Journal for Nature Conservation 46 (2018) 66–78

Contents lists available at ScienceDirect

Journal for Nature Conservation

journal homepage: www.elsevier.com/locate/jnc

The role of biodiversity data in High Nature Value Farmland areas identification process: A case study in Mediterranean agrosystems

Tommaso Campedelli[a,b,*], Gianpiero Calvi[a,c], Patrizia Rossi[d], Antonella Trisorio[e], Guido Tellini Florenzano[a,b]

[a] Italian Common Birds Monitoring Program, Italy
[b] DREAM Italia, Via Garibaldi 3, I-52015 Pratovecchio Stia, AR, Italy
[c] Studio Pteryx, Via Risorgimento 9, I-20060 Basiano, MI, Italy
[d] Lega Italiana Protezione Uccelli (LIPU/BirdLife Italia), Via Udine 3/a, I-43122, Parma, PR, Italy
[e] CREA, Research Centre for Agricultural Policies and Bioeconomy, Via Po, 14, 00198 Roma, Italy

ARTICLE INFO

Keywords:
High nature value farming
Farmland birds
Species richness
Italian common birds monitoring program
Spatial distribution models
Mediterranean steppes
Italian rural network

ABSTRACT

The concept of High Nature Value Farmland (HNVF) was introduced in the early 1990s to highlight the crucial role of low intensity farming systems for the conservation of biodiversity in Europe. HNVF is a biodiversity indicator and the maintenance or the enhancement of HNVF is a goal of the EU's rural development policy. Several different approaches currently exist for identifying such areas, and a number of studies have shown that outcomes have often been unsatisfactory, at least as concerns biodiversity conservation. In this study, we use birds as indicators to assess the correlation between HNVF types identified according to the land cover approach and farmland areas important for biodiversity in Apulia, a southern Italian region that is among the most important in the Mediterranean area for farmland biodiversity. Our results suggest that unless the current land cover approach – which is mainly based on criteria relating to vegetation types and landscape structure – is accompanied by an objective analysis of local biodiversity levels, it risks excluding from HNVF some of the most important areas for biodiversity, thus reducing indicator effectiveness because of the lack of a proper assessment of HNVF extent and quality. Thus, our study shows a possible method to better identify HNVF type 3, thus increasing the effectiveness of the HNVF indicator.

1. Introduction

The concept of High Nature Value Farmland (HNVF) was introduced in the early 1990s to highlight the crucial role of low intensity agriculture for the conservation of biodiversity in Europe (Baldock, Beaufoy, Bennet, & Clark, 1993; Beaufoy, Baldock, & Clark, 1994). Andersen et al. (2003) identified three types of HNVF: (1) farmland with a high proportion of semi-natural vegetation (e.g. natural grazing land); (2) farmland with a mosaic of low intensity agriculture and natural and structural elements (e.g. hedgerows, dry stone walls, woodlots, rows of trees, small watercourses, etc.); and, (3) farmland supporting rare species or a high proportion of European or global populations. HNVF acquired particular importance in 2005 when it was adopted as an indicator by the Common Monitoring and Evaluation Framework of the Rural Development Programmes (European Council, 2006). Although the European Commission has drafted guidelines for its identification (European Communities, 2009), it did not provide a common method for identifying HNVF (Lomba, Alves, Jongman, & McCracken, 2015; Lomba et al., 2014; van Doorn & Elbersen, 2012) thus opting for a flexible system allowing Member States to assess HNVF types (common parameters) using data and methodology appropriate to their specific situation.

One of the main issues in the whole assessment process is the integration of criteria referring to distinct conceptual and methodological problems: on one hand HNVF types 1 and 2 address the need to select areas with the prevalence of low-intensity farming systems, supposed to support high levels of biodiversity; on the other hand, HNVF type 3 directly refers to areas supporting high levels of biodiversity regardless of land use types. This is probably one of the causes that hinder the ability to reach a common HNVF assessment.

Indeed, a great degree of diversity can be found between the various methods used by European Countries for assessing HNV farming (Pepiette, 2011; Lomba et al., 2014), due to the extreme variability both in the availability of data and in the characteristics of the Countries.

* Corresponding author at: Italian Common Birds Monitoring Program, Italy.
E-mail address: campedelli@dream-italia.net (T. Campedelli).

https://doi.org/10.1016/j.jnc.2018.09.002
Received 8 August 2017; Received in revised form 10 September 2018; Accepted 10 September 2018
1617-1381/ © 2018 Elsevier GmbH. All rights reserved.

According to Pepiette (2011), out of the 24 assessments carried out at national or regional level, 13 were based on maps of land cover which were combined, almost in all cases, with other sources of information, mainly regarding the farming systems; in 12 cases data on biodiversity were used, in terms of designated sites at European and/or national level or habitat type. In only one case (Germany) the method was based on a sample-survey approach. On the types of HNV farmland, identified according to Andersen et al. (2003), the greatest difficulties emerged for type 2, which was detected in less than 20% of cases, even though in more than half the cases, some description of it was provided. Type 1 was detected in almost all cases (18) and type 3 in more than 50% of cases. Although the methods are based on some rather divergent approaches, especially concerning the type of data used and how they were processed (Acebes, Pereira, & Oñate, 2016; Almeida, Guerra, & Pinto-Correia, 2013; Brunbjerg et al., 2016), the main difference lies in the use – or lack thereof – of indicators related to biodiversity, especially the presence of animal or plant species of conservation interest. The type of indicator used significantly influences the HNVF identification process, and the use of different methods can lead to widely divergent results.

According to case studies carried out at regional scale in Italy (Forconi et al., 2010), specifically in Tuscany and Sicily - two areas of great importance for farmland biodiversity (ARPA Sicilia, 2008) – the lack of use of biodiversity indicators resulted in the non-designation as HNVF of the most part of agricultural landscapes of greater naturalistic value. In particular, they excluded the so-called cereal steppes, extensive cereal cropland with low landscape diversity, which provide habitat for many typical steppic species (Bellini, Cillo, Giacoia, & Gustin, 2008; Campedelli, Londi, La Gioia, Frassanito, & Florenzano, 2015), especially birds, many of which - such as Lesser Kestrel *Falco naumanni*, Eurasian Skylark *Alauda arvensis*, Greater Short-toed Lark *Calandrella brachydactyla*, and Calandra Lark *Melanocorypha calandra* (BirdLife International, 2015; Burfield, 2005) - have an unfavourable conservation status or are threatened. Similar results emerge from other studies, both elsewhere in Italy - such as in the Marche region, where HNVF were identified exclusively on the basis of vegetation structure and characteristics (Galdenzi, Pesaresi, Casavecchia, Zivkovic, & Biondi, 2012) - and in France, where statistical information was used (Pointereau et al., 2007). In the Marche region, Morelli and Girardello (2013) and Morelli, Jerzak, and Tryjanowski, (2014) studied the relationship between HNVF and breeding bird species: they found that while HNVF generally coincided with agricultural mosaics, they did not include areas of species of conservation interest, such as Eurasian Skylark and Ortolan Bunting *Emberiza hortulana*, which are tied to less diversified agricultural landscapes. The French case study is also of great interest: Doxa et al. (2010); Doxa, Paracchini, Pointereau, Devictor, & & F, 2012 compared certain bird population parameters in areas with varying degrees of HNVF extent - including areas that are not officially recognized as HNVF but which the authors deemed potential HNVF of national interest. They found a positive correlation between population trends for farmland birds (Farmland Bird Index, FBI) - including both generalist and specialist species - and the extent of HNVF. A similar correlation exists with another index, the Community Specialization Index (CSI, Julliard, Clavel, Devictor, Jiguet, & Couvet, 2006). Nevertheless, if we consider farmland birds only (the CSI assesses the degree of specialization of a community regardless of habitat type), the correlation is negative for many of them (Eurasian Skylark, Tawny Pipit *Anthus campestris,* Eurasian Stone-curlew *Burhinus oedicnemus,* Grey Partridge *Perdix perdix,* Ortolan Bunting and Corn Bunting *Embriza calandra*). As the authors themselves point out, this is due to the fact that simpler agricultural landscapes lacking in structural elements - which are the key habitats for these species - have been excluded from HNVF.

These results suggest that identifying HNVF solely on the basis of vegetation characteristics, as many methods currently do, results in only heterogeneous landscapes being chosen, in addition to natural habitats used for livestock (meadows and semi-natural pastures). This might exclude agricultural landscapes that, even if they are not intensive but rich in biodiversity, are not identified as HNVF.

However, the use of biodiversity indicators is not always a response to this identification problem: in a German case study (Aue, Diekötter, Gottschalk, Wolters, & Hotes, 2014), where criteria for identifying HNVF included the presence of plant species of conservation interest, the farmland bird species most closely correlated with HNVF were generalists (bird data were derived from the German Common Breeding Bird Survey scheme, using a methodological approach very similar to our own). Additionally, in many cases, such as in Italy (Rete Rurale Nazionale, 2014; Trisorio, De Natale, & Pignatti, 2013), the biodiversity indicator was merely the richness of species associated with Natura 2000 network sites. As shown in Italy (Campedelli, Tellini Florenzano, Londi, Cutini, & Fornasari, 2010) and Spain (Traba, García de la Morena, Morales, & Suárez, 2007), these sites only protect a subset of habitats, with serious gaps in farmland environments, especially extensive ones such as cereal crops. In most of the Mediterranean area, these habitats have largely replaced original steppe habitats and are particularly important for the conservation of threatened species (Buisson & Dutoit, 2006; Campedelli et al., 2015).

In the last few years progress has been made in the development of methods for HNVF identification, based on increased understanding of the concept of HNVF. Many gaps still have to be filled, nevertheless improvements in the use of biodiversity indicators to overcome some of the previously described limits have occurred (European Commission, 2016).

The aim of our study is to assess to which extent HNVF identified in Italy (Rete Rurale Nazionale, 2014) overlaps with the most important areas for breeding birds tied to typical Mediterranean farmland habitats. Our study also aims to show the usefulness of relying on existing biodiversity monitoring programmes in order to improve the assessment of HNVF. For this aim we analysed the correlation between HNVF identified in the Apulia region according to the RRN (Italian Rural Network) method (Rete Rurale Nazionale, 2014), and farmland areas important for biodiversity, identified by using common breeding birds as an indicator.

2. Methods

2.1. Study area

Apulia (Fig. 1) is a southern Italian region with a surface area of about 19,350 km2, over 80% of which is farmland, and 30% non-irrigated arable crops, essentially cereal crops. In addition, there are almost 1100 km2 of pastures (almost 6%), including Mediterranean steppe, classified as habitat of conservation interest by the EU Directive UE 92/43/EEC (habitat codes 6210 and 6220). Apulia hosts some of the largest and best-preserved continuous expanses of Mediterranean steppe in the entire basin.

