available at www.sciencedirect.com

ScienceDirect

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

Evaluating cost-effectiveness of conservation management actions in an agricultural landscape on a regional scale

Annelie Holzkämper, Ralf Seppelt*

UFZ Centre for Environmental Research Leipzig-Halle, Department of Computational Landscape Ecology (CLE), Permoserstr. 15, D-04318 Leipzig, Germany

ARTICLE INFO

Article history:
Received 25 July 2006
Received in revised form
7 November 2006
Accepted 14 November 2006

Keywords:
Spatially explicit optimisation
Cost–benefit analysis
Habitat suitability
Ecological-economic modelling
Regionalisation

ABSTRACT

Agricultural landscapes are the dominating landscape types in many parts of the world. Land-use intensification and spatial homogeneity are major threats to biodiversity in these landscapes. Thus cost-effective strategies for species conservation in large-scale agricultural landscapes are required. Spatial optimisation methods can be applied to identify the most effective allocation of a given budget for conservation. However, the optimisation of spatial land-use patterns in real landscapes on a large spatial scale is often limited by computational power. In this paper, we present a simplifying methodology for analysing cost-effectiveness of management actions on a regional scale. A spatially explicit optimisation approach is employed to identify optimum agricultural land-use patterns with respect to an ecological-economic goal function. Based on the optimisation results for small scale landscape samples we derive a target- and site-specific cost–benefit function that can be applied to predict ecological improvement as a function of costs and local conditions on a large spatial scale. Thus, it is possible to identify areas where management actions for ecological improvement are most efficient with respect to a certain conservation goal. The fitted function is validated independently. In a case study, we analyse cost-effectiveness of management actions to enhance habitat suitability for three different target species. The approach is flexible and could be applied to a variety of other landscape planning problems dealing with the effective allocation of management measures.

1. Introduction

Agricultural land use dominates landscapes in many parts of the world. Species inhabiting agricultural landscapes are threatened by land-use intensification or land-use conversions, e.g. from natural habitat to agriculture or urban area (Matson et al., 1997; Main et al., 1999; Freemark and Kirk, 2001; Tilman et al., 2001) resulting in migration or even local extinction (Woinarski and Catterall, 2004). However, species protection measures are often expensive and in conflict with the multifarious human demands for land. Thus, it is necessary to ascertain how to best allocate a limited budget to maximise the conservation goal.

During the last few years the relevance of these issues for conservation management was more and more taken into account. An increasing number of interdisciplinary studies considering both conservation goals and economic constraints emerged, many of them dealing with problems of optimum reserve site selection (Haight, 1995; Hof and Raphael, 1997; Moilanen and Cabeza, 2002; Nalle et al., 2004; Polasky et al.,

* *Corresponding author:* Tel.: +49 341 235 3945; fax: +49 341 235 3939.
E-mail address: annelie.holzkaemper@ufz.de (A. Holzkämper).
0006-3207/$ - see front matter
doi:10.1016/j.biocon.2006.11.011

2005). However, for species conservation in human-dominated landscapes it is necessary to look beyond the boundaries of protected areas and consider the landscape as a whole, taking into account ecological and economic demands to allow for a coexistence of conservation and profitability (Bennett et al., 2006; Margules and Pressey, 2000; Hughey et al., 2003; Polasky et al., 2005). Few studies consider these aspects when dealing with the problem of effective allocation of management actions. For example, Drechsler and Wätzold (2001) developed a theoretical model to analyse the cost-effective spatial allocation of subsidies for biodiversity-enhancing land use. Johst et al. (2002) present an ecological-economic modelling procedure to ascertain the optimum spatio-temporal allocation of a given budget for species protection. These studies deal with hypothetical landscapes and do not explicitly consider spatial configurations and landscape heterogeneity. For finding an optimum land-use configuration with respect to a certain management objective in a real landscape, the combinatorial optimisation problem soon becomes very complex; especially if a large spatial scale with a multitude of decision units is considered (Seppelt and Voinov, 2002). Thus, the application of spatial optimisation approaches to real landscapes on a large spatial scale is often limited by computational power.

In this paper, we present a new simplifying approach for analysing cost-effectiveness of management actions to enhance an ecological value in a real landscape on a large spatial scale. A spatially explicit optimisation approach is used to identify optimum land-use patterns with respect to an ecological-economic objective function. Optimum trade-offs can differ spatially as site conditions like soil characteristics influence the ecological as well as the economic function. Thus, the optimisation model is applied to a chosen set of smaller sample sites in the study area and the results are used to derive a function that describes the spatially varying cost–benefit relationship. This function can then be used for regionalisation of optimisation results on a large spatial scale. As a result it is possible to identify areas where certain management actions would be most cost-effective without having to apply the optimisation model to the whole region.

The approach was tested in a case study where the land-use pattern of an agricultural landscape is optimised with respect to habitat suitability for three different bird species while considering loss of profits from land use.

2. Method

2.1. Spatially explicit optimisation task

In this study, we applied a spatially explicit optimisation model to identify land-use patterns that represent optimum trade-offs between ecological improvements and economic requirements. The optimisation target was to maximise an ecological value E (e.g. habitat suitability, biodiversity) determined by a land-use map M, while minimising an economic function (e.g. profit loss, costs) C evaluated over M (see Table 1 for summary of all notations). These are two contrasting objectives with different units. Therefore, we introduced a weighting coefficient λ in €/ha to allow for an integration of both objectives. The goal function J was then given by:

Table 1 – General notations

C	Economic function
E	Ecological value
eff	Effectiveness of management actions
E_{opt}	Predicted ecological value
fs	Mean fertility score
h	Mean elevation
HSI	Mean habitat suitability
$hsi(x,y)$	Habitat suitability index at location x,y
HSI_0	Initial mean habitat suitability
HSI_{max}	Maximum possible mean habitat suitability
HSI_{opt}	Prediction of optimised mean habitat suitability
J	Optimisation criterion
M	Land-use map
P	Profit loss
$p_0(x,y)$	Initial profit from land use at location x,y (€/ha)
$p_M(x,y)$	Profit from land use at location x,y according to modified land-use map M in €/ha
sa	Mean proportion of sand
sd	Mean annual sunshine duration
$v_k(x,y)$	Habitat variables at location x,y
$v_{lsm}(M(x,y))$	Landscape metrics calculated in a certain radius around location x,y
$v_s(x,y)$	Local site characteristics at location x,y
ΔHSI	Difference between HSI_{max} and HSI_0
λ	Weighting coefficient

$$J(M) = \lambda E(M) - C(M) \quad (1)$$

Thus, the optimisation task was to find an optimum land-use pattern M^*, where $J(M^*) > J(M)$. The value of λ determined the relative importance of the economic and the ecological objective function, respectively, resulting in different optimum trade-off solutions. We considered a land-use pattern to be an optimum trade-off solution as soon as no further modification can be found that would result in both lower economic costs and higher ecological benefit (Pareto optimality).

