/land-cover diversity index was calculated for agricultural landscapes using a base map in addition to dissimilarity values derived from an additional data source such as remote-sensing data (see formulae (4) and (5) for an example of dissimilarity values). This diversity index (based on the quadratic diversity index of Rao [1982]) was calculated for each cell k as follows:

$$Q_k = \sum_i^S \sum_j^S p_{k,i} \cdot p_{k,j} \cdot d_{i,j}, \quad (1)$$

$$d_{i,j} = 1 - \text{Sim}_{i,j}, \quad (2)$$

where S is the total number of land-use/land-cover types, $p_{k,i}$ and $p_{k,j}$ are the proportions of cells of land-use/land-cover type i and j in the surrounding space unit (landscape) of cell k , respectively, and $d_{i,j}$ is the dissimilarity between land-use/land-cover types. $\text{Sim}_{i,j}$ is an element of the similarity matrix of land-use/land-cover types (see also Fig. 1). Note that the quadratic diversity index was used for comparison with the MSI because the original SI was based on Simpson's diversity index (Lande 1996), which is a special version of quadratic diversity index (the similarity matrix is an identity matrix). Finally, the natural and semi-natural (i.e., non-agricultural) land-use/land-cover types were weighted following the procedures of Kadoya and Washitani (2011), assuming that a landscape including a higher proportion of agricultural lands contributes less to biodiversity. The final heterogeneity index (DSI) is as follows:

$$\text{DSI}_k = Q_k \cdot (1 - p_{k,\text{agri}}), \quad (3)$$

where $p_{k,\text{agri}}$ is the proportion of agricultural land-use cells in the landscape surrounding cell k . Because our scope is agricultural landscapes, DSI was not calculated when $p_{k,\text{agri}} = 0$, as was the case for the MSI.

Assigning dissimilarity values to all possible combinations of land-use/land-cover types was challenging. Objective methods for deriving dissimilarity values are needed. If available biological data for a study area are limited, which is often the case, environmental

information, such as the spectral information obtained from remote-sensing data, may be useful in calculations of similarity. Some remote-sensing data, such as satellite images, span broad spatio-temporal scales at a high resolution; they are frequently used for mapping land-use/land-cover types. Thus, land-use/land-cover maps often correspond well to remote-sensing data. In addition, remote-sensing data can be ecologically meaningful because habitat selection by flying multi-habitat users is expected to be related to spectral information (Trierweiler et al. 2013; Kays et al. 2015). Furthermore, some relevant data are available cost free and preprocessed.

Case study

Study system and data

To demonstrate the applicability of the DSI, the approach was applied to the whole Japanese archipelago using three readily available land-use/land-cover maps with different spatial resolutions and land-use/land-cover classifications (Table S1). A map based on the land-use classification prepared by Ogawa et al. (2013) (hereafter, the “Ogawa map”; see also Akasaka et al. 2014; Environment Agency, Japan and Asia Air Survey Co., Ltd., 1999) provided a high-resolution plot that included a detailed classification scheme specific to Japan (27 land-use types, see also Tables S1 and S2). In addition, two global maps with 20 land-cover types (see Tables S1, S3, S4 for detail) provided by the International Steering Committee for Global Mapping (ISCGM) (Tateishi et al. 2011; Tateishi et al. 2014) were used (hereafter, “GLCNMO2003 map” and “GLCNMO2008 map,” respectively). The GLCNMO2008 map was a modified version of the GLCNMO2003 map with a higher spatial resolution (Tateishi et al. 2014). Note that the GLCNMO2003 and GLCNMO2008 maps were global in scale, whereas the Ogawa map covered only Japan, but was better able to detect cells of agricultural land use, especially in mountainous regions where patches are generally small and undifferentiated in low-resolution maps. Yoshioka et al. (2013) used the Ogawa maps to calculate the national SI (hereafter, MSI).

To calculate the dissimilarity for each combination of land-use/land-cover types based on the three maps, estimates of the normalized difference vegetation index (NDVI), a product of remote sensing, were used. NDVI is the scaled proportion of spectral reflectance in near-infrared regions to visible red regions at the focal location; the index ranges from −1 to 1. High values are obtained for locations with high productivity (e.g., forested land), and extremely low (negative) values are obtained for aquatic locations (Jones and Vaughan 2010). Owing to the continuum of values along the gradient of productivity,

Fig. 1 Schematic of the procedure to estimate the dissimilarity-based Satoyama index (DSI). According to the original Satoyama index (SI) procedure described in Kadoya and Washitani (2011), a single value was calculated for each 6-km grid cell; here, we adopted the procedures of Imai et al. (2013) and Yoshioka et al. (2013), which obtained a MSI value for each 50-m cell using information from the surrounding 6-km unit space to generate high-resolution maps. *NDVI* normalized difference vegetation index

differences in NDVI between land-use/land-cover types should reflect dissimilarity in a quantitative manner. Intuitively, high values are expected for forest-type land-use/land-cover, moderate values for grassland-type land-use/land-cover, and low values for inland water-type land-use/land-cover.