2.2. HNVF indicator

In Italy, HNVF were identified using an integrated approach, based on land cover data derived from sampling (AGRIT2010 survey, Ministry of Agricultural, Food, and Forestry Policies), combined with data from Corine Land Cover and the national database of Natura 2000 sites (Rete Rurale Nazionale, 2014). The analysis, which focused on areas of low-intensity farmland, was conducted at the smallest scale for which data were available for all three layers of information, 10 × 10 km cells. The classification of potential HNVF was based on three indicators corresponding to the three types defined by Andersen et al. (2003): 1) percentage of cover of permanent meadows and pastures; 2) presence of relevant “natural” landscape features (density of trees outside of forests and density of margins of natural and semi-natural areas); and, 3) number of species of conservation interest reported in Natura 2000

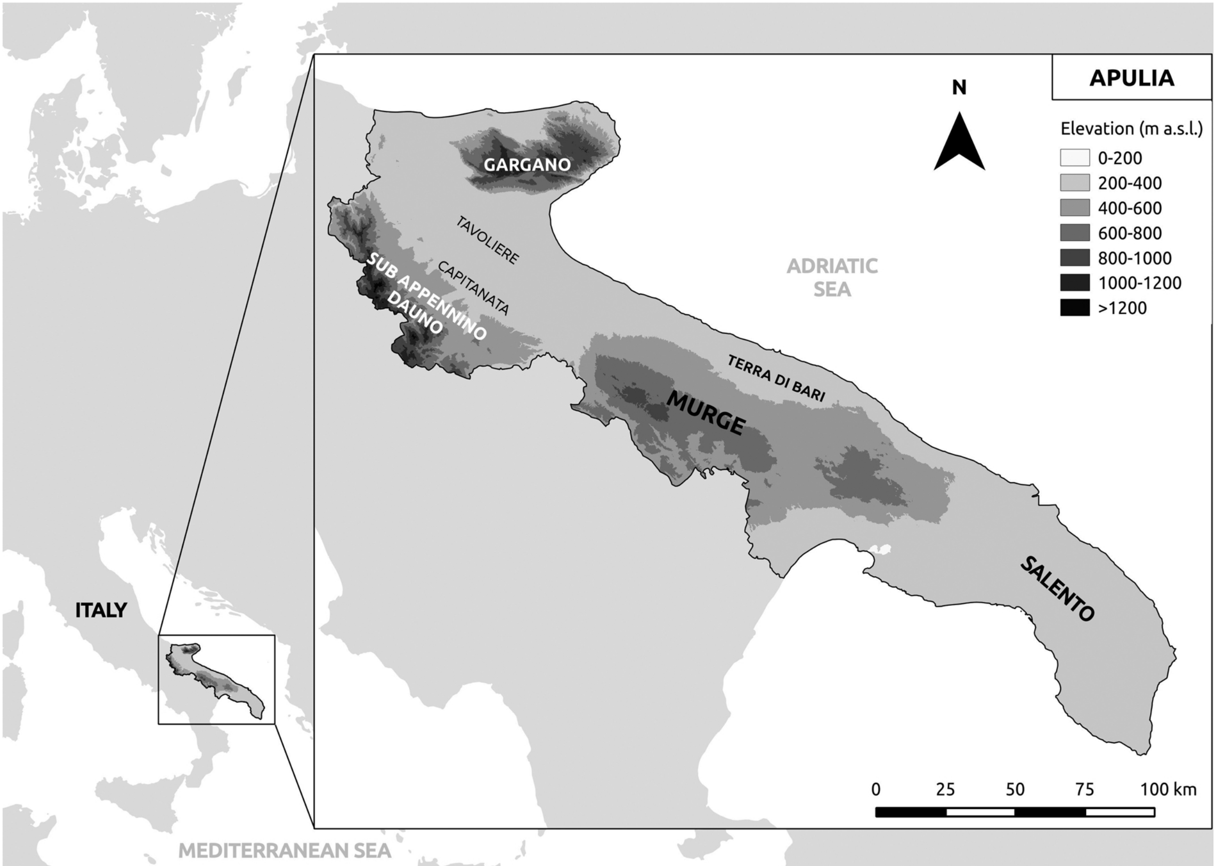

Fig. 1. Study area. In the detailed map of Apulia region are indicated names and positions of some sub-regional territories mentioned in the results and in the discussion.

sites. By combining the results of the criteria-based classification, and by attributing to each cell the highest class among those assigned on the basis of the individual criteria, the Italian agricultural landscapes have been classified in four HNVF classes: Low (L), Medium (M); High (H); and, Very High (VH). Overall, HNVF adds up to about 45% of agricultural land in Apulia, broken down as follows: 34% low value (L); 6% medium (M); 4% high (H); and, 1% very high (VH).

2.3. Bird data

Bird data was obtained from the Italian Common Birds Monitoring Program (ICBMP) database (Campedelli et al., 2012). Data pertaining to Apulia include a total of 31,502 records of 164 species collected in 2000–2014 in 1282 point count stations throughout the region (sampled every year between 15 May and 30 June). We then selected, on the basis of known ecological needs, a set of species tied to farmland, especially those typical of the Mediterranean area; the species we used are listed in Table 1.

2.4. Environmental data

The environmental variables used in all the analyses were obtained from the Apulia regional administration land use map (following standard CORINE land-cover map codes, www.sit.puglia.it), in addition to climatic and biogeographical variables. The Roughness Index, which describes the morphological variability of the landscape, was derived from a Digital Terrain Model (Apulia Region SIT, cell size 8 m). Land use variables and the Roughness Index were calculated using the Moving Window method (Dale et al., 2002) on raster maps at a scale of 100 m × 100 m. As a simple measure of environmental heterogeneity we chose the number of land-use categories (Atauri & de Lucio, 2001; Fahrig et al., 2011; Farina, 1997) because, in our opinion, in simplified landscapes such those of Apulia, the presence of a species and the overall bird species richness depend on the presence of land-use types, rather than on their relative extension. As a general rule, we calculated all variables within a 300 m radius from the census point. For some key-factors for farmland birds, we additionally evaluated their effect at a broader scale, namely within a 600 m radius (De Juana, 2005). The key-factors are: i) non irrigated arable land; ii) shrub and/or herbaceous vegetation; iii) land-use heterogeneity, as being the most important breeding habitat descriptors; and, iv) artificial surfaces, as a limiting factor for these species presence. The variables used are listed in Table 2.

2.5. Statistical analyses

Important areas for breeding birds were identified using two different approaches: a) those hosting the richest breeding bird communities, considering both the total number of species and only those breeding in typical Mediterranean farmlands; and, b) those being suitable for species of conservation concern.

2.5.1. Community parameters

In calculating overall richness and richness for Mediterranean farmland species, we tried to maximize the spatial and temporal representativeness of available data, dividing the timeframe of the database (2000–2014) into two sub-periods: 2000–2008 and 2009-2014. We made this choice because starting from 2009 the bird monitoring programme was characterized by an important increase in the sampling effort.

Table 1
Farmland species monitored by ICBMP in Apulia. For each species we report the number of observations and the number of sites where the species were detected. The SDM column shows species for which we carried out Spatial Distribution Models.

Species		n. observations	n. sites	SDM
White Stork	*Ciconia ciconia*	2	2	
Black Kite	*Milvus migrans*	21	16	
Red Kite	*Milvus milvus*	7	7	
Egyptian Vulture	*Neophron percnopterus*	1	1	
Montagu's Harrier	*Circus pygargus*	11	10	
Lesser Kestrel	*Falco naumanni*	213	106	x
Common Kestrel	*Falco tinnunculus*	473	309	
Lanner Falcon	*Falco biarmicus*	2	2	
Common Quail	*Coturnix coturnix*	137	86	
Eurasian Stone-curlew	*Burhinus oedicnemus*	7	6	
European Roller	*Coracias garrulus*	21	12	
Calandra Lark	*Melanocorypha calandra*	252	118	x
Greater Short-toed Lark	*Calandrella brachydactyla*	250	125	x
Crested Lark	*Galerida cristata*	2017	827	
Woodlark	*Lullula arborea*	46	38	x
Skylark	*Alauda arvensis*	211	126	x
Tawny Pipit	*Anthus campestris*	8	8	
European Stonechat	*Saxicola rubicola*	199	151	x
Black-eared Wheatear	*Oenanthe hispanica*	33	22	
Zitting Cisticola	*Cisticola juncidis*	827	518	
Spectacled Warbler	*Sylvia conspicillata*	16	14	
Red-backed Shrike	*Lanius collurio*	20	16	
Lesser Grey Shrike	*Lanius minor*	53	46	x
Woodchat Shrike	*Lanius senator*	92	80	x
Rock Sparrow	*Petronia petronia*	4	3	
Black-headed Bunting	*Emberiza melanocephala*	8	8	
Corn Bunting	*Emberiza calandra*	868	374	

We then selected the 722 point count stations that were visited at least once in each period (Fig. 2). For each point we then selected one visit for each period; for points that were visited more than once in the same period, selection was randomized. For each point, we then selected total species richness (S_tot), namely the total number of species recorded over the two visits, and farmland species richness (S_farm), selecting only those species listed in Table 1.

For each richness parameter we prepared a spatial distribution model using GLM (Generalized Linear Models; McCullagh & Nedler, 1989) and assuming a Poisson distribution for residuals.

We conducted preliminary analyses to assess the presence of multicollinearity between variables (Dormann et al., 2013) or spatial autocorrelation of residuals (Dormann et al., 2007). These analyses showed that the simultaneous presence in the models of non irrigated arable lands, measured at both scales, (variable codes: Crop and Crop_600), and olive groves (variable code: Oliv) generates variance inflation problems (Variance Inflation Factor > 5 for both variables in both models). The Variance Inflation Factors (VIF) measures how much the variance of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related (Dormann et al., 2013). We therefore decided to retain only one of the two variables for each analysis (see below).

In each model, residuals were spatially autocorrelated (Moran's $I > 0.04$; $P < 0.001$). Of the various available models to account for spatial autocorrelation (Dormann et al., 2007), the Spatial Eigenvector Mapping model, hereafter SEVM, has shown good flexibility and performance in estimating model parameters (Dormann et al., 2007; Mauricio Bini et al., 2009; Peres-Neto & Legendre, 2010). This method is based on the concept that the spatial structure of data can be expressed in explanatory variables (eigenvectors) that capture spatial effects at various scales. Among the possible implementations of SEVM, we chose the one that calls for the generation of eigenvectors using Moran's Eigenvector Mapping (Dray, Legendre, & Peres-Neto, 2006; Peres-Neto & Legendre, 2010; Siesa, Manenti, Padoa-Schioppa, De Bernardi, & Ficetola, 2011).