2.2. Land-use changes and spatial representation

We applied the spatially explicit optimisation model of Holzkämper et al. (2006) to approach optimum trade-off solutions between the two conflicting objective functions $E(M)$ and $C(M)$. In the grid-based optimisation framework patches of identical land use, that are assumed to be managed as entire units, are subject to change (e.g. agricultural fields). For this study, the approach was extended to allow for an incorporation of linear land-use changes such as the planting of hedges which might be relevant for certain species (e.g. Red-Backed Shrike) and processes (e.g. erosion, biocontrol). Patch boundaries were assumed to be potential areas for linear land-use changes (Fig. 1). Within the optimisation identified patches and patch boundaries are subject to changes.

2.3. Regionalisation

The optimisation task to find an optimum configuration of land use in patches and patch boundaries is a highly complex problem due to the exponentially growing number of possible combinations with increasing number of identified patches and patch boundaries. Thus, it is often computationally

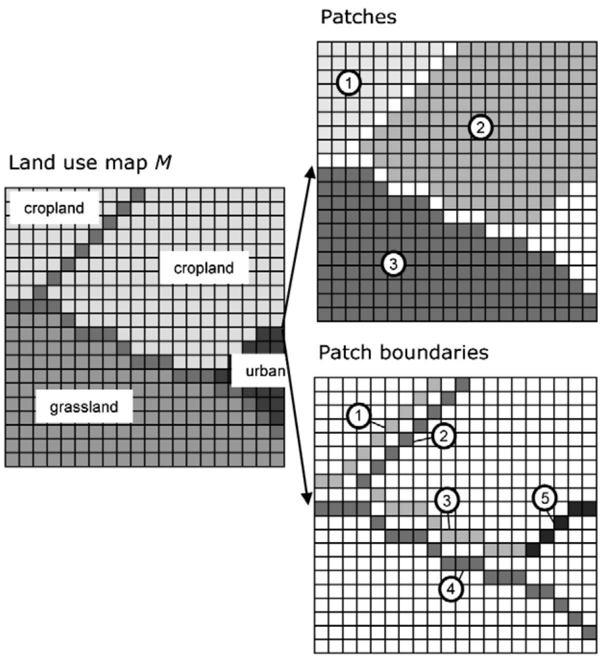

Fig. 1 – Representation of the grid landscape within the optimisation: patches of class cropland and grassland are potential locations for areal land-use change; urban area is excluded from land-use change simulations. Edge cells of crop- and grassland are assigned to five different patch boundaries according to the adjacent land-use types.

infeasible to find a global optimum land-use configuration, even with a heuristic search algorithm like the genetic algorithm applied in Holzkämper et al. (2006). To still analyse cost-effectiveness of management actions on a large scale with a multitude of possible land-use pattern combinations, we applied a simplifying method. The cost–benefit relationship can differ spatially as site conditions like soil characteristics might affect the ecological and the economic function. Thus, we divided the study area into study sites that were small enough so that the spatial optimisation could be applied and the variability of site conditions in the study area was captured in the different study sites. Study sites were large enough to allow the evaluation of the objective (if the objective is neighbourhood-dependent, at least the considered neighbourhood has to be within the study site). A representative set of these study sites was chosen in that they cover the ranges of initial conditions. Based on these optimisation results for these study sites we fitted a non-linear regression function (Bates and Watts, 1988) to describe the cost–benefit relationship for all study sites. The function to be fitted was a saturation function as any ecological value can only be increased from its initial value to a certain maximum. Maximum ecological values had to be derived for each study site by applying an economically unconstrained optimisation (with $C(M) = 0$ in Eq. (1)) to all study sites. Fitting the non-linear regression, we tested several different saturation functions (e.g. exponential saturation function, exponential sigmoid function). We checked for correlations between the residuals and variables that could potentially explain the spatial variability of the cost–benefit relationship (e.g. soil characteristics) to determine which variables needed to be incorporated into the non-linear regression function. The fitted function could be used to predict ecological improvement E_{opt} as an approximation for the optimisation result $E(M^{*})$ at any given economic constraint for each of the study sites in the study area. Thus, cost-effectiveness of management actions to improve an ecological value could be analysed on a large spatial scale without having to apply the spatial optimisation to the whole region. The fitted function was validated based on a set of independent optimisation results. We quantified cost-effectiveness *eff* by calculating the first derivative of the fitted function. The derivative describes the tangent slope of the function with $C = 0$ for each study site and can thus be interpreted as cost-effectiveness of management actions *eff* [1/€/ha] for a certain ecological goal.

$$eff = \left.\frac{dE_{\text{opt}}(C)}{dC}\right|_{C=0} \tag{2}$$

3. Case study

The method described above was tested in the administrative district of Leipzig, where agriculture is the main land-use type. In large parts of this area the agricultural land-use pattern is very homogenous (very large field sizes of up to 30 ha). The dominance of agricultural land use and high land-use homogeneity are supposed to have negative effects for habitats of rare or endangered species (Weibull et al., 2003). Thus, the aim of this case study was to analyse cost-effectiveness of management actions (land-use changes) to enhance habitat conditions for species that represent important habitat types in this area.

3.1. *Study area and species selection*

The administrative district of Leipzig is an area of about 441,000 ha (Fig. 2). The altitude in the study area increases from about 100 m a.s.l. in the North to 250–300 m a.s.l. in the South East. We made use of several different data sets with 40 m cell size to describe the characteristics of the study area. The input raster maps used for our study contained information on land use, elevation, soil texture, soil fertility and climate (mean annual sunshine duration, mean annual temperature, mean annual precipitation) (see Table 2 for more detailed description).

The bird species Middle-Spotted Woodpecker (*Dendrocopos medius*), Woodlark (*Lullula arborea*) and Red-Backed Shrike (*Lanius collurio*) were chosen as target species because they inhabit different habitat types in the study area and prefer different structural features of the landscape. The Middle-Spotted Woodpecker lives in large compact deciduous forests. The Woodlark can be found in coniferous heath forests with dry and sandy soils. The Red-Backed Shrike prefers open and semi-open areas with boundary structures such as hedgerows. The Middle-Spotted Woodpecker and the Wood Lark are threatened through land-use conversions from deciduous and coniferous forest to agricultural land use and are Red List species in Saxony 1999 (Rau et al., 1999). The Red-Backed Shrike was chosen as target species as it has been