MOD13Q1 products from the Moderate-Resolution Image Spectroradiometer (MODIS), which contain well-compiled NDVI data, were used (Huete et al. 1999). Data were collected for 16-day periods at a 250-m spatial resolution. For the Ogawa map and the GLCNMO maps, NDVI data for Japan collected in late May 2000, 2003, and 2008 were obtained from the online data pool provided by the NASA Land Processes Distributed Active Archive Center (LP DAAC 2013). The chronological years of the products were adjusted to the corresponding base maps [the oldest MODIS products were used for the Ogawa map because the map was compiled from national vegetation survey data collected through 1998 (Environment Agency, Japan and Asia Air Survey Co., Ltd. 1999; Ogawa et al. 2013)]. The NDVI data were assembled for a period corresponding to the rice-planting season in Japan, when the water surfaces in paddy fields are easily detectable. The mean NDVI value was obtained for each land-use/land-cover type for the whole study area to calculate the dissimilarity.

To examine the relationship between the DSI and biodiversity, distribution data for damselflies (Zygoptera) in Japan were obtained; these data had been compiled and published by the Ministry of Environment, Japan (2009). Damselfly communities use multiple habitats and have low dispersal ability, making them sensitive to environmental changes and suitable indicators (Yoshioka et al. 2014). In the original dataset, the distribution records of Odonata were compiled at a 10-km grid cell resolution; 2494 cells containing observations on Odonata were extracted from the dataset. Cells without data for damselflies or dragonflies were discarded. Furthermore, presence–absence data for only damselflies within the extracted cells were used for the subsequent analysis, because for dragonflies presence–absence data can be subject to weather and dispersal, rather than landscape properties. Chlorocyphidae, Calopterygidae, and Euphaeidae were also excluded from the analysis because they are usually lotic (Sugimura et al. 1999) and not dependent on agricultural landscapes. The spatial data were processed using ArcGIS 10.2 (ESRI Japan).

Calculation of the DSI

Multivariate approaches can be used to calculate the dissimilarity between land-use/land-cover types; however, for simplicity, only one variable was used in this analysis (NDVI across Japan). Dissimilarity values for each

combination of land-use/land-cover i and j (excluding urban and/or residential land use) were calculated using the scaled Euclidean distance of NDVI values:

$$Sim_{i,j} = 1 - ed_{i,j}/\max(\mathbb{ED}), \quad (4)$$

$$ed_{i,j} = \sqrt{(\text{NDVI}_i - \text{NDVI}_j)^2}, \quad (5)$$

where $\mathbb{ED}$ is an $i \times j$ Euclidean distance matrix comprising $ed_{i,j}$ values and $Sim_{i,j}$ is the similarity between land-use/land-cover types.

For each cell k in the selected base map, we calculated dissimilarity $d_{i,j}$ and Q_k in the landscape (square-shaped unit encompassing ~ 3 km surrounding the focal cell, i.e., 7×7 , 13×13 , and 121×121 cells in the GLCNMO 2003 map, the GLCNMO 2008 map, and the Ogawa map, respectively), using Eqs. (1) and (2). A spatial unit of this size (i.e., about $6 \text{ km} \times 6 \text{ km}$) was assumed to be sufficiently large to accommodate persistent populations of plants and animals that share habitats with humans in the countryside or in *Satoyama* landscapes (Imai et al. 2013; Kadoya and Washitani 2011). For comparative purposes, MSI was also calculated for each base map following the procedures of Kadoya and Washitani (2011) and Yoshioka et al. (2013). We calculated the DSI using the proportion of (semi-)natural areas obtained by Eq. 3 only if $p_{k,\text{agri}} > 0$. In accordance with the procedures of Yoshioka et al. (2013), plantation forest cells were excluded from the calculations (along with residential and/or urban area cells) because their contributions to biodiversity were considered to be insignificant. The inclusion of plantations as agricultural or non-agricultural land-use/land-cover types had little effect on the outcomes of statistical analyses (data not shown).