The analyses thus adopted the following procedure, based in part on Le Rest, Pinaud, and Bretagnolle, (2013): 1) extraction of eigenvectors starting from the empty models (no predictors); 2) selection of the best models according to the Akaike Information Criterion corrected for small samples (AICc; Burnham & Anderson, 2002), using as predictors environmental variables (Table 2) and spatial eigenvectors; and, 3) parameters estimation through model averaging (Burnham & Anderson, 2002).

Table 2
List of environmental variables tested in the Spatial Distribution Models.

Variable name	Corine Land Cover Map Code	Variable description
climatic variables		
Ombr.		Ombrotype, climatic classification based on annual rainfall (Blasi et al. 2004)
morphological variables		
Rough.		Roughness Index, estimated at a 200 m scale
land use variables		
Urb	1	Extension of artificial surfaces (within 300 m)
Urb_600	1	Extension of artificial surfaces (within 600 m)
Crop	211	Extension of non irrigated arable land (within 300 m)
Crop_600	211	Extension of non irrigated arable land (within 600 m)
I_Crop	212	Extension of permanently irrigated land (within 300 m)
Vine	221	Extension of vineyards (within 300 m)
Orch	222	Extension of orchards (within 300 m)
Oliv	223	Extension of olive groves (within 300 m)
H_Lan	24	Extension of heterogeneous agricultural areas (within 300 m)
Wood	31	Extension of woodlands (within 300 m)
Pas	321	Extension of pastures (within 300 m)
Srb	32	Extension of shrub and/or herbaceous vegetation association (within 300 m)
Srb_600	32	Extension of shrub and/or herbaceous vegetation association (within 600 m)
Bare	33	Extension of open spaces with little or no vegetation (within 300 m)
Wetl	4	Extension of wetlands (within 300 m)
Lake	5	Extension of water bodies (within 300 m)
Het		Land-use heterogeneity (no. land-use categories within 300 m)
Het_600		Land-use heterogeneity (no. land-use categories within 600 m)
biogeographic variables		
Grad		Longitudinal gradient

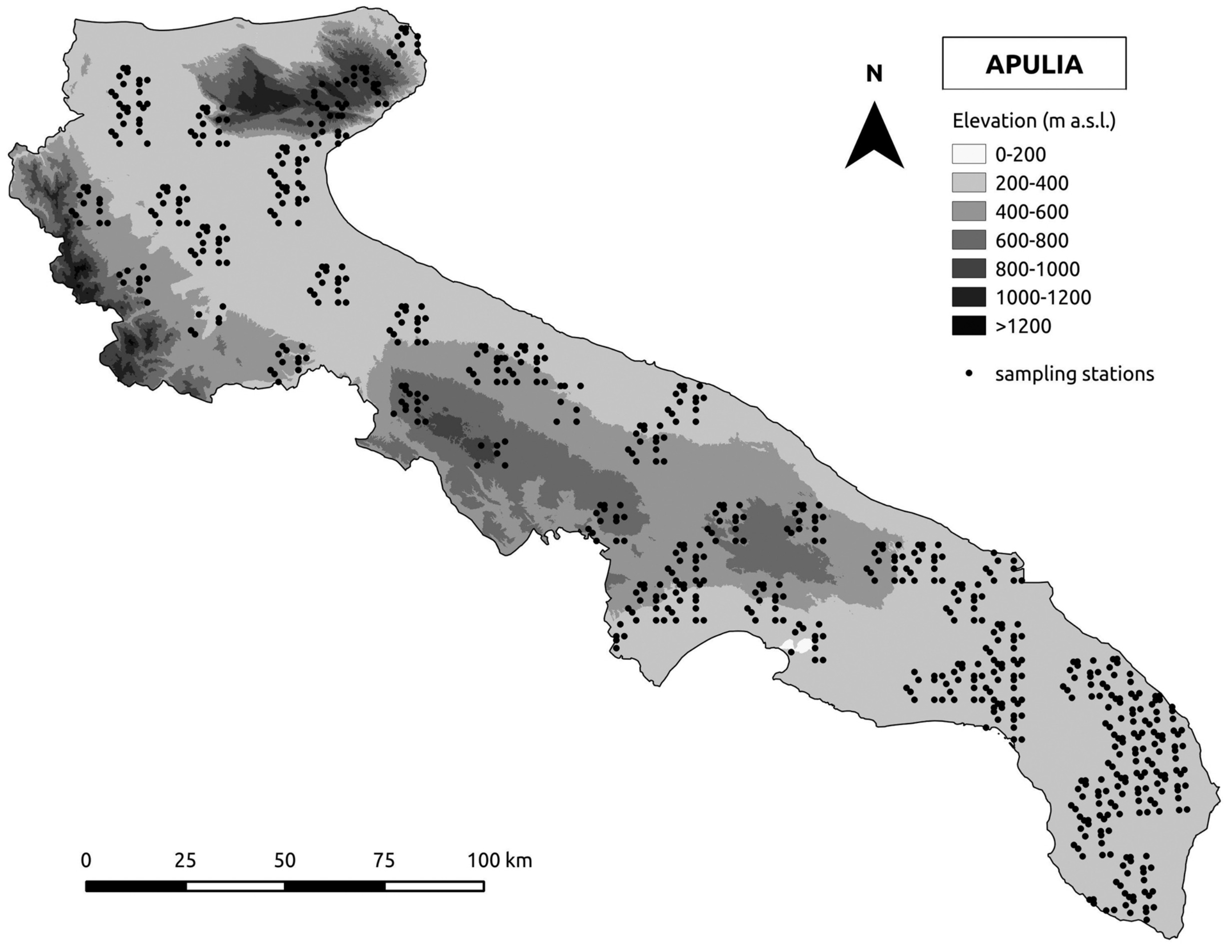

Fig. 2. Distribution of the 906 sampling points used for the analyses.

All analyses on community parameters were performed using R software (R Core Team, 2017).

We decided to discard some predictors before running the analyses in order to limit the number of possible models; this grows exponentially with the number of predictors (number of possible models = 2 N, where N is the number of predictors). The variables omitted were those that led to the least significant single-variable Poisson GLM (LRT with $P > 0.5$) and, at the same time, to the biggest increase in AICc with respect to the null model. In this way, we tried to leave out the variables that were presumably less linked to species richness.

We used the same criterion to decide which variable to retain between non irrigated arable lands and olive groves (we retained non irrigated arable lands for Mediterranean farmland species richness and olive groves for total species richness) and which radius to consider (300 m or 600 m) for the variables in the Mediterranean farmland species analyses.

For both species richness measures we ran all possible models through the 'dredge' function in MuMIn package (Bartoń, 2016) and we ordered the models according to their AICc value.

The use of AIC as selection criterion may select overly complex models, therefore we considered a complex model as a candidate one only if there was not a simpler nested model with lower AICc (Richards, Whittingham, & Stephens, 2011).

We obtained model-averaged parameter estimates for the variables contained in the best models (with ΔAICc < 2). We conducted analyses on standardized predictors in order to show directly comparable model-coefficients.

As a measure of predictive performance for the species richness models, we used the Pearson's correlation coefficient between fitted and observed values (CFO, Zheng & Agresti, 2000). CFO is easily interpretable (values bounded between 0 and 1) and is highly correlated with other well known measures of predictive performance like, for instance, adjusted cross validation of prediction error (CVPE): we tested this statement for total species richness (correlation test between CFO and CVPE for all candidate models: mean $r = -0.892$, P always < 0.001, $N = 77$). Moreover, CFO does not vary at each calculation like CVPE does.

We used model-averaged coefficients to draft two predictive richness distribution charts, spatializing eigenvectors via ordinary kriging (N'Goran et al., 2012).

2.5.2. Species of conservation concern

The species for which we developed habitat suitability models were selected among those tied to farmland habitats (Table 1) in accordance with two criteria: 1) conservation interest, thus all species in Annex I of the Birds Directive 2009/147/EC (Lesser Kestrel, Calandra Lark, Greater Short-toed Lark, Woodlark, Lesser Grey Shrike) or with highly negative population trends (according to Campedelli et al., 2012) at the national level (European Skylark, European Stonechat, Woodchat Shrike); and, 2) size of the sample, with the minimum threshold set to 40 different localizations over the entire survey period (2000–2014), considering all the available data.

Habitat suitability models for individual species were built with MaxEnt (Phillips & Dudík, 2008; Phillips, Anderson, & Schapire, 2006), an analytical method that uses presence data only, and tests the effects of the same environmental variables used for richness (Table 2). MaxEnt is often used in conservation biology and ecology, since it provides reliable results even with limited samples, often the case for rare species (Papeş & Gaubert, 2007; Pearson, Raxworthy, Nakamura, & Townsend Peterson, 2007). Although MaxEnt is better than other models in accounting for uneven sampling levels, the presence of strong biases in the distribution of samples can negatively affect the performance of the models and the ability to interpret the obtained results (Kramer-Schadt et al., 2013; Syfert, Smith, & Coomes, 2013). To reduce the potential effects of uneven sampling, such as those caused by sampling units that are not evenly distributed among the various habitats, Fourcade, Engler, Rödder, and Secondi, (2014) proposed four different methods, including the use of a bias file; this is the model we chose. A bias file is an information layer, much like those normally used in ecological analyses (e.g. land use type, DEM), which contains the sampling intensity in each spatial unit as georeferenced information. The bias file was built using the overall number of point counts carried out in each grid of the ICBMP project (10 × 10 km squares). MaxEnt was used at its default settings.

In order to rule out the presence of correlations between variables, we carried out a Spearman correlation analysis; in all cases - with the exception of land use variables calculated at two different spatial scales which were never used simultaneously - the Spearman correlation was never higher than 0.5. The models were built using a step procedure, eliminating the variable whose contribution was null. For each species, models were selected according to an informative-theoretical approach based on the AICc value (Burnham & Anderson, 2002). The models were built using a subset of available data, selected at random and amounting to 80% of the total. As suggested by Warren and Seifert (2011), validation was made using the totality of the available sample.

Species models were evaluated using validation datasets. Model evaluation should deal with two aspects, the performance and the significance of the model (Peterson et al., 2011; Tarjuelo, Morales, Traba, & Delgado, 2014). Model performance shows how well, or poorly, the model classifies absence, or better pseudo-absence, and presence. Omission error rate (OER, the proportion of presence occurrence records of the evaluation dataset that fall in an area predicted as unsuitable for the species) was used as a measure of model performance, expecting low omission rates for good models (Peterson et al., 2011; Tarjuelo et al., 2014). This measure of model performance was selected because it does not require true absence records, as the MaxEnt software does (Peterson et al., 2011; Tarjuelo et al., 2014). To assess model significance, i.e. whether the model predicts presence from the evaluation dataset better than expected under random predictions (Peterson et al., 2011), we performed one-tailed binomial tests (one per model) to evaluate whether the proportion of correctly classified occurrences differs from the proportion of area predicted as presence by the model (Tarjuelo et al., 2014).