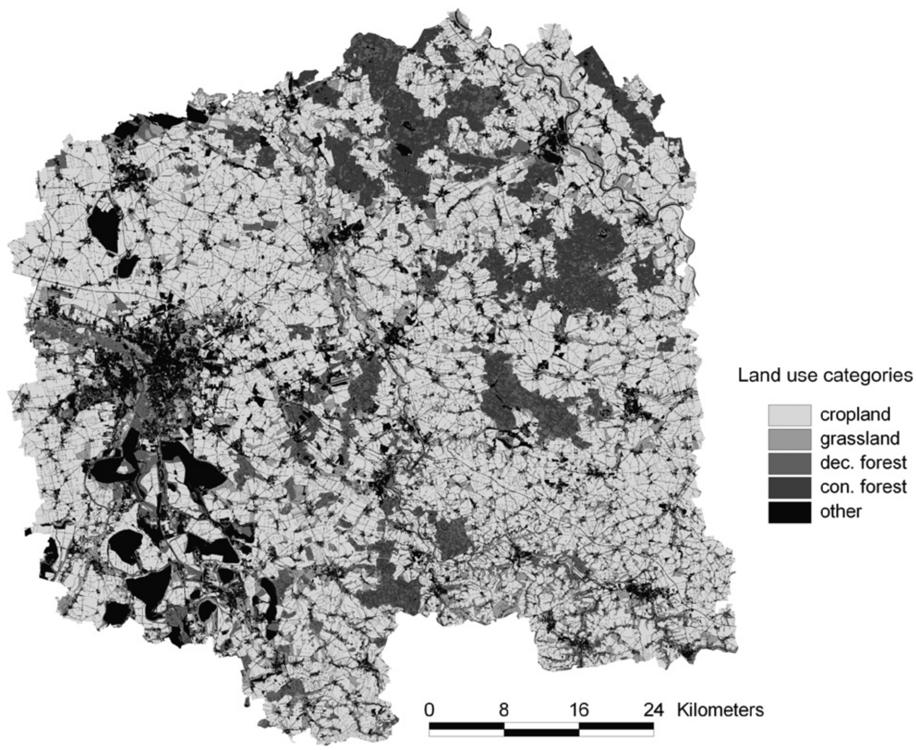

Fig. 2 – Study area with main land-use categories (land-use map 1994).

Table 2 – Data base

Thematic layer	Units	Resolution/scale	Date	Source
Land use	Categories	10 m	1994	Visual interpretation of data from different sources (satellite imagery, aerial photographs, topographic maps and land-use mappings)
Elevation	m	20 m	2001	Federal Land Surveying Office Saxony (2001)
Soil map[a]	Categories	1:25,000	1970–1990	Saxonian Federal Bureau of Environment and Geology
Annual sunshine duration	h	1 km	1961 and 1990	German National Meteorological Service (DWD)
Mean annual temperature	°C	1 km	1961 and 1990	German National Meteorological Service (DWD)
Mean annual precipitation	mm	1 km	1961 and 1990	German National Meteorological Service (DWD)
Soil fertility	10 (very invertile)–100 (very vertile)	Municipality	1930s	"Reichsbodenschätzung" carried out by governmental institutions

a Based on AG Boden (1994), information on the proportion of soil texture was derived from the mapped soil types.

shown to be sensitive to land-use heterogeneity in agricultural landscapes (Latus et al., 2004). The three species are taken to be representatives for different habitat types and therefore their conservation would also result in the protection of sympatric species.

3.2. *Model application*

Mean habitat suitability *HSI* of *M* was used to quantify habitat conditions and thus the ecological objective. To consider the productivity of the landscape, we used loss of profits from land use compared to the initial landscape *P*(*M*) as the economic function. Thus, the general goal function *J* (Eq. (1)) was specified as follows:

$$\begin{aligned} E(M) &= HSI(M) \\ C(M) &= P(M) \\ J(M) &= \lambda HSI(M) - P(M) \end{aligned} \tag{3}$$

In our application patches of cropland and grassland, which were assumed to be managed as entire units, were subject to potential land-use changes. They could be changed into grassland, deciduous or coniferous forest. Field boundaries of crop- and grassland were assumed to be potential locations for hedgerows.

The land-use map of the study area was divided into 95 study sites of equal size (36 km^2, 150 × 150 cells). For each of the three species initial mean habitat suitabilities in all study sites were divided into classes of equal ranges and from each range class one sample site was selected. As the range of

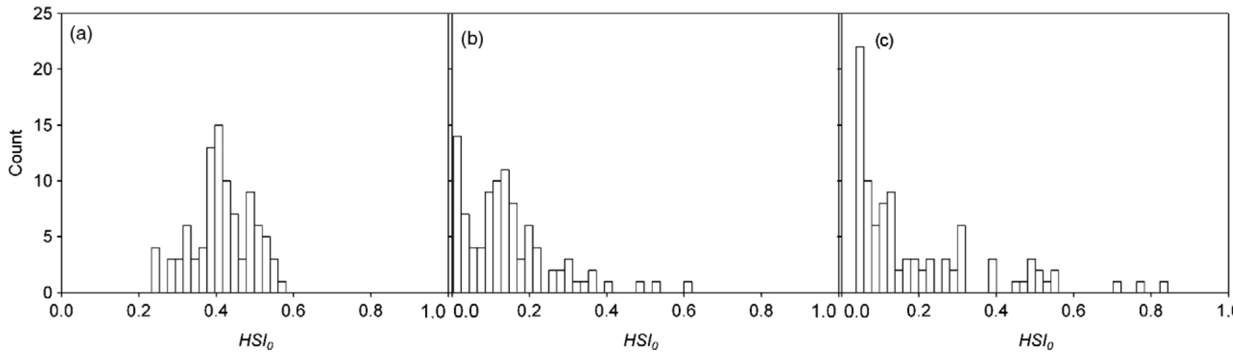

Fig. 3 – Distributions of initial habitat suitabilities for Red-Backed Shrike (a), Middle-Spotted Woodpecker (b) and Wood Lark (c) in the 95 study sites of the study area.

initial mean habitat suitability values was much wider for the Wood Lark than for the Red-Backed Shrike, more sample sites had to be drawn for Wood Lark to receive a representative set of sample sites (Fig. 3). For the Red-Backed Shrike 13 sample study sites were chosen, 24 for the Middle-Spotted Woodpecker and 35 for the Wood Lark.

For each of the three target species the spatial optimisation model was applied to the chosen sample study sites with objective function (3) with six different weightings λ. Based on these results three non-linear regression functions were fitted. The fitted functions were validated independently based on optimisation results for randomly chosen study sites with 3×3 km^2 (75×75 cells) and size-dependent effects of validity were tested by comparing predictions for different study site sizes with optimisation results. Finally, the derived functions were used to predict cost-effectiveness of management actions for each of the three species in the whole study area according to Eq. (2).