Statistical analysis

To determine whether the incorporation of dissimilarity information makes the DSI an appropriate heterogeneity index that is tightly associated with some component of biodiversity, we examined the relationship between the DSI and the distribution of damselfly species richness using a proper conditional autoregressive (CAR) model with a Poisson error distribution (Bivand et al. 2015) based on the GLCNMO2003, GLCNMO2008, and Ogawa maps. A proper CAR model is a Bayesian statistical model able to handle spatial autocorrelation in species distribution data based on neighboring grid cells. For model comparison, the marginal likelihood (the probability that data can be obtained under a Bayesian model, where higher values indicate a better model) derived from a Bayesian model was used as a goodness-of-fit indicator. The ratio of marginal likelihoods of two Bayesian statistical models is called the Bayes factor and is often used to compare the likelihood of statistical models (Kass and Raftery 1995).

Following the procedures of Kadoya and Washitani (2011), the species richness of damselflies per 10-km grid cell was the explained variable in the models; the explanatory variable was the maximum DSI value in the grid cells. Note that the dispersal ability of damselflies is relatively high (several kilometers) and they can select preferable locations from a relatively large area (Kadoya et al. 2008). Accordingly, damselflies are likely to be recorded in a 10-km cell if there is at least one preferable location within the cell. Thus, we can expect that the maximum, rather than mean DSI values within the 10-km cell explain the species richness of the cell if a landscape with a high DSI value appropriately includes the species-rich locations. In the CAR model, the hypothesized relationship between DSI and damselfly species richness can be expressed as follows:

$$\log(\mu_h) = \beta_0 + DSI_h \cdot \beta_1 + \rho_h, \quad (6)$$

where species richness in the 10-km grid cell h was assumed to follow a Poisson distribution with an expected mean of μ_h , β_1 is a regression coefficient associated with the DSI and is hypothesized to be positive, and β_0 is the intercept. Each grid cell has a spatial random effect ρ_h that adjusts the probability of damselfly species richness and is dependent on the values of neighboring cells (eight adjacent cells in our analysis). Similar models were constructed using the MSI (i.e., assuming no similarity between land-use/land-cover types; hence, the similarity matrix in this case was an identity matrix) and their log-transformed marginal likelihoods were compared. Statistical analyses were implemented in the INLA package in R 3.0.3 (R Core Team 2014).

RESULTS

We calculated the mean NDVI for each land-use/land-cover type (Tables S2–S4) and the similarity between types (Table S5–S7) for each base map. In all cases, the similarity between paddy fields and inland water areas exceeded the similarities between other croplands and inland water areas. DSI maps were produced (Figs. 2, 3, 4); locations with high values were more limited in the DSI maps than in the MSI maps. Among the 2494 10-km cells with Odonata records, 2025, 2310, and 2482 were assigned DSI values in the GLCNMO 2003, GLCNMO 2008, and Ogawa maps, respectively. The upper limit of DSI values was positively correlated to the corresponding MSI values; cells with high MSI values were often down-weighted in the DSI maps (Figs. 2, 3, 4, S1).

Proper CAR model calculations showed that the DSI values in the three maps were significantly positively correlated with damselfly species richness (Tables 1, 2, 3).

When the Ogawa map was used as a base map, the MSI was negatively correlated with richness (Table 1), despite a potential correlation with biodiversity. Using the GLCNMO2008 map, the DSI values (with and without similarity information) were positively correlated with species richness, and the log-transformed Bayes factor comparing models for DSI with MSI exceeded seven (Table 3). Log-transformed Bayes factors of greater than five provide very strong evidence that the former model is more likely than the latter (Kass and Raftery 1995). However, the log marginal likelihood of the DSI was slightly lower than that of the MSI when we used GLCNMO2003 as the base map (Table 2).

DISCUSSION

In this case study, we demonstrated that our approach improves the performance of the agricultural landscape heterogeneity index MSI (Kadoya and Washitani 2011; Yoshioka et al. 2013) by replacing Simpson's diversity index with Rao's quadratic diversity index. Adding information on only a single common and easily obtainable parameter obtained from remote-sensing data (the NDVI) improved the model fits and/or provided a more appropriate correlation in comparison with models that do not consider dissimilarity (using the Ogawa and GLCNMO 2008 maps as base maps).

