Spatial optimisation of land-use patterns with respect to habitat functions

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„Die Natur ist das einzige Buch, das auf allen Blättern großen Inhalt bietet.“

(Johann Wolfgang von Goethe)

Contents

List of abbreviations

AIC	Akaike' Information Criterion
AUC	Area under the ROC-curve
CA	Landscape metric "class area"
COH	Landscape metric "patch cohesion"
CONTAG	Landscape metric "contagion index"
DWD	Deutscher Wetterdienst (German meteorological service)
ED	Landscape metric "edge density"
GA	Genetic algorithm
GAlib	Genetic algorithm library by Wall (1996)
GIS	Geographical Information System
HSI	Habitat suitability index
ID	Identifier
LPI	Landscape metric "largest patch index"
LUPOlib	Land-Use Pattern Optimisation library
MMK 25	Mittelmaßstäbige Landwirtschaftliche Standortkartierung (Medium-Scaled Agricultural Site Mapping) 1: 25 000
MSW	Middle-Spotted Woodpecker
MSW_opt	Optimisation for Middle-Spotted Woodpecker
NP	Landscape metric "number of patches"
RBS	Red-Backed Shrike
RBS_opt	Optimisation for Red-Backed Shrike
ROC	Receiver Operating Characteristic
SHDI	Landscape metric "Shannon diversity index"
UFZ	Umweltforschungszentrum Leipzig (Helmholtz-Centre for Environmental Research)
w_MSW	Weighting for Middle-Spotted Woodpecker
w_RBS	Weighting for Red-Backed Shrike
w_WL	Weighting for Wood Lark
WBK 25	Waldbodenkarte (Forest Soil Map) 1: 25 000
WL	Wood Lark
WL_opt	Optimisation for Wood Lark

List of general notations

$a_{p,l}$	area (m²) of patch *p* with land use *l*
A_r	total area within radius *r* (m²)
B	logistic regression model estimates
C	total number of cells
c_l	number of cells of class *l*
coh_l	cohesion index of land use *l* within a radius around a location
$\mathrm{COH_l}$	map of cohesion indices of land use *l* within a radius around each location
$c_{p,l}$	area of patch *p* with land use *l* in terms of number of cells
C_r	total number of cells in the radius *r*
E	ecological value
$ec_{p,l,m}$	number of edge cells of patch *p* with land use *l* bordering land use m
ed_l	edge density of land use *l* within a radius around a location
$\mathrm{ED_l}$	map of edge densities of land use *l* within a radius around each location
eff	effectiveness of management actions
E_{opt}	predicted ecological value
$e_{p,l}$	total length (m) of edge of patch *p* with land use *l*
$es_{l,m}$	number of edge cells between land use types *l* and *m within* a radius around a location
$\mathrm{ES_{l,m}}$	map of number of edge cells between land use types *l* and *m* within a radius around a location
F	economic function (e.g. profit loss, costs)
f_{con}	constraint
fs	mean fertility score
G	regular grid
g	GA-genome
h	mean elevation
he	local height
HE	elevation map
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
id	unique identifier
J	optimisation criterion
J_{con}	constrained objective function
l	local land use

L_g	land-use categories of the allele set
lpi	largest patch index within a radius around a location
LPI	map of largest patch indices within a radius around each location
M	land-use map
$N_{x'y'}$	cell neighbourhood
P	profit loss
$p_0(x,y)$	initial profit from land use at location x,y [€/ha]
p_{cross}	probability of GA-crossover
p_{init}	probability of random disturbance in initial GA-population
$p_M(x,y)$	profit from land use at location x,y according to modified land-use map M in €/ha
p_{mut}	probability of GA-mutation
$p_{p,l}$	perimeter of patch p with land use l in terms of number of cell surfaces
pr	local precipitation
PR	mean annual precipitation map
p_{repl}	proportion of replacement in steady-state GA
psa	local proportion of sand
PSA	map of sand proportions
R	grid of habitat variables
sa	mean proportion of sand
sd	mean annual sunshine duration
ssd	local sunshine duration
SSD	sunshine duration map
tm	local temperature
TM	mean annual temperature map
u	decision unit
$v_k(x,y)$	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
w_s	weighting coefficient for species s
x	x-coordinate
y	y-coordinate
z	cell attribute
ΔHSI	difference between HSI_{max} and HSI_0
λ	weighting coefficient