3.3. *Quantification of habitat suitability*

The first part of the objective function (Eq. (3)), $HSI(M)$, was quantified based on statistical habitat suitability models for the three focal species as presented in Holzkämper et al. (2006) (Table 3). The habitat suitability models were built using logistic regression. Occurrence probabilities or habitat suitability values hsi at location (x,y) were predicted for each species based on model estimates d (d_0 = intercept; d_k = coefficients) and n species-specific habitat variables v_k at location (x,y), where $hsi \in [0,1]$:

$$hsi(x,y) = \exp\left(d_0 + \sum_{k=1}^{n} d_k v_k(x,y)\right)\left[1 + \exp\left(d_0 + \sum_{k=1}^{n} d_k v_k(x,y)\right)\right]^{-1}$$

Possible habitat variables $v_k(x,y)$ for each species comprised specific site conditions of the study area v_s (elevation, sunshine duration, precipitation, temperature, proportion of sand) and landscape metrics v_{lsm} (largest patch index, class area, edge density, edge sum, patch cohesion). v_s included site conditions at location (x,y), whereas v_{lsm} were calculated within the species' home ranges around location (x,y). As v_{lsm} were spatially referenced and depended on a given land-use map M, v_k could be identified through $v_k(x,y) = \{v_s(x,y), v_{lsm}(M(x,y))\}$. For the three chosen species home ranges of ~10 ha were assumed (Flade, 1994). The land-use pattern within the home range was incorporated as an attempt to consider the species' responses to landscape pattern on a territo-

Table 3 – Habitat suitability models for target species (COH, patch cohesion; ED, edge density); model performance was evaluated using AUC, area under the ROC (receiver-operating-characteristics)-curve (Fielding and Bell, 1997); effects of interaction and quadratic terms were tested, but could not improve the model fit

	Estimates	Standard error
Red-Backed Shrike		
Intercept	−0.0201	0.0082
v_s		
Mean annual temperature	0.2804	0.0654
Mean annual precipitation	−0.3026	0.0653
v_{lsm}		
Largest patch index	−0.4437	0.0555
ED groves/trees	0.2137	0.0508
ED hedges/tree rows	0.1564	0.0407
ED cropland	0.3137	0.0481
ED build-up area	−0.7263	0.0629
Edge cells of dec. forest to cropland	0.2605	0.0621
Edge cells of con. forest to cropland	0.1376	0.0367
COH grassland	0.163	0.0378
AUC	**0.7607**	**0.0093**
Middle-Spotted Woodpecker		
Intercept	−0.4581	0.1301
v_s		
Elevation	−1.1355	0.2782
Mean annual sunshine duration	−1.4966	0.3711
v_{lsm}		
COH deciduous forest	2.5704	0.2608
AUC	**0.9717**	**0.0082**
Wood Lark		
Intercept	−0.1084	0.0567
v_s		
Proportion of sand	0.7084	0.1546
v_{lsm}		
COH deciduous forest	0.7219	0.1996
COH coniferous forest	1.747	0.2116
AUC	**0.9287**	**0.0201**

rial scale. v_{lsm} quantified certain aspects of land-use pattern. The largest patch index described landscape homogeneity, the class area of land-use types quantified landscape composition, the metrics edge density, edge sum and patch cohesion of land-use types quantified certain aspects of spatial configuration such as fragmentation, neighbourhood relationships and aggregation of land-use types. The dependency of $hsi(x,y)$ on v_{lsm} is explicitly considered in the spatial optimisation as the objective evaluation is performed based on the modified raster land-use map.

HSI(*M*) is the mean of local habitat suitability values $hsi(x,y)$ derived from land-use map *M*.

$$HSI(M) = \frac{1}{|M|} \sum_{(x,y)\in M} hsi(x,y)$$

where $|M|$ denotes the size of *M*.

3.4. Quantification of economic function

Based on estimated profits from land use per year, profit loss *P*(*M*) was calculated for changing land-use patterns according to the following formula:

$$P(M) = \frac{1}{|M|} \sum_{(x,y)\in M} (p_0(x,y) - p_M(x,y))$$

where $p_0(x,y)$ is the profit from the original land use at location *x*,*y* in €/ha and $p_M(x,y)$ is the profit from land use at location (x,y) according to modified land-use map *M* in €/ha. *P*(*M*) is typically positive as land-use changes were usually made to land-use types with lower profitability (Table 4). The estimation of $p_0(x,y)$ and $p_M(x,y)$, respectively, was based on land-use profits derived from crop statistics of the Saxonian State Office for Agriculture in the year 2005. According to the distribution of crop types on a municipal level (State Office for Statistics of Saxony, 2003) and soil fertility scores (see Table 2), we derived mean profits from cropland for all municipalities. Profit values for grasslands were estimated on the municipality level based on soil fertility scores, averaged profit margins from grasslands and averaged profits from pastures. Thereby, we assumed 75% of all grassland to be pasture. Profits from forests were estimated based on information derived from Mixdorf (1996). We assumed averaged values of profit from deciduous and coniferous forests for the whole study area according to soil fertility scores. Table 4 summarises the assumed ranges of profits from the land-use types cropland, grassland, deciduous and coniferous forest and hedgerows. Profits from crop- and grassland vary not only with soil fertility, but also with the utilisation of crop- and grasslands in each district. Table 4 shows the ranges of assumed profits from crop- and grassland varying on the municipal level. Profits from hedges are negative because they are not used, but need to be maintained every 5–10 years. According to information from local landscape conservationists we assumed costs for maintenance to be 15 €/m every 7 years.

4. Results

4.1. Cost–benefit relationships

Optimisation results showed that the cost–benefit relationships differed not only between the species, but also between study sites (see Figs. 4 and 5). The relations between $HSI(M^*)$ and $P(M^*)$ for each of the three target species could be described by three exponential saturation functions (Eqs. (4)–(6)). For all three species HSI_{opt} as an approximation for $HSI(M^*)$ depended on initial mean habitat suitability HSI_0, maximum possible mean habitat suitability HSI_{max}, profit loss *P* and mean soil fertility *fs*. The slope in the exponential saturation function increased with increasing ΔHSI. First results of the non-linear regression fitting showed that this increase was overestimated in the exponential saturation function. Thus, ΔHSI was incorporated in all functions. Likewise, the mean fertility score *fs* decreased the functions' slopes, because the profit loss was higher on sites with higher fertility scores.

In Eqs. (4)–(6) the coefficient *k* determines the impact of profit loss on habitat improvement, while *a* determines the relevance of the fertility score. The estimates for all coefficients of the three fitted functions are shown in Tables 5–7.

For the Red-Backed Shrike, we identified the acceptable profit loss *P*, the maximum possible habitat suitability for the Red-Backed Shrike HSI_{max}, initial habitat suitability HSI_0 and mean fertility score *fs* to be the controlling factors for HSI_{opt} (Eq. 4). Table 5 shows the estimated coefficients of this non-linear regression model.

$$HSI_{opt}(P, HSI_{max}, HSI_0, fs) = \Delta HSI \cdot (1 - e^{-k \cdot P \cdot (1-\Delta HSI) \cdot (a - fs)}) + HSI_0 \tag{4}$$

The function to predict optimised mean habitat suitability for Middle-Spotted Woodpecker HSI_{opt} additionally incorporates the variables height *h* and sunshine duration *sd* and therefore has the following form:

$$HSI_{opt}(P, HSI_{max}, HSI_0, fs, h) = \Delta HSI \cdot (1 - e^{-k \cdot P \cdot (1-\Delta HSI) \cdot (a-fs) \cdot (b-h) \cdot (c-sd)}) + HSI_0 \tag{5}$$

Coefficient *b* determines the relevance of variable height *h* incorporated in function (5) and coefficient *c* defines the relevance of variable mean annual sunshine duration *sd* (see Table 6 for estimated coefficients).