The habitat suitability maps prepared for each species were overlaid summing the value of the MaxEnt logistic output (suitability values) in order to identify the most suitable areas for Mediterranean farmland species.

2.6. Assessment of HNVF

In order to assess the extent to which areas of importance for farmland species of conservation interest and areas with the richest bird communities are represented in the various HNVF classes, we applied a Kruskal-Wallis one-way ANOVA: for each species we compared the median value of suitability as represented by the MaxEnt logistic output; at the same time for the two community parameters (S_tot and S_farm) we compared the median number of predicted species. The comparison was made by sub-dividing the spatial units into three classes on the basis of the HNV value: a) low, b) medium and c) high or very high (these two categories were lumped as their number would have been too low otherwise). In cases in which the variance test found a significant difference, we used a Bonferroni-corrected Conover post-hoc test (Conover, 1999) to identify the difference between the three groups.

3. Results

3.1. General results

Data used to analyse species richness contained information concerning 109 species (see supplementary material): 89 species were detected between 2000 and 2008 and 95 between 2009 and 2014. The median number of detected species per point count was 7 between 2000 and 2008 (maximum = 23) and 8 between 2009 and 2014 (maximum = 18). Total species richness was on average higher in the second period (Wilcoxon signed rank test: $V = 63,651$; $P < 0.001$). During selected point counts 22 species of typical Mediterranean farmland birds were detected (19 in the first period and 20 in the second one). The median number of these species detected during a point count (1) did not vary between periods, with maximum values of 7 between 2000 and 2008 and 6 between 2009 and 2014.

3.2. Community parameters

Through the analyses of total species richness we identified seven most supported models (ΔAICc < 2 – Table 3). For all of these models variance inflation was not an issue (VIF always < 2) as well as spatial autocorrelation (for all models Moran's I test $P > 0.437$).

Looking at the full averaged coefficients (Table 4) we can argue that

Table 3
Best models describing variation in species richness on the basis of environmental variables. Models are ranked according to their ΔAICc; the model with the lowest ΔAICc is the best AICc model.

Model description	df	AICc	Δ AICc	w
Total species richness				
Het + Wood + SEVs(2) + Rough + Ombr + Urb + Orch	9	3505.75	0.000	0.2187
Het + Wood + SEVs(2) + Rough + Ombr + Orch	8	3506.04	0.290	0.1892
Het + Wood + SEVs(2) + Rough + Urb + Orch	8	3506.55	0.799	0.1467
Het + Wood + SEVs(2) + Rough + Ombr + Urb	8	3506.69	0.932	0.1373
Het + Wood + SEVs(2) + Rough + Orch	7	3507.12	1.368	0.1103
Het + Wood + SEVs(2) + Rough + Urb	7	3507.33	1.574	0.0996
Het + Wood + SEVs(2) + Rough + Ombr	7	3507.36	1.602	0.0982
Mediterranean farmland species richness				
Urb_600 + Crop_600 + I_Crop + Wood + PAS + SEVs(5) + H_LAN	12	2057.99	0.000	0.2763
Urb_600 + Crop_600 + I_Crop + Wood + PAS + SEVs(5)	11	2058.01	0.018	0.2739
Urb_600 + Crop_600 + I_Crop + Wood + PAS + SEVs(4) + H_LAN	11	2058.31	0.322	0.2352
Urb_600 + Crop_600 + I_Crop + Wood + PAS + SEVs(4)	10	2058.50	0.506	0.2146

AICc, Akaike information criterion corrected for the dimension of sample; ΔAICc, difference between the AICc of each model and the AICc of the best model; w, AICc weight of the model; div.3, land use diversity within 300 m; SEVs(n) number of spatial eigenvectors. For the environmental parameters see Table 2.

Table 4
Full model-averaged parameters estimates with 95% CI limits and relative importance (RI) based upon most supported models (ΔAICc < 2) for total (S_tot) and farmland (S_farm) species richness. Number of spatial eigenvectors retained in the best models and the Pearson's Correlation between Fitted and Observed values (C.F.O.; Zheng & Agresti, 2000) are also reported.

			95% CI		
	Predictors	Estimate	lower	upper	RI
Total species richness (7 models) C.F.O. = 0.422	Het	**0.0384**	**0.0139**	**0.0629**	**1.00**
	Ombr	0.0136	−0.0142	0.0414	0.64
	Rough	**0.0295**	**0.0050**	**0.0540**	**1.00**
	Urb	−0.0113	−0.0367	0.0141	0.60
	Orch	0.0127	−0.0120	0.0374	0.66
	Wood	**0.0372**	**0.0134**	**0.0609**	**1.00**
	+ 2 spatial eigenvectors	**0.0327**	**0.0111**	**0.0543**	**1.00**
Mediterranean farmland species richness (4 models) C.F.O. = 0.711	Urb_600	**−0.2245**	**−0.3181**	**−0.1309**	**1.00**
	Crop_600	**0.3142**	**0.2531**	**0.3754**	**1.00**
	I_Crop	**0.1939**	**0.1501**	**0.2377**	**1.00**
	H_Lan	−0.0281	−0.1051	0.0490	0.51
	Wood	**−0.1185**	**−0.1991**	**−0.0379**	**1.00**
	Pas	**0.1542**	**0.1072**	**0.2012**	**1.00**
	+ 5 spatial eigenvectors	**0.0671**	**0.0189**	**0.1154**	**1.00**

total species richness is positively influenced by the land-use heterogeneity, by the landscape morphological variability, and by the extent of woodlands, the latter being very scarce in Apulia. Other predictors have been retained in some of the most supported models, but they seem to have a weak effect on total species richness: namely ombrotype, urban areas and orchards. The model for total species richness has a poor predictive performance (correlation between predicted and observed values, CFO = 0.422).

With regards to species richness for typical Mediterranean farmland birds, the analyses identified four most supported models (ΔAICc < 2 - Table 3). For all of these models variance inflation was not an issue (VIF always < 2) as well as spatial autocorrelation (for all models Moran's I test $P > 0.091$).

Non irrigated arable lands seem to be the most important factor in determining the distribution of these species, influencing positively species richness. Pastures and irrigated arable lands are other variables that seem to positively influence farmland species richness, even if with a smaller effect size. On the other hand the extent of urban areas and of woodlands show a negative influence on the outcome. The model for Mediterranean farmland species richness has a better predictive performance (correlation between predicted and observed values, CFO = 0.711). The information in the models translates into two maps that are largely contrasting (Figs. 3 and 4).

3.3. Species of conservation concern

The models for all eight species are all highly coherent from an ecological point of view, and successfully select the habitat parameters that best describe the breeding ecology and regional distribution of these species (Table 5).

Using AUC to assess the accuracy of predictive models (0.9–1 excellent, 0.8–0.9, good, 0.7–0.8 fair, 0.6–0.7 poor, 0.5–0.6 fail - Metz, 1978; Lüdemann, Grieger, Wurm, Wust, & Zimmer, 2006), one showed excellent predictive performance, four were good, two fair and one was poor.

The models with the worst predictive performance concerned species that, at least in Apulia, occur in a wide range of landscapes and habitats (e.g. European Stonechat and Woodchat Shrike). In such cases, it is objectively difficult to identify ecological parameters that can specifically identify the ecological preferences of these species; however these models have been very usefull as they successfully identified the geographic range of these species, as shown by the low OER value. Finally, all models show a high level of significance, never higher than 0.001.

On average, the most important predictive variable was arable land, which was present in six models, either with a positive effect (five models) or with a quadratic relation (one model). For Lesser Kestrel, Calandra Lark, Greater Short-toed Lark, Skylark and European Stonechat this variable was the most important one. All these species, with the exception of the Lesser Kestrel and European Stonechat, show positive relationships with the amount of arable land at larger scale, stressing their well known steppic-character. Another important predictive variable was the amount of urban area, particularly at broader scale: except for European Stonechat that shows a quadratic relationship, five species have a negative relationship with this variable: Calandra Lark, Woodlark, Skylark, Lesser Grey Shrike and Woodchat Shrike (for the last two species, Urb_600 was the most important predictor). Interestingly, urban areas seem to not affect negatively the presence of Greater Short-toed Lark, another iconic steppe-species of Mediterranean farmland. However, it is known that this species is less sensitive to human presence and it is able to adapt also in moderately urbanized landscapes (Campedelli et al., 2015). Another general negative effect, with few exceptions, concerns woodlands (three models), vineyards and olive groves (respectively three and four models each); these variables express the presence of arboreal vegetation, albeit in drastically different manners. The only species showing an important positive effect of these predictors are Woodlark (Wood) and Woodchat Shrike (Oliv). Other variable types have a smaller effect; it is interesting to note that land-use heterogeneity has no effect whatsoever.

The overall map incorporating those developed for each species (Fig. 5) clearly highlights three areas of particular interest for Mediterranean farmland species of conservation concern: the Gargano steppes, the rural landscapes of the Subappennino Dauno and Tavoliere, and finally the Murge area.

3.4. Assessment of HNVF

To evaluate the degree of similarity among the three output maps (total and farmland richness and overall suitable map), we performed a pixel by pixel Spearman rank correlation analysis. The total species richness model showed very low and negative correlation with the models based on typical Mediterranean farmland species (respectively $r = -0.324$ for richness and $r = -0.124$ for overall habitat suitability), which are instead highly correlated ($r = 0.859$).

To show the extent to which current HNVF classifications (Rete Rurale Nazionale, 2014) fits to farmland relevant for avifauna protection, and especially birds tied to Mediterranean farmland, Table 6 reports the results of a comparison between various classes of HNVF with regards to: habitat suitability values for individual species; and, for community parameters (total richness and farmland species richness).

Variance analysis shows significant differences in only two cases out of 10: total species richness, and at the individual species level only for Woodlark. Nevertheless, the post-hoc test never shows a prevalence for H-HH areas, which are never differentiated from medium-value (M) areas.

4. Discussion

Our study showed the importance of using biodiversity indicators to effectively identify High Nature Value Farmland. According to the results of the analyses, the most important farmland areas within the study area are the southern part of Gargano peninsula, Monti Dauni, Tavoliere, and Murge. These areas were identified using the two chosen analytical approaches: the first one is the identification of the richest avian communities, the second one is based on the ecological preferences of individual species of high conservation interest.