NDVI values obtained during the rice-planting season in Japan roughly corresponded to three ecosystem types (forest, grassland, and inland waters) along a gradient of productivity, as expected. However, some land-cover types that are rare in Japan (e.g., needleleaf deciduous forest and sparse vegetation) were not well represented by the NDVI values (Tables S3 and S4). Paddy fields had values closer to those of inland waters than did any of the other croplands in all base maps (Tables S2–S4). This similarity improved model fitting for the DSI because multi-habitat dwellers in Japanese *Satoyama* landscapes, such as damselflies, depend on landscapes that contain both forest and inland water ecosystems. As expected, the MSI, which does not ecologically differentiate landscapes with forest and paddies from those with forests and other croplands, had low positive correlations or even negative relationships with damselfly species richness (Tables 1, 2, 3). The negative relationship for MSI based on the Ogawa map may be explained by the high MSI values owing to small and redundant land-use types that are not important for damselflies. Considering the small cell size (50 m × 50 m), Simpson's diversity index might indicate negative effects due to habitat fragmentation. However, the difference in index performance was not apparent when we used the GLCNMO 2003 map. The DSI values in the relatively

Fig. 2 Maps of dissimilarity-based Satoyama index (DSI) values in Japan based on the land-use map of Ogawa et al. (2013). **a** Map incorporating similarity information for land-use types based on the normalized difference vegetation index (NDVI) and **b** map without considering similarity information (corresponding to the MSI values in Yoshioka et al. 2013). Note that the values were not defined in the *white areas*

Fig. 3 Map of dissimilarity-based Satoyama index (DSI) values in Japan based on the land-cover map produced by the International Steering Committee for Global Mapping (2009). **a** Map incorporating similarity information for land-cover types based on the normalized difference vegetation index (NDVI) and **b** map without considering similarity information (corresponding to the MSI values in Yoshioka et al. 2013). Note that the values were not defined in the *white areas*

Fig. 4 Map of dissimilarity-based Satoyama index (DSI) values in Japan based on the land-cover map produced by the International Steering Committee for Global Mapping (2013). **a** Map incorporating similarity information for land-cover types based on the normalized difference vegetation index (NDVI) and **b** map without considering similarity information (corresponding to the MSI values in Yoshioka et al. 2013). Note that the values were not defined in the *white areas*

Table 1 Proper CAR model results for damselfly species richness in Japan by the dissimilarity-based Satoyama index (DSI) and modified Satoyama index (MSI, Yoshioka et al. 2013) produced from the Ogawa map

Explanatory variable	Mean	95% confidence interval
Model with similarity information		
Intercept	4.81×10^{-2}	$[-1.59 \times 10^{-1}, 2.52 \times 10^{-1}]$
Coefficient for DSI	1.95	[1.03, 2.88]
Log-transformed marginal likelihood		−5326.40
Model without considering similarity		
Intercept	9.04×10^{-1}	$[6.53 \times 10^{-1}, 1.15]$
Coefficient for MSI ^a	−1.02	$[-1.49, -5.44 \times 10^{-1}]$
Log-transformed marginal likelihood		−5326.92
Log-transformed Bayes factor		0.52

^a Corresponds to DSI given an identity matrix as a similarity matrix (assuming that there is no productivity gradient across the land-use cover types)

Table 2 Proper CAR model results explaining damselfly species richness in Japan for the dissimilarity-based Satoyama index (DSI) and modified Satoyama index (MSI) produced from the GLCNMO 2003 map (Tateishi et al. 2011)

Explanatory variable	Mean	95% confidence interval
Model with similarity information		
Intercept	4.33×10^{-1}	$[2.61 \times 10^{-1}, 6.02 \times 10^{-1}]$
Coefficient for DSI	8.77×10^{-1}	$[1.29 \times 10^{-2}, 1.74]$
Log-transformed marginal likelihood		−4552.19
Model without considering similarity		
Intercept	2.37×10^{-1}	$[-6.93 \times 10^{-2}, 5.39 \times 10^{-1}]$
Coefficient for MSI ^a	5.49×10^{-1}	$[7.96 \times 10^{-2}, 1.02]$
Log-transformed marginal likelihood		−4552.16
Log-transformed Bayes factor		−0.03

^a Corresponds to DSI given an identity matrix as a similarity matrix (assuming that there is no productivity gradient across the land-cover types)

Table 3 Proper CAR model results for damselfly species richness in Japan for the dissimilarity-based Satoyama index (DSI) and modified Satoyama index (MSI) produced from the GLCNMO 2008 map (Tateishi et al. 2014)