The optimised mean habitat suitability for Wood Lark HSI_{opt} is predicted as a function of acceptable profit loss *P*, HSI_{max}, HSI_0, *fs* and mean proportion of sand *sa*, as

Table 4 – Estimated profits from land use per year (see Table 2 for description of soil fertility scores)

Soil fertility score	Cropland (€/ha)	Grassland (€/ha)	Deciduous forest (€/ha)	Coniferous forest (€/ha)	Hedges (€/m)
⩽44	89–139	52–63	−13	35	−2.14
>44–55	140–330	174–199	23	70	−2.14
>55–70	341–543	227–337	59	110	−2.14
>70	398–646	313–366	94	155	−2.14

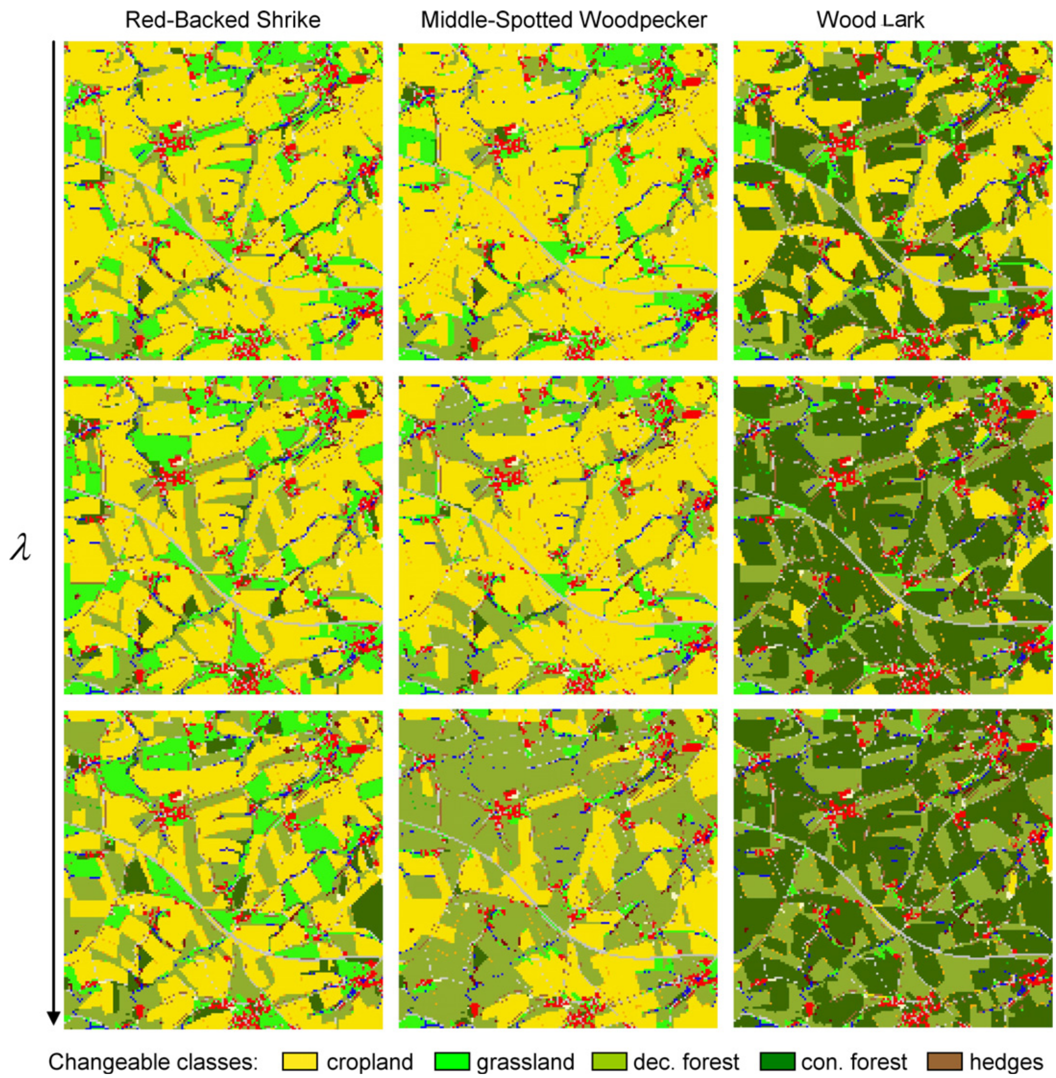

Fig. 4 – Exemplary set of optimum trade-off solutions for the three species given different values for λ.

$$HSI_{opt}(P, HSI_{max}, HSI_0, fs, sa) = \Delta HSI \cdot (1 - e^{-k\cdot(1-\Delta HSI)\cdot P\cdot(a-fs)\cdot(d+sa)}) + HSI_0 \quad (6)$$

Coefficient d defines the relevance of variable mean proportion of sand sa, which is incorporated in function (6) to predict optimised Wood Lark habitat suitability (see Table 7 for estimated coefficients).

Fig. 6 illustrates the model fits for all training data sets, which were very good for all three models with Pearsons's product moment correlation coefficients between 0.99 and 1.00.

4.2. *Regionalisation*

The results of the independent validation with study sites of 3×3 km^2 shown in Fig. 7 indicate that the fitted non-linear regression functions predicted HSI_{opt} also fairly well for the smaller study sites. As it is shown in Fig. 8, correlations between predicted HSI_{opt} and optimisation results do not significantly differ between study site sizes.

Based on Eq. (2) we calculated cost-effectiveness of management actions *eff* for each of the three target species in all study sites (Fig. 9). Thus, we can identify areas where habitat improvement for the three focal species is more efficient than in other areas. The highest values of *eff* were reached for Wood Lark, while *eff* for Red-Backed Shrike took generally the lowest values (Fig. 9). For all three species the highest *eff* were found in the Northern part of the study area. However, the values of *eff* for the Red-Backed Shrike and the Middle-Spotted Woodpecker were also fairly high in the South-Western part of the study area. Improvement opportunities for Wood Lark were highest in the North to North-East of the study area.

Table 8 shows how the predicted distributions of *eff* were correlated to local characteristics. The observed correlations were not surprising, as cost-effectiveness of management actions was determined by local land-use profitability and local conditions influencing the species habitat suitability. However, it is interesting to see that there are also correlations to factors that were not incorporated in Eqs. (4)–(6). Temperature and precipitation were correlated to *eff* for the Red-Backed Shrike even though these variables were not included in Eq. (4).