The fact that both approaches led to the identification of the same

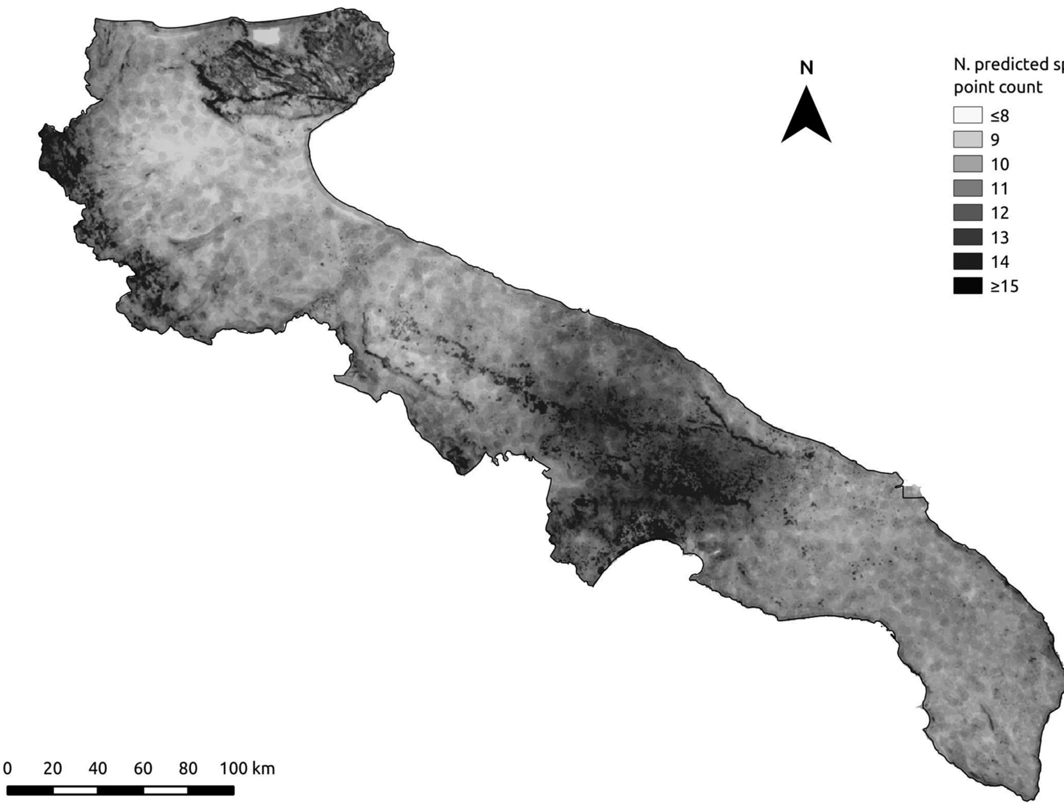

Fig. 3. Model prediction for total specie richness.

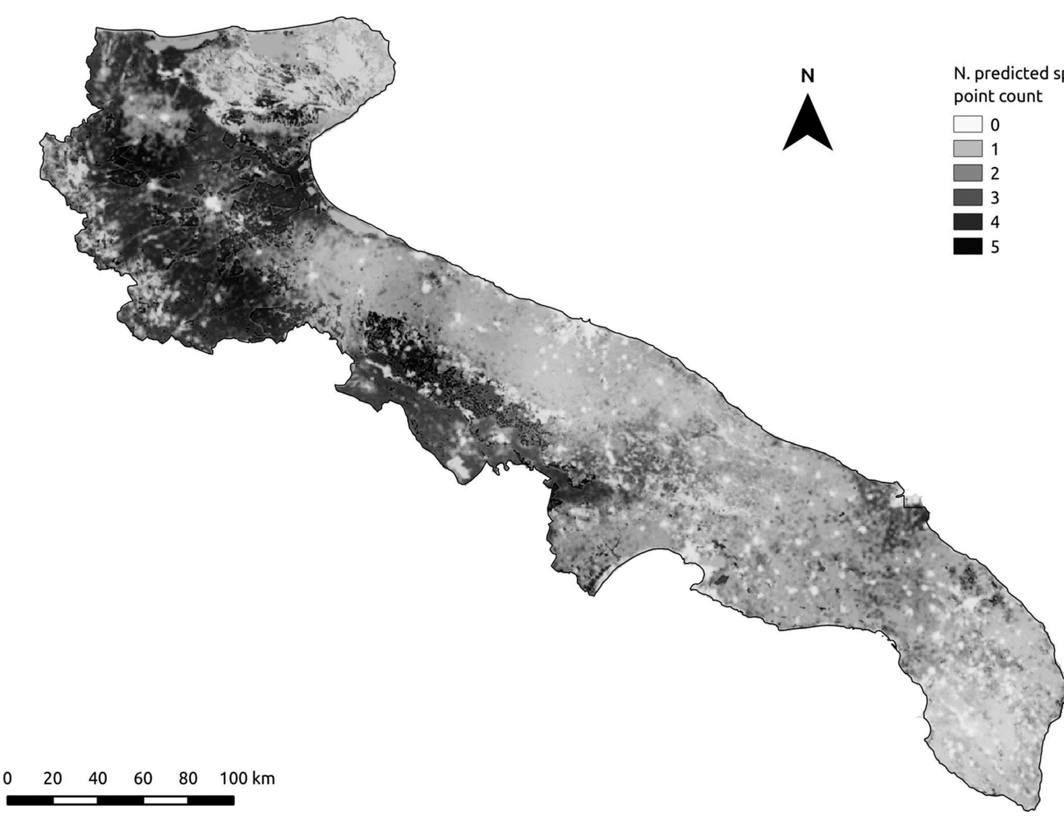

Fig. 4. Model prediction for richness of species linked to Mediterranean farming systems.

Table 5
Results of the MaxEnt models for farmland species. For each variable we report the percent contribution (only if bigger than 1%) and the sign of the relationships (brackets stand for a threshold effect). Moreover, for each model we report two parameters to describe their efficiency: the area under the ROC curve (AUC) and the Omission Error Test (OER). Species abbreviations: *F.n.* = Lesser Kestrel, *M.c.* = Calandra Lark, *C.b.* = Greater Short-toed Lark, *A.a.* = Skylark, *S.r.* = European Stonechat, *L.m.* = Lesser Grey Shrike, *L.s.* = Woodchat Shrike.).

	F.n.	*M.c.*	*C.b.*	*L.a.*	*A.a.*	*S.r.*	*L.m.*	*L.s.*
variables								
Rough.	−8.7	(4.5)		+ 27.5				
Urb				−13.4				
Urb_600		−2.2			−4.5	(27.2)	−54.9	−65.3
Crop	+ 47.5							
Crop_600		+ 47.9	+ 58		+ 37.4	(51.1)	+ 7.9	
I_Crop		(4.4)	(5.2)		+ 16.4			
Vine	−12.4	−5.7		−13.1				
Orch	(2.9)	+ 4.2			(2.0)			
Oliv	+ 3.9	−24.3	−21.8		−33.6		−4.1	+ 34.7
H_Lan				−5.9	−1.9			
Wood		(5.2)	−7.3	(3.0)	−3.3		−24.5	
Pas	+ 24.6							
Srb				−5.9				
Srb_600			−7.7			(21.7)	+ 8.6	
Grad				(31.0)				
model performance								
AUC	.857	.897	.863	.901	.854	.720	.797	.640
OER	.120	.037	.073	.024	.078	.154	.064	.197

areas reinforces the validity of the results. Moreover, these areas are of great importance for other Mediterranean farmland species that were excluded from our analyses either because they are rare, or because they are difficult to survey using ICBMP methodology. These include the Stone Curlew (*Burhinus oedicnemus*), which has one of its largest Italian breeding populations in Apulia (Brichetti & Fracasso, 2004), mostly in the Tavoliere, Murge, and Gargano steppes (Meschini, 2010), and several raptor species such as the Red Kite (*Milvus milvus*), whose population has been dropping in recent years and which is mostly found in the Monti Dauni and Gargano (Liuzzi et al., 2013). The last known haunts of the Little Bustard (*Tetrax tetrax*), a species now considered extinct in Apulia (Bux et al., 2013), are also included in the areas we identified (mainly Tavoliere and Gargano steppes). These remarks confirm both the validity of the results and that the use of indicator species, including common and widespread ones, is an effective method for biodiversity analyses.

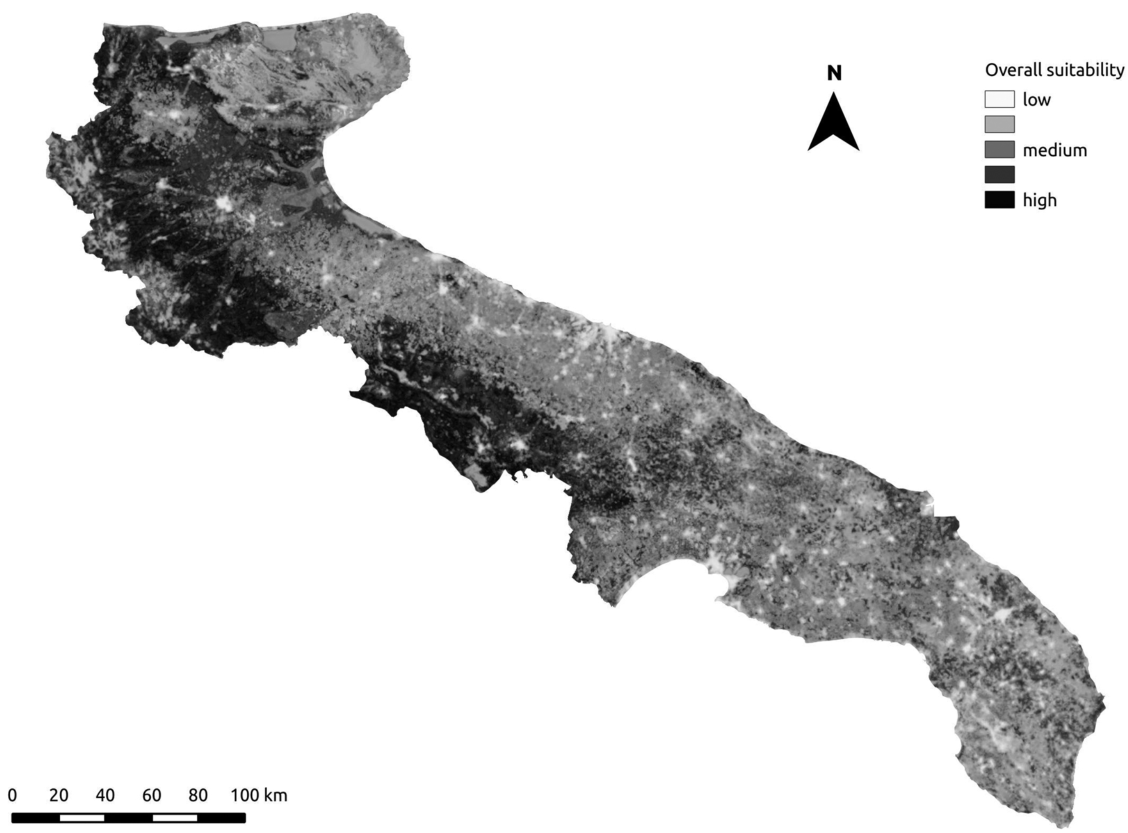

Fig. 5. Overall map summarizing habitat suitability (i.e sum of the logistic outputs of each species' model) for all species of conservation concern linked to Mediterranean farmland systems.