Explanatory variable	Mean	95% confidence interval
Model with similarity information		
Intercept	1.90×10^{-1}	$[2.76 \times 10^{-2}, 3.49 \times 10^{-1}]$
Coefficient for DSI	1.77	[1.07, 2.48]
Log-transformed marginal likelihood		−5051.83
Model without similarity information		
Intercept	-4.85×10^{-2}	$[-3.77 \times 10^{-1}, 2.76 \times 10^{-1}]$
Coefficient for MSI ^a	8.30×10^{-1}	$[3.54 \times 10^{-1}, 1.31]$
Log-transformed marginal likelihood		−5058.28
Log-transformed Bayes factor		6.45

^a Corresponds to DSI given an identity matrix as a similarity matrix (assuming that there is no productivity gradient across the land-cover types)

high-elevation zones appeared to be underestimated, perhaps because small traditional paddies at high elevations were not detected. High similarity values between forest types may also account for the low DSI values in these areas. Considering that the species richness of damselflies

was not low near the border between lowlands and mountainous zones (the Ministry of Environment, Japan 2009), the underestimated heterogeneity in relatively high elevation zones may result in a lower correlation with species richness.

As the rate of farmland abandonment increases, the incorporation of differences among the three main ecosystem types will become highly relevant to the evaluation and prediction of the future status of agricultural landscapes (Queiroz et al. 2014). The ecological effects of land abandonment on biodiversity are context dependent. For example, abandoned paddies become either dry grassland or wetland (Osawa et al. 2013), and the difference between these two fates is important for multi-habitat dwellers that contribute to the biodiversity of agricultural landscapes because flooded rice paddies provide substantial bodies of water for aquatic organisms and multi-habitat dwellers (Kadoya et al. 2009). Hence, our approach should appropriately evaluate the effects of these differences in future agricultural landscapes.

However, our approach has room for improvement. Although we demonstrated that adding dissimilarity information improves the heterogeneity index MSI, the approach is not always easily applicable and the extent of improvement may be context dependent. Other geographic regions may require more or different information for improved model performance. For example, we used the NDVI in a particular season to differentiate terrestrial and inland water ecosystems. This may be effective in parts of Asia where rice paddies are dominant, but it may not be effective in Europe, where meadows and other croplands are dominant and should be differentiated by other information and procedures. Adding more information, other than the NDVI, to calculate ecological dissimilarity considering ecological knowledge of focal regions will improve the DSI.

In addition, comparisons with other heterogeneity indices remain a challenge for future study. For example, some edge indices, such as the total edge contrast index (TECI), incorporate environmental contrast between habitat patches of landscapes (McGarigal and Marks 1995) and may be highly correlated with multi-habitat dwellers. Nevertheless, the utility of the DSI and these edge indices may differ and be dependent on focal species. The proportion of areas of available habitat types within a landscape, indicated by diversity indices, including DSI, assumes that the focal species move freely within a landscape and can reflect the diversity of habitat types in the landscape more directly. Thus, the DSI is expected to be highly correlated with data for various birds and/or flying insects if the spatial scale of the landscape is appropriately set. TECI may be correlated with data for species with low dispersal ability, such as frogs. Furthermore, edge indices such as TECI can reflect the landscape configuration more directly than diversity indices and might be more negatively correlated with biodiversity for the focal species in more highly fragmented landscapes (e.g., Zhang and Zang 2011).

It is necessary to note that a set of similar habitat types in a landscape does not always negatively affect biodiversity, and some species benefit from homogeneous landscapes (Jeliazkov et al. 2016). The incorporation of such species may require another type of index.

CONCLUSION

Our application of a dissimilarity-based approach yielded similar results for (i) land-cover maps with coarse classification schemes covering a broad area and (ii) a national land-use map with a detailed classification scheme covering a single country, at least for damselflies. Therefore, our approach may provide an improved agricultural landscape heterogeneity index that is tightly associated with biodiversity when appropriate dissimilarity information is provided. We expect our approach to be effective and applicable at the national scale when concrete plans and actions will be implemented to meet international commitments to biodiversity conservation in agricultural landscapes. Diverse high-resolution remote-sensing data are becoming available (Jetz et al. 2012; Kays et al. 2015) and should provide adequate information for the validation and improvement of the DSI. Advances in computing power and data assimilation techniques may facilitate the statistical estimation of dissimilarity between land-use/land-cover types using distribution data for target taxa. The development of remote-sensing and GIS techniques will increase the spatial and temporal resolutions of land-use/land-cover maps and improve user accessibility. Thus, our approach to converting existing land-use/land-cover maps holds promise for future applications.

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