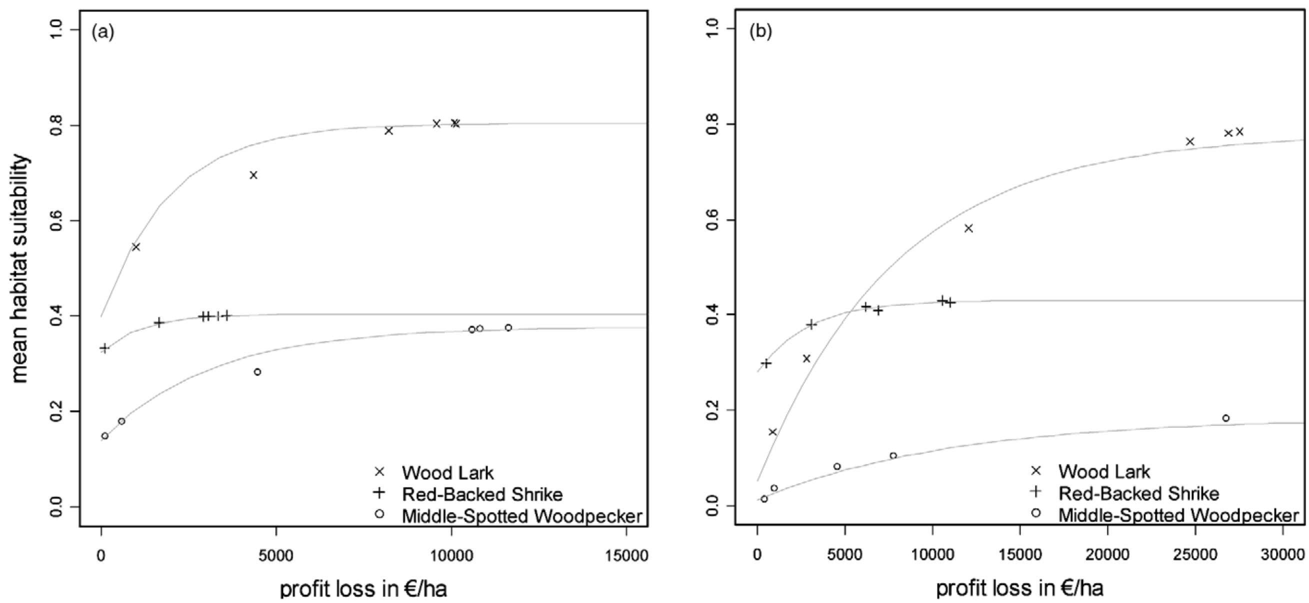

Fig. 5 – Optimisation results for all three species in two different study sites (a) and (b) with $n = 18$ for each study site (mean soil fertility score = 48.2 in site (a), 71.4 in site (b)); lines show predictions of Eqs. (4)–(6).

Table 5 – Estimated coefficients for non-linear regression function (4)

Coefficient	Estimate	Standard error	*t* Value	Pr(>|t|)
k	6.31E−07	4.39E−08	14.37	<2e−16***
a	89.08	1.61	55.42	<2e−16 ***

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.0045 on 76 degrees of freedom; adjusted $R^2 = 0.99$.

Table 6 – Estimated coefficients for non-linear regression function (5)

Coefficient	Estimate	Standard error	*t* Value	Pr(>|t|)
k	2.29E−11	5.06E−12	4.52	1.01e−5***
a	94.97	3.61	26.31	<2e−16***
b	251.00	5.47	45.89	<2e−16***
c	1690.00	31.71	53.30	<2e−16***

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.0239 on 213 degrees of freedom; adjusted $R^2 = 0.99$.

Table 7 – Estimated coefficients for non-linear regression function (6)

Coefficient	Estimate	Standard error	*t* Value	Pr(>|t|)
k	3.02E−09	4.97E−10	6.07	4.31e−16***
a	98.58	4.34	22.73	<2e−16***
d	143.80	39.08	−3.68	0.00028***

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Residual standard error: 0.0359 on 277 degrees of freedom; adjusted $R^2 = 0.97$.

5. Discussion

The cost–benefit relationships could be described by exponential saturation functions, because within the optimisation agriculturally less profitable areas were changed first to enhance habitat suitability. Thus, more and more areas of higher fertility were changed if the acceptable loss in profits was increased, which led to a saturation of the cost–benefit function curve with increasing loss in profits. The cost–benefit relationship differed not only between species, but also between study sites as both, the ecological and the economic part of the objective function, were spatially dependent. For example, the loss in profits was related to local soil fertility *fs* and the habitat suitability for the three focal species depended on various site characteristics v_s. In the non-linear regression functions the effects of this spatial variability were captured by incorporating the mean fertility score *fs* and HSI_{max} and HSI_0 in the derived exponential saturation functions. For the Red-Backed Shrike the effects of the static habitat variables mean annual temperature and mean annual precipitation were implicitly captured in the variables HSI_{max} and HSI_0. For the Wood Lark and the Middle-Spotted Woodpecker, additionally, habitat variables had to be included in the non-linear regressions to describe the species- and site-specific cost–benefit functions, because for these two species the slope of the cost–benefit function varies stronger between sites. For the same reason more study sites had to be sampled for these two species to achieve acceptable fits for the non-linear regressions. As the derived functions describe the curve of optimum trade-offs between loss in profits from land use and habitat improvement, they can be interpreted as species- and site-specific Pareto frontiers.

The slope of the cost–benefit function in its origin *eff* represents cost-effectiveness for low budgets. For larger budgets the distribution of cost-effectiveness might change according to the derived functions.

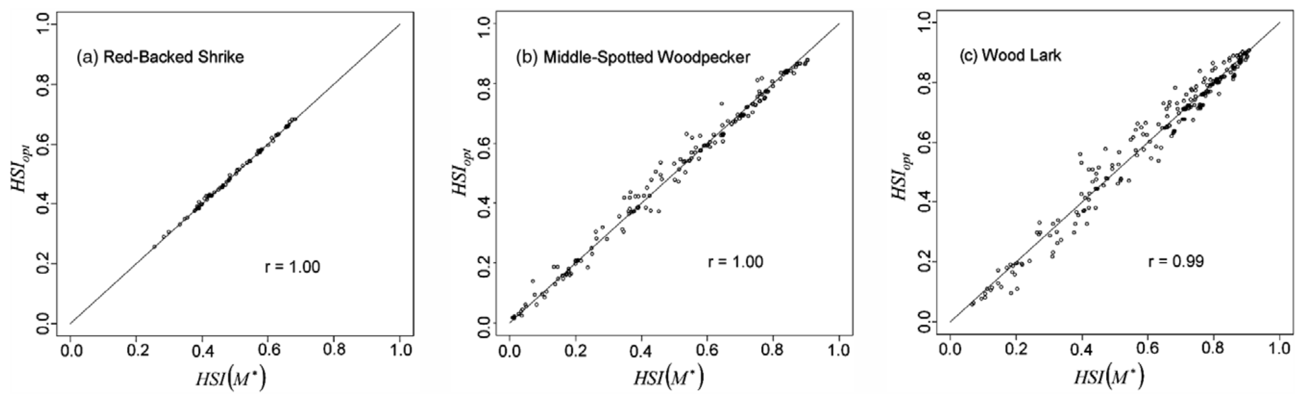

Fig. 6 – Correlations between optimised mean habitat suitabilities and mean habitat suitabilities predicted based on the fitted non-linear regressions for the three focal species in the chosen training study sites; *n* = 78 for (a), *n* = 144 for (b), *n* = 210 for (c); *r* = Pearsons's product moment correlation coefficient.