Table 6
Results of variance analysis; for each ornithological parameters we report the results of Kruskal-Wallis and Bonferroni-corrected Conover post-hoc tests. For the species, the values of different HVNF classes stand for the median value of their habitat suitability; for the richness models the values stand for the number of species expected by the models. (*High Nature Value Farmland abbreviations: L = Low; M = Medium; H = High; VH = Very High*).

	High Nature Value				
Species	L	M	H-VH	P Kruskal	groups
Falco naumanni	0.181	0.210	0.215	n.s.	
Melanocorypha calandra	0.029	0.154	0.083	n.s.	
Calandrella brachydactyla	0.115	0.204	0.139	n.s.	
Lullula arborea	0.121	0.253	0.393	< 0.001	ABB
Alauda arvensis	0.054	0.160	0.108	n.s.	
Saxicola torquatus	0.453	0.456	0.463	n.s.	
Lanius minor	0.426	0.421	0.388	n.s.	
Lanius senator	0.500	0.454	0.454	n.s.	
Richness					
S_farm	1.436	2.036	1.847	n.s.	
S_tot	10.753	11.442	11.101	< 0.01	A B AB

4.1. Community parameters

The total species richness model identified Apulia's most species rich areas at the broad scale (Liuzzi et al., 2013). However, total species richness is largely influenced by generalist species and by species characteristic of habitats other than farmland, surely not the best parameter to identify HNVF. This situation can be explained by the (pixel by pixel) correlation between the models' outputs.

A completely different situation affects the richness for typical Mediterranean farmland birds. In this case, the only important factors positively influencing the models are the extent of cereal non irrigated cropland coupled, to a lesser extent, with pastures and irrigated croplands. Moreover, it is worth noting the negative effect of woodland and urban areas extents. This situation leads to an almost completely different spatial pattern of species rich areas, if compared to the total richness one (Fig. 3 vs Fig. 4).

4.2. Species of conservation concern

The models for individual species are effective and the habitat suitability maps produced largely matched the known distribution for nearly all species (La Gioia, 2009; Liuzzi et al., 2013), showing that the habitat parameters used in drafting the ecological models do affect their distribution.

The Woodchat Shrike is the only species for which discrepancies emerge from its known distribution (Chiatante, Brambilla, & Bogliani, 2014), but these discrepancies, presumably caused by the different data collection methods, which in the study by Chiatante et al. (2014) were targeted specifically for Woodchat Shrikes, have little influence on the identification of the most important areas for farmland birds.

4.3. Assessment of HNVF

The differences between the three identified types of HNVF in relation to habitat suitability for individual species or predicted species richness are rather minor, yet highly indicative. Indeed, there are no significant differences in habitat suitability between HNVF identified types for species such as Calandra Lark, Greater Short-toed Lark, or Lesser Grey Shrike, which are considered of conservation interest at the European level (Birds Directive 2009/147/EC) and are closely tied to the presence of extensive non-irrigated arable land (cereal steppes) and landscapes with low habitat variability (cf. Table 5). These habitats are not among those identified by the first two types of HNVF, that rely on landscape structure and vegetation. The situation seems a little different for the Woodlark, a species tied to more varied habitats, which are included within type 2 of HNVF: for this species we found significance differences in mean habitat suitability between HNVF categories; however, areas classified as high value are not significantly differentiated from medium value areas.

The same results are obtained when we analyse the comparisons carried out with the two richness indexes. For farmland bird richness, there is no significant difference between the three classes of HNVF; for total richness, which is higher in areas of greater land-use heterogeneity (Field et al., 2009; Stein, Gerstner, & Kreft, 2014), the situation appears better in H-HH areas even if they are not distinguished from medium-value areas (M).

Taken as a whole, these comparisons indicate that, in Apulia, HNVF selection and evaluation criteria failed to identify the most important areas for Mediterranean farmland birds, and thus for species of conservation interest, as required by type 3 HNVF "*farmland supporting rare species or a high diversity of species of European or global interest*" (Andersen et al., 2003).

This situation is caused by two factors: the first concerns the nature of the first two criteria, namely the selection of particular crop and landscape types linked to HNVF indicators 1 and 2, while the second has to do with the chosen application of the third criterion.

Concerning the first two types of HNVF, as already stated in the introduction, they have been formulated to pinpoint low-intensity farming systems supposed to support high levels of biodiversity. On the other hand HNVF type 3 should identify farmlands supporting rare species or a high proportion of species populations regardless of land-use type. It could be difficult to integrate these different conceptual frameworks. Looking at HNVF types 1 and 2 in our case study, it is evident that their poor representativeness in terms of biodiversity depends on the failure to include cereal cropland among the AGRIT land cover classes supposed to be farmed at low intensity and therefore included in the process of HNVF type 2 identification (Rete Rurale Nazionale, 2014).

If we analyse the distribution of the areas with the largest extent of HNVF (Fig. 6), we can see that it does not include the most important areas for Mediterranean farmland birds identified in this study (Figs. 4 and 5).

This map clearly shows that the most important category, at least in terms of surface area, is represented by olive groves, which are particularly widespread in the southern part of the region (Salento). When managed properly (e.g. low chemical input, ploughing to get an understory of many annual flowers), olive groves can provide important habitats for many animal species (Davy, Russo, & Fenton, 2007). However, when using birds as indicators, they are clearly less important than cereal steppes.

The other factor that determines the complementarity between high-biodiversity areas and HNVF is criterion 3, which was meant to take into consideration more explicit biodiversity criteria tied to the presence of species of conservation interest. As it is often the case, Italian HNVF (Rete Rurale Nazionale, 2014) was identified using, as criterion 3, the richness of species of conservation concern as reported by Natura 2000 site forms. While these are truly representative of the most important areas for biodiversity conservation in habitats such as forests and wetlands, and protected areas, Natura 2000 sites in general are scarcely representative of agroecosystems (Campedelli et al., 2010). Indeed, in spite of their acknowledged value in terms of biodiversity, landscape, history, culture, and ecosystem services (Swinton, Lupi, Robertson, & Hamilton, 2007), agricultural areas are under-protected almost everywhere (Oldfield, Smith, Harrop, & Leader-Williams, 2004; Scott et al., 2001; Tuvi, Vellak, Reier, Szava-Kovats, & Pärtel, 2011; Yip, Corlett, & Dudgeon, 2004). It is thus crucial for type 3 HNVF to be identified using a different approach, which takes into account the actual distribution of species of conservation interest, regardless of the location of protected areas. All too often – and including in Italy (Pratesi, 2001) – protected areas have been established according to

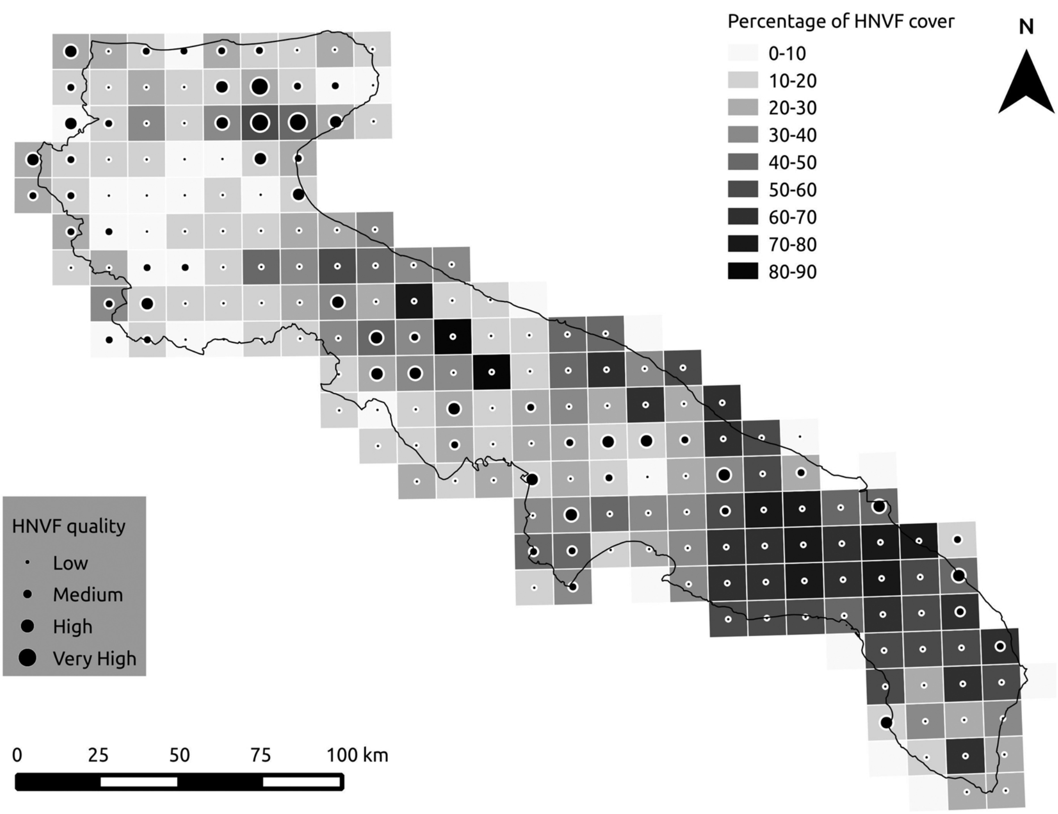

Fig. 6. Map showing the extension and the overall classification of HNVF in the 10 x 10 km cells used as working units in this paper.

political criteria aiming to minimize conflict with human activities – which obviously take place in farmland areas – rather than with the aim of protecting the most deserving areas (Araújo, Lobo, & Moreno, 2007; Oldfield et al., 2004).

HNVF is an indicator that aims to assess the impact of agricultural policies on biodiversity. The process to identify such areas is thus quite fraught, since the indications arising from the analysis of HNVF trends over time depend on it. In our study area, for instance, the criteria used so far would fail to fully identify a decrease in cereal steppes and in the species of conservation interest associated with them. It is thus important to carefully consider the indicators chosen for identifying the three types of HNVF.

Concerning the types of cropland and landscapes to be considered in defining HNVF, it is very important to carefully evaluate the local characteristics of the area in question. There is an immense variety of local conditions in EU Member States (ranging from the size and types of farms, prevailing land use patterns, data availability, and so forth), so that at a certain scale it would be both impossible and inappropriate to impose common methods for the identification of HNVF, alternatively local adjustments are required reflecting site-specific conditions and based on detailed data available at local level.