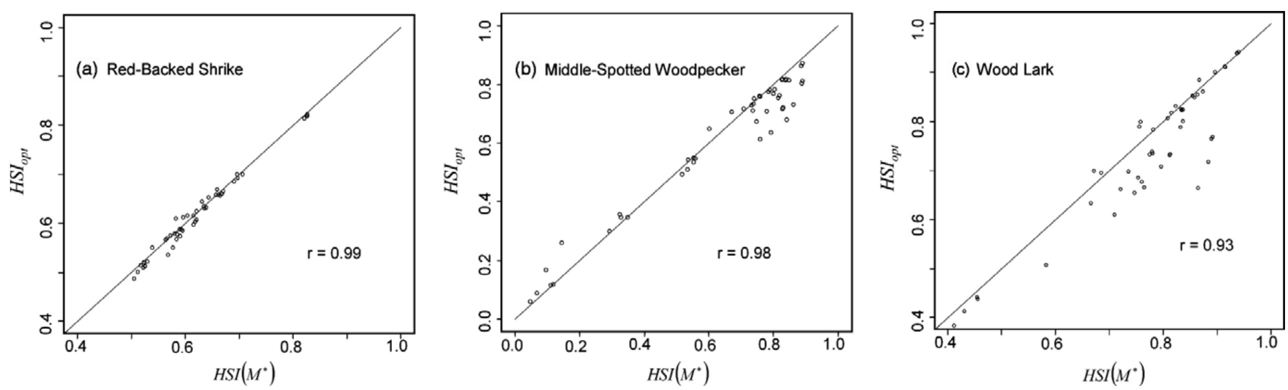

Fig. 7 – Correlations between optimised mean habitat suitabilities for randomly chosen study sites (3×3 km^2) and mean habitat suitabilities predicted based on the non-linear regressions for the three focal species fitted with results of larger study sites (6×6 km^2); *n* = 48 for (a), (b) and (c); *r* = Pearsons's product moment correlation coefficient.

The distributions of regionalised *eff* were mainly driven by soil fertility (Fig. 9, Table 8). Thus, *eff* for all three species was highest in the Northern part of the study area, where soil fertility is lower and management actions were connected with the least loss in profits. Cost-effectiveness was generally highest for species whose habitat enhancement was associated with the least loss in profits and if possible management actions had a high influence on habitat suitability.

Cost-effectiveness of management actions was always significantly positively correlated with initial habitat suitability due to the fact that favourable site conditions positively affect current habitat suitability and also provide good opportunities for an ecologically effective habitat improvement (Table 8). This result indicates that habitat enlargement is most cost-effective, which was also found to be reasonable when considering optimum habitat enhancement on a population level (Drechsler and Wätzold, 2001).

The presented methodology for regionalisation is especially useful, as complex spatial optimisation exercises are often limited by computational power. Unlike the study of Seppelt and Voinov (2003) our approach did not aim at predicting optimum land-use compositions on a large spatial scale. However, the spatial optimisation model can be applied to a small scale landscape subset that was identified according to the regionalised efficiencies of management actions to study the optimum land-use pattern. Thereby, landscape composition and configuration are explicitly considered and spatial dependencies and interactions can be incorporated. The presented approach does not consider the temporal aspect of land-use changes as the habitat suitability models assume equilibrium. However, short-term cost-effectiveness could easily be evaluated if successional states were incorporated in the habitat suitability evaluation.

We showed that the approach is applicable for different species. The best fit of the non-linear regression was achieved for the most generalist species with the lowest spatial habitat variability. The validation based on a set of independent study sites of smaller sizes proved that the derived functions could successfully be applied to predict HSI_{opt} for study sites of different sizes. It also confirmed our assumption that the chosen study site sizes were small enough to capture the variability of site conditions in the study area. By comparing model predictions for different study site sizes we could prove that the validity of model predictions is independent of study site size.

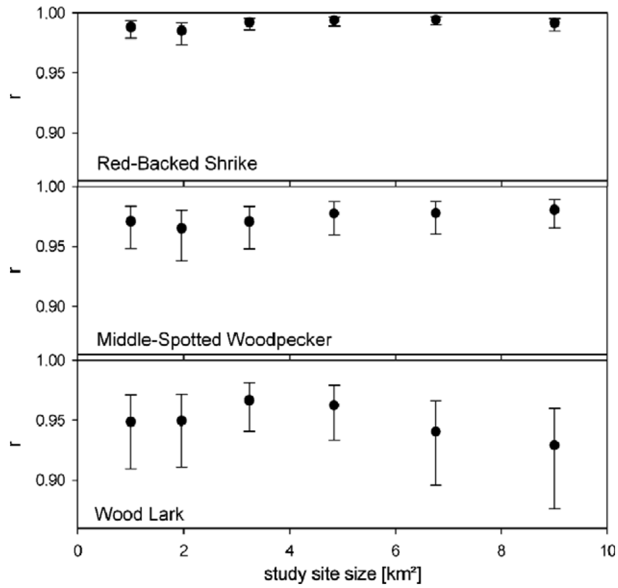

Fig. 8 – Pearsons's product moment correlation coefficient with 95%-confidence intervals for correlations between predicted optimised mean habitat suitabilities and optimisation results for the three focal species for different study sites sizes.

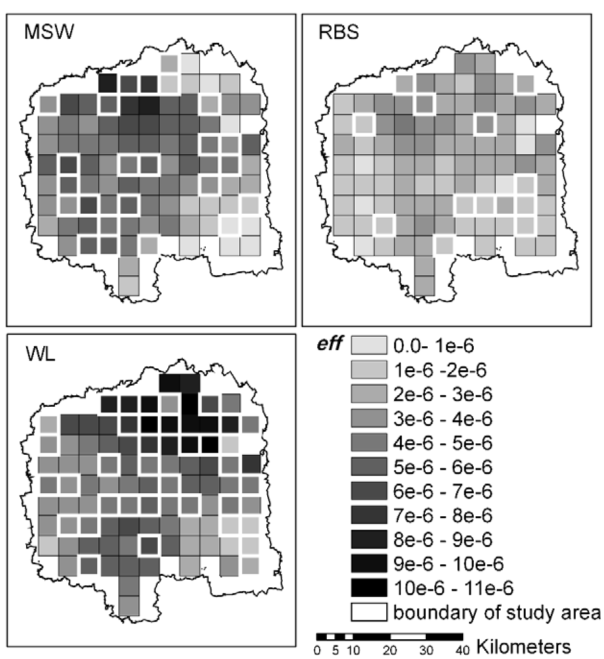

Fig. 9 – Regional distributions of *eff* for the three focal species (MSW, Middle-Spotted Woodpecker; RBS, Red-Backed Shrike; WL, Wood Lark); training study sites marked with white frames.