4.4. Type 3 HNV and the use of available data

Concerning type 3 HNVF, we think it is crucially important to use available databases on local biodiversity. Additionally, since HNVF is an indicator that has to be calculated over time it is also important to have biodiversity data collected with continuity and with standardized methods. From this point of view, birds play a key role, since they are one of the few animal groups for which standardized monitoring programmes are already in place in nearly all Member States (Klvaňová, Voříšek, Gregory, van Strien, & Meyling, 2009). These monitoring programmes generally ensure both good spatial coverage and the presence of long-term temporal series.

Current data analysis tools can maximize the value of the information present in the databases of existing monitoring programmes, and can use such information for purposes and in ways other than those for which they were originally collected. ICBMP data, whose goal is to calculate population trends for common and widespread species, have helped in identifying HNVF areas in Apulia, using a multi-methodological approach that improves the reliability of the results obtained.

One of the strengths of the approach detailed here consists in having obtained these results beginning with available information from an existing database. As mentioned in the section on results, while the most important areas were identified using relatively common species, these same areas are also the most important ones for a number of rare and local species that would otherwise have required specific monitoring programmes at a much greater expense. Our results underscore the importance of biodiversity monitoring (Magurran et al., 2010; Niemelä, 2000; Pereira & Cooper, 2006) and the need for institutional support and significant funding for such efforts, in order to ensure high qualitative standards during all phases, especially concerning the setting of proper goals (Green et al., 2005). Indeed, biodiversity monitoring efforts generate crucial data for the proper steering of biodiversity management strategies (Lindenmayer et al., 2012).

5. Conclusions

HNVF is a very useful indicator that can help assessing the outcomes of the EU's rural biodiversity policies. It is of crucial importance for both targeting interventions and evaluating their effects. Its effectiveness is strictly related to the appropriate assessment of HNVF extent and quality and, therefore, on methodology and data used. Our results clearly highlight the importance of using specific biodiversity indicators and appropriate biodiversity data in the HNVF identification process, with particular reference to HNVF type 3. Indeed, the latter allows for identification of farmlands of highest natural value that an approach based solely on landscape structure and vegetation types might fail to identify. Our results also highlight the need to use an approach based on the analysis of the actual distribution of species of conservation interest based on monitoring programmes, and show the limits of relying on the distribution of protected areas or data drawn from them. Indeed, especially with regards to farmland habitats, the distribution of protected areas and that of species of conservation interest often do not overlap. As these species are often rare and not widespread, data collected about them are difficult to extrapolate to an entire region, therefore the use of common species, that could be also used as indicators of rarer species presence, is a particularly useful approach. Nearly all European countries currently have large-scale, multi-taxa monitoring programmes, and wide availability of evenly distributed environmental data layers, thus allowing analysis of the distribution of many species. This suggests the importance of efficient use of all available data.

Acknowledgements

We really want to thank all the people involved in the ICBMP, particularly those from the Apulia region, who collected, mostly on a voluntary basis, the bird data from 2000 to 2008. Moreover, we want to thank the Italian Ministry of agricultural, food, and forestry policies and the Italian Rural Network (www.reterurale.it) for funding the Farmland Bird Index projects from 2009 thanks to which it has been possible to continue to collect bird data and to realize the research presented here.

References

Acebes, P., Pereira, D., & Oñate, J. J. (2016). Towards the identification and assessment of HNV dehesas: A meso-scale approach. *Agroforestry Systems, 90*(1), 7–22.

Almeida, M., Guerra, C., & Pinto-Correia, T. (2013). Unfolding relations between land cover and farm management: High nature value assessment in complex silvo-pastoral systems. *Geografisk Tidsskrift-Danish Journal of Geography, 113*(2), 97–108.

Andersen, E., Baldock, D., Bennett, H., Beaufoy, G., Bignal, E., Brouwer, F., ... Zervas, G. (2003). *Developing a high nature value indicator.* Copenhagen: European Environment Agency.

Araújo, M. B., Lobo, J. M., & Moreno, J. C. (2007). The effectiveness of iberian protected areas in conserving terrestrial biodiversity: Performance of iberian protected areas. *Conservation Biology, 21*(6), 1423–1432.

ARPA Sicilia (2008). *Atlante della biodiversità della sicilia: Vertebrati terrestri.* Palermo: ARPA Sicilia.

Atauri, J. A., & de Lucio, J. V. (2001). The role of landscape structure in species richness distribution of birds, amphibians, reptiles and lepidopterans in Mediterranean landscapes. *Landscape Ecology, 16*(2), 147–159.

Aue, B., Diekötter, T., Gottschalk, T. K., Wolters, V., & Hotes, S. (2014). How High Nature Value (HNV) farmland is related to bird diversity in agro-ecosystems—Towards a versatile tool for biodiversity monitoring and conservation planning. *Agriculture, Ecosystems & Environment, 194*, 58–64.

Baldock, D., Beaufoy, G., Bennet, G., & Clark, J. (1993). *Nature conservation and new directions in the common agricultural policy.* London: Institute for European Environmental Policy.

Bartoń, K. (2016). *MuMIn: Multi-model inference. R package version 1.15.6.* https://CRAN.R-project.org/package=MuMIn.

Beaufoy, G., Baldock, D., & Clark, J. (1994). *The nature of farming. Low intensity farming systems in nine European countries.* London: Institute for European Environmental Policy.

Bellini, F., Cillo, N., Giacoia, V., & Gustin, M. (2008). *L'avifauna di interesse comunitario delle gravine ioniche.* Laterza (TA): Oasi LIPU Gravina di Laterza.

BirdLife International (2015). *European Red list of birds.* Luxembourg: Office for Official Publications of the European Communities.

Brichetti, P., & Fracasso, G. (2004). *Ornitologia italiana. Tetraonidae-scolopacidae, Vol. 2.* Bologna: Alberto Perdisa Editore.

Brunbjerg, A. K., Bladt, J., Brink, M., Fredshavn, J., Mikkelsen, P., Moeslund, J. E., ... Ejrnæs, R. (2016). Development and implementation of a high nature value (HNV) farming indicator for Denmark. *Ecological Indicators, 61*, 274–281.

Buisson, E., & Dutoit, T. (2006). Creation of the natural reserve of La Crau: Implications for the creation and management of protected areas. *Journal of Environmental Management, 80*, 318–326.

Burfield, I. J. (2005). The conservation status of steppic birds in Europe. In G. Bota, M. B. Morales, S. Mañosa, & J. Camprodon (Eds.). *Ecology and conservation of steppe-land birds* (pp. 119–140). Barcelona: Lynx Edicions & Centre Tecnològic Forestal de Catalunya.

Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multimodel inference: A practical information-theoretic approach* (2nd edn). New York: Springer.

Bux, M., Rizzi, V., Palumbo, G., & Sigismondi, A. (2013). *Studio di fattibilità per la reintroduzione della gallina prataiola (Tetrax Tetrax) nel parco nazionale dell'Alta Murgia.* Retrieved fromParco Nazionale dell'Alta Murgiahttp://www.parcoaltamurgia.gov.it/images/conservazionenatura/PROGETTOGALLINAPRATAIOLA/Studio%20di%20fattibilita%20Tetrax%20tetrax.pdf.

Campedelli, T., Buvoli, L., Bonazzi, P., Calabrese, L., Calvi, G., Celada, C., ... Tellini Florenzano, G. (2012). Andamenti di popolazione delle specie comuni nidificanti in Italia: 2000-2011. *Avocetta, 36*, 121–143.

Campedelli, T., Londi, G., La Gioia, G., Frassanito, A. G., & Florenzano, G. T. (2015). Steppes vs. crops: Is cohabitation for biodiversity possible? Lessons from a national park in southern Italy. *Agriculture, Ecosystems & Environment, 213*, 32–38.

Campedelli, T., Tellini Florenzano, G., Londi, G., Cutini, S., & Fornasari, L. (2010). Effectiveness of the italian national protected areas system in conservation of farmland birds: A gap analysis. *Ardeola, 57*(S), 51–64.

Chiatante, G., Brambilla, M., & Bogliani, G. (2014). Spatially explicit conservation issues for threatened bird species in Mediterranean farmland landscapes. *Journal for Nature Conservation, 22*(2), 103–112.

Conover, W. (1999). *Practical nonparametric statistics* (3rd edition). New York: Wiley.

Dale, M. R., Dixon, P., Fortin, M.-J., Legendre, P., Myers, D. E., & Rosenberg, M. S. (2002). Conceptual and mathematical relationships among methods for spatial analysis. *Ecography, 25*(5), 558–577.

Davy, C. M., Russo, D., & Fenton, M. B. (2007). Use of native woodlands and traditional olive groves by foraging bats on a Mediterranean island: Consequences for conservation. *Journal of Zoology, 273*(4), 397–405.

De Juana, E. (2005). Steppe birds: A characterisation. In G. Bota, M. B. Morales, S. Mañosa, & J. Camprodon (Eds.). *Ecology and conservation of steppe-land birds* (pp. 25–48). Barcelona: Lynx Edicions & Centre Tecnològic Forestal de Catalunya.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*, 27–46.

Dormann, C. F., McPherson, J. M., Araújo, M. B., Bivand, R., Bolliger, J., Carl, G., ... Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography, 30*, 609–628.

Doxa, A., Bas, Y., Paracchini, M. L., Pointereau, P., Terres, J.-M., & Jiguet, F. (2010). Low-intensity agriculture increases farmland bird abundances in France. *Journal of Applied Ecology, 47*(6), 1348–1356.

Doxa, A., Paracchini, M. L., Pointereau, P., Devictor, V., & & F, J. (2012). Preventing biotic homogenization of farmland bird communities: The role of high nature value farmland. *Agriculture, Ecosystems & Environment, 148*, 83–88.

Dray, S., Legendre, L., & Peres-Neto, P. R. (2006). Spatial modelling: A comprehensive framework for principal coordinate analysis of neighbour matrices (PCNM). *Ecological Modelling, 196*, 483–493.

European Commission (2016). *Report. Preparing the assessment of HNV farming in RDPs 2014-2020: Practices and solutions*Brussels: Good Practice Workshop, Bonn 7-8 June 2016.

European Communities (2009). *Guidance document. "The application of the high nature value impact indicator. Programming period 2007-2003*.

European Council (2006). *Council decision of 20 February 2006 on Community strategic guidelines for rural development (programming period 2007 to 2013) (2006/144/EC)*.

Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., ... Martin, J. L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters, 14*, 100–111.

Farina, A. (1997). Landscape structure and breeding bird distribution in a sub-Mediterranean agro-ecosystem. *Landscape Ecology, 12*, 365–378.

Field, R., Hawkins, B. A., Cornell, H. V., Currie, D. J., Diniz-Filho, J. A. F., Guégan, J.-F., ... Turner, J. R. G. (2009). Spatial species-richness gradients across scales: A meta-analysis. *Journal of Biogeography, 36*(1), 132–147.

Forconi, V., Mandrone, S., & Vicini, C. (Eds.). (2010). *Aree agricole ad alto valore naturale: dall'individuazione alle gestione. Manuali e linee guida*. Roma: ISPRA.

Fourcade, Y., Engler, J. O., Rödder, D., & Secondi, J. (2014). Mapping species distributions with MAXENT using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS One, 9*(5), e97122.

Galdenzi, D., Pesaresi, S., Casavecchia, S., Zivkovic, L., & Biondi, E. (2012). The phytosociological and syndynamical mapping for the identification of high nature value farmland. *Plant Sociology, 49*(2), 59–69.

Green, R. E., Balmford, A., Crane, P. R., Mace, G. M., Reynolds, J. D., & Turner, R. K. (2005). A framework for improved monitoring of biodiversity: Responses to the world summit on sustainable development. *Conservation Biology, 19*, 56–65.

Julliard, R., Clavel, J., Devictor, V., Jiguet, F., & Couvet, D. (2006). Spatial segregation of specialists and generalists in bird communities. *Ecology Letters, 9*, 1237–1244.

Klvaňová, A., Voříšek, P., Gregory, R., van Strien, A., & Meyling, A. G. (2009). Wild birds as indicators in Europe: Latest results from the Pan-European common bird monitoring Scheme (PECBMS). *Avocetta, 33*, 7–12.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., ... Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions, 19*(11), 1366–1379.

La Gioia, G. (2009). *Atlante degli uccelli nidificanti in provincia di Lecce (2000–2007)*. Lecce: Edizioni del Grifo.

Le Rest, K., Pinaud, D., & Bretagnolle, V. (2013). Accounting for spatial autocorrelation from model selection to statistical inference: Application to a national survey of a diurnal raptor. *Ecological Informatics, 14*, 17–24.

Lindenmayer, D. B., Gibbons, P., Bourke, M., Burgman, M., Dickman, C. R., Ferrier, S., ... Zerger, A. (2012). Improving biodiversity monitoring. *Austral Ecology, 37*(3), 285–294.

Liuzzi, C., Mastropasqua, F., & Todisco, S. (Eds.). (2013). Avifauna pugliese…..130 anni dopo. Editore Favia, Bari.

Lomba, A., Alves, P., Jongman, R. H. G., & McCracken, D. I. (2015). Reconciling nature conservation and traditional farming practices: A spatially explicit framework to

assess the extent of high nature value farmlands in the European countryside. *Ecology and Evolution, 5*(5), 1031–1044.
Lomba, A., Guerra, C., Alonso, J., Honrado, J. P., Jongman, R., & McCracken, D. (2014). Mapping and monitoring high nature value farmlands: Challenges in European landscapes. *Journal of Environmental Management, 143*, 140–150.
Lüdemann, L., Grieger, W., Wurm, R., Wust, P., & Zimmer, C. (2006). Glioma assessment using quantitative blood volume maps generated by T1-weighted dynamic contrast-enhanced magnetic resonance imaging: A receiver operating characteristic study. *Acta Radiologica, 47*(3), 303–310.
Magurran, A. E., Baillie, S. R., Buckland, S. T., Dick, J. M., Elston, D. A., Scott, E. M., ... Watt, A. D. (2010). Long-term datasets in biodiversity research and monitoring: Assessing change in ecological communities through time. *Trends in Ecology & Evolution, 25*(10), 574–582.
Mauricio Bini, L., Diniz-Filho, J. A. F., Rangel, T. F., Akre, T. S., Albaladejo, R. G., Albuquerque, F. S., ... Hawkins, B. A. (2009). Coefficient shifts in geographical ecology: An empirical evaluation of spatial and non-spatial regression. *Ecography, 32*(2), 193–204.
McCullagh, P., & Nedler, J. A. (1989). *Generalized linear models.* London: Chapman & Hall.
Meschini, A. (2010). *L'occhione. Tra i fiumi e le pietre.* Latina: Edizioni Belvedere.
Metz, C. E. (1978). *Basic principles of ROC analysis. Seminars in nuclear medicine, Vol. 8*, Elsevier283–298. Retrieved from http://www.sciencedirect.com/science/article/pii/S0001299878800142.
Morelli, F., & Girardello, M. (2013). Buntings (Emberizidae) as indicators of HNV of farmlands: A case of study in Central Italy. *Ethology Ecology & Evolution,* 1–8 (ahead-of-print).
Morelli, F., Jerzak, L., & Tryjanowski, P. (2014). Birds as useful indicators of high nature value (HNV) farmland in Central Italy. *Ecological Indicators, 38*, 236–242.
N'Goran, P. K., Boesch, C., Mundry, R., N'Goran, E. K., Herbinger, I., Yapi, F. A., ... Kuehl, H. S. (2012). Hunting, law enforcement, and African primate conservation. *Conservation Biology, 26*(3), 565–571.
Niemelä, J. (2000). Biodiversity monitoring for decision-making. *Annales Zoologici Fennici, 37*, 307–317.
Oldfield, T. E. E., Smith, R. J., Harrop, S. R., & Leader-Williams, N. (2004). A gap analysis of terrestrial protected areas in England and its implications for conservation policy. *Biological Conservation, 120*(3), 303–309.
Papeş, M., & Gaubert, P. (2007). Modelling ecological niches from low numbers of occurrences: Assessment of the conservation status of poorly known viverrids (Mammalia, Carnivora) across two continents. *Diversity and Distributions, 13*, 890–902.
Pearson, R. G., Raxworthy, C. J., Nakamura, M., & Townsend Peterson, A. (2007). Predicting species distributions from small numbers of occurrence records: A test case using cryptic geckos in Madagascar. *Journal of Biogeography, 34*(1), 102–117.
Pepiette, Z. (2011). *The challenge of monitoring environmental priorities: The example of HNV farmland. Paper prepared for The 122nd EAAE seminar "evidence-based agricultural and rural policy making: Methodological and empirical challenges of policy evaluation" Ancona, February 17-18, 2011*.
Pereira, H. M., & Cooper, H. D. (2006). Towards the global monitoring of biodiversity change. *Trends in Ecology & Evolution, 21*(3), 123–129. https://doi.org/10.1016/j.tree.2005.10.015.
Peres-Neto, P. R., & Legendre, P. (2010). Estimating and controlling for spatial structure in the study of ecological communities. *Global Ecology and Biogeography, 19*(2), 174–184.
Peterson, A. T., Soberón, J., Pearson, R. G., Anderson, R. P., Martinez-Meyer, E., Nakamura, M., ... Araujo, M. B. (2011). *Ecological niches and geographic distributions.* Princeton and Oxford: Princeton University Press.
Phillips, S. J., & Dudík, M. (2008). Modeling of species distributions with maxent: New extensions and a comprehensive evaluation. *Ecography, 31*(2), 161–175.
Phillips, S., Anderson, R., & Schapire, R. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*(3–4), 231–259.
Pointereau, P., Paracchini, M. L., Terres, J. M., Jiguet, F., Bas, Y., & Biala, K. (2007). *Identification of high nature value farmland in France through statistical information and farm practices surveys, JRC report EUR 22786 EN*.
Pratesi, F. (2001). *Storia della natura d'Italia.* Roma: Editori Riuniti.
R Core Team (2017). *R: A language and environment for statistical computing.* URLVienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.
Rete Rurale Nazionale (2014). *Aree agricole ad alto valore naturale. Approccio della copertura del suolo. Rete Rurale Nazionale.* http://www.reterurale.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/13563.
Richards, S. A., Whittingham, M. J., & Stephens, P. A. (2011). Model selection and model averaging in behavioural ecology: The utility of the IT-AIC framework. *Behavioral Ecology and Sociobiology, 65*, 77–89.
Scott, J. M., Davis, F. W., McGhie, R. G., Wright, R. G., Groves, C., & Estes, J. (2001). Nature reserves: Do they capture the full range of America's biological diversity? *Ecological Applications, 11*(4), 999–1007.
Siesa, M. E., Manenti, R., Padoa-Schioppa, E., De Bernardi, F., & Ficetola, G. F. (2011). Spatial autocorrelation and the analysis of invasion processes from distribution data: A study with the crayfish *Procambarus clarkii*. *Biological Invasions, 13*, 2147–2160.
Stein, A., Gerstner, K., & Kreft, H. (2014). Environmental heterogeneity as a universal driver of species richness across taxa, biomes and spatial scales. *Ecology Letters, 17*(7), 866–880.
Swinton, S. M., Lupi, F., Robertson, G. P., & Hamilton, S. K. (2007). Ecosystem services and agriculture: Cultivating agricultural ecosystems for diverse benefits. *Ecological Economics, 64*(2), 245–252.
Syfert, M. M., Smith, M. J., & Coomes, D. A. (2013). The effects of sampling bias and model complexity on the predictive performance of MaxEnt species distribution models. *PLoS One, 8*(2), e55158.
Tarjuelo, R., Morales, M. B., Traba, J., & Delgado, M. P. (2014). Are species coexistence areas a good option for conservation management? Applications from fine scale modelling in two steppe birds. *PLoS One, 9*(1), e87847.
Traba, J., García de la Morena, E. L., Morales, M. B., & Suárez, F. (2007). Determining high value areas for steppe birds in Spain: Hot spots, complementarity and the efficiency of protected areas. *Biodiversity and Conservation, 16*(12), 3255–3275.
Trisorio, A., De Natale, F., & Pignatti, G. (2013). *Le aree agricole ad alto valore naturale in Italia: una stima a livello regionale. Agriregionieuropa.* 33. www.agriregionieuropa.it.
Tuvi, E.-L., Vellak, A., Reier, Ü., Szava-Kovats, R., & Pärtel, M. (2011). Establishment of protected areas in different ecoregions, ecosystems, and diversity hotspots under successive political systems. *Biological Conservation, 144*(5), 1726–1732.
van Doorn, A., & Elbersen, B. (2012). *Implementation of high nature value farmland in agri-environmental policies: What can be learned from other EU member states? Alterra report 2289*Alterra, Wageningen, The Netherlands . Retrieved from http://edepot.wur.nl/200676.
Warren, D. L., & Seifert, S. N. (2011). Ecological niche modeling in maxent: The importance of model complexity and the performance of model selection criteria. *Ecological Applications, 21*(2), 335–342.
Yip, J. Y., Corlett, R. T., & Dudgeon, D. (2004). A fine-scale gap analysis of the existing protected area system in Hong Kong, China. *Biodiversity and Conservation, 13*(5), 943–957.
Zheng, B., & Agresti, A. (2000). Summarizing the predictive power of a generalized linear model. *Statistics in Medicine, 19*, 1771–1781.