Depending on the research question other cost-functions could be applied (e.g. compensation payments for land-use conversions). The possibility to incorporate linear changes in the spatially explicit optimisation model can be useful for investigating research questions such as optimum allocations of hedges to reduce erosion or enhance biocontrol.

Table 8 – Pearsons's product moment correlation coefficients explaining eff for the three focal species (RBS, Red-Backed Shrike; MSW, Middle-Spotted Woodpecker; WL, Wood Lark)

r	*eff* for RBS	*eff* for MSW	*eff* for WL
hsi_{init}	0.43***	0.42***	0.51***
hsi_{max}	0.61***	0.6***	0.51***
Soil fertility score	**−0.63*****	**−0.51*****	**−0.85*****
Temperature	0.21*		
Precipitation	−0.18		
Elevation		**−0.53*****	
Sunshine duration		−0.25*	
Proportion of sand			**−0.79*****

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

6. Conclusions

We presented a new approach for deriving target- and site-specific Pareto frontier functions that can be applied on a large spatial scale based on optimisation results for small scale landscape samples.

The results of our case study are promising and indicate that the approach could be a flexible tool to support landscape management. The application is not limited to the chosen objective functions and management actions. The methodology could be applied for analysing a variety of management actions (e.g. concerning land-use intensity or cultivation methods) with different spatially referenced conservation goals (e.g. biodiversity, erosion, leaching of nutrients). It could be investigated, where ecological improvement is highest, given a certain acceptable economic constraint, or how much costs would have to be accepted to reach a certain ecological goal on a large regional scale. The results of this analysis could be used to identify optimum areas for management actions or to design compensation payment schemes. The optimisation model could then be applied to the chosen areas to investigate the optimum allocation of management actions on a smaller scale.

Acknowledgements

We thank Carsten Dormann, Martin Drechsler, Vanessa Stauch and Lutz Tischendorf for helpful comments on the manuscript, Marcus Brinkmann for his technical support. The software of this work used the GAlib genetic algorithm package, written by Matthew Wall at the Massachusetts Institute of Technology (Wall, 1996) as well as a routine for deriving ID maps from a categorical map from Michael Müller, Department of Ecological Modelling, UFZ Leipzig-Halle. The software package R was used for fitting the nonlinear regression.

REFERENCES

Bates, D.M., Watts, D.G., 1988. Nonlinear Regression Analysis and Its Applications. Wiley, New York.

Bennett, A.F., Radford, J.Q., Haslem, A., 2006. Properties of land mosaics: implications for nature conservation in agricultural environments. Biological Conservation 133, 250–264.
Boden, A.G., 1994. German Guidelines for Soil Survey, Hannover (in German).
Drechsler, M., Wätzold, F., 2001. The importance of economic costs in the development of guidelines for spatial conservation management. Biological Conservation 97, 51–59.
Federal Land Surveying Office Saxony, 2001. ATKIS-DGM: Digital Elevation Model, Dresden.
Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/ absence models. Environmental Conservation 24 (1), 38–49.
Flade, M., 1994. The Breeding Bird Communities of Eastern and Northern Germany: Principles for the Usage of Ornithological Data in Landscape Planning. IHW-Verlag, Eching (in German).
Freemark, E.K., Kirk, D.A., 2001. Birds on organic and conventional farms in Ontario: partitioning effects of habitat and practices on species composition and abundance. Biological Conservation 101, 337–350.
Haight, R.G., 1995. Comparing extinction risk and economic cost in wildlife conservation planning. Ecological Applications 5 (3), 767–775.
Hof, J., Raphael, M.G., 1997. Optimization of habitat placement: a case study of the Northern Spotted Owl in the Olympic Peninsula. Ecological Applications 7 (4), 1160–1169.
Holzkämper, A., Lausch, A., Seppelt, R., 2006. Optimizing landscape configuration to enhance habitat suitability for species with contrasting habitat requirements. Ecological Modelling 198, 277–292.
Hughey, K.F.D., Cullen, R., Moran, E., 2003. Integrating economics into priority setting and evaluation in conservation management. Conservation Biology 17 (1), 93–103.
Johst, K., Drechsler, M., Wätzold, F., 2002. An ecological-economic modelling procedure to design compensation payments for the efficient spatio-temporal allocation of species protection measures. Ecological Economics 41, 37–49.
Latus, C., Schultz, A., Kujama, K., 2004. Occurence of Red-Backed Shrike (*Lanius collurio*) depends on natural factors and mode of land use in the Quillow catchment, Germany. Biological Letters 41 (2), 87–93.
Main, M.B., Roka, F.M., Noss, R.F., 1999. Evaluating costs of conservation. Conservation Biology 13 (6), 1262–1272.
Margules, C.R., Pressey, R.L., 2000. Systematic conservation planning. Nature 405, 243–253.
Matson, P.A., Parton, W.J., Power, A.G., Swift, M.J., 1997. Agricultural intensification and ecosystem properties. Science 277 (5325), 504–509.
Mixdorf, U., 1996. Net Yield Costing as a Measure for Economic Efficiency of Forest Inventory Types. Free State of Saxony, State Ministry for Agriculture, Nutrition and Forestry (in German).
Moilanen, A., Cabeza, M., 2002. Single-species dynamic site selection. Ecological Applications 12 (3), 913–926.
Nalle, D.J., Montgomery, C.A., Arthur, J.L., Polasky, S., Schumaker, N.H., 2004. Modeling joint production of wildlife and timber. Journal of Environmental Economics and Management 48, 997–1017.
Polasky, S., Nelson, E., Lonsdorf, E., Fackler, P., Starfield, A., 2005. Conserving species in a working landscape: land use with biological and economic objectives. Ecological Applications 15 (4), 1387–1401.
Rau, S., Steffens, R., Zöphel, U., 1999. Red List of Threatened Vertebrates. Saxonian Federal Bureau of Environment and Geology, Dresden (in German).
Seppelt, R., Voinov, A., 2002. Optimization methodology for land use patterns using spatially explicit landscape models. Ecological Modelling 151, 125–142.
Seppelt, R., Voinov, A., 2003. Optimization methodology for land use patterns – evaluation based on multiscale habitat pattern comparison. Ecological Modelling 168, 217–231.
State Office for Statistics of Saxony, 2003. Agricultural Census (in German).
Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W.H., Simberloff, D., Swackhamer, D., 2001. Forcasting agriculturally driven global environmental change. Science 292, 281–284.
Wall, M., 1996. GALib: a C++ Library of Genetic Algorithm Components. Version 2.4. Available from: <http://lancet.mit.edu/ga/>.
Weibull, A.-C., Östman, Ö., Granquist, A., 2003. Species richness in agroecosystems: the effect of landscape, habitat and farm management. Biodiversity and Conservation 12, 1335–1355.
Woinarski, J.C.Z., Catterall, C.P., 2004. Historical changes in the bird fauna at Coomooboolaroo, northeastern Australia, from the early years of pastoral settlement (1873) to 1999. Biological Conservation 116, 379–401.