Chapter 1

Introduction

1.1 Land-use change and its impacts on landscape functions

Landscapes are formed by human actions nearly everywhere in the world. Influenced by social, economic and political factors, humans employ the land and its resources for a variety of purposes. These purposes – defined as land use (Meyer 1995) – vary from energy supply, industry, food production to housing, recreation and conservation. Changes in land use take place where human demands to the landscape alter over time (Turner et al. 2001). For example, the period of industrialisation in Europe in the 19th century was characterised by an increased demand for space, material and energy. As a result, the area of forests and woodlands decreased drastically. Today, urban expansion, agricultural intensification and simultaneous marginalisation of farmland are among the most important processes that alter European landscapes (Jongman 2002).

Land-use changes have impacts on landscape functions such as biodiversity, water quality, water availability, flood regulation, nutrient cycles, carbon balance and climate (Asner et al. 2004). In general, biodiversity seems to be negatively affected by a reduction of landscape heterogeneity through land-use intensification (Böhning-Gaese 1997, Weibull et al. 2000, Atauri & de Lucio 2001, Stoate et al. 2001, Weibull et al. 2003, Luoto et al. 2004, Tews et al. 2004). Hydrology-related landscape functions like water availability, water quality and flood regulation are influenced by land-use change, which alters catchment hydrology through the processes of evaporation, transpiration, interception and surface runoff (Fohrer et al. 2001, Hundecha & Bárdossy 2004, Hörmann et al. 2005). Nitrogen emissions from agricultural land use affect the nutrient cycle and may lead to eutrophication (Lenhart et al. 2003, Baron et al. 2004). Finally, land-use changes can affect the terrestrial carbon cycle through the CO2-fixation and -release of the vegetation and the soil compartment (Houghton & Goodale 2004). The climate can be affected by land-use change through altered net radiation as well as sensible and latent heat fluxes (Bonan 2004).

The implications of land-use change are especially pronounced in densely populated regions where exploitation pressure is high. Agro-ecosystems are usually intensively used landscapes and a major environmental issue in agricultural landscapes is the threat to biodiversity (Donald et al. 2001, Tscharntke et al. 2005, Reidsma et al. 2006). Not only species that require natural habitats are threatened through habitat loss (Bennett & Ford 1997, Trzcinski et al. 1999, Villard et al. 1999, Pino et al. 2000, Boulinier et al. 2001, Bailey et al. 2002, Olff & Richie 2002, Radford et al. 2005, Bennett et al. 2006), but also species inhabiting cultivated habitats are at risk as land-use intensification increases and traditional agricultural practices are abandoned (Bignal & McCracken 1996, Sotherton 1997, Bruun & Smith 2003, Zamora et al. 2007, Harrop *in press*). Many species even require different landscape elements within their activity radius to obtain resources for breeding and foraging (Law & Dickman 1998) or they might require different conditions at different stages in their life cycle (Pope et al. 2000). Considering the impacts of agricultural land use on biodiversity and the fact that about two-third of plant and animal species in Central Europe belong to agro-ecosystems and are hence dependent on human land uses, there is a strong need to implement biodiversity targets into regional land-use planning (Duhme et al. 1997, Bennett et al. 2006, Fuller et al. 2007).

This thesis considers the effects of changing land-use patterns on species and investigates how changes in agricultural land-use patterns could enhance species' habitat functions.

1.2 Landscape planning and supportive computer-based methods

Landscape planning aims to regulate the different demands on the landscape and to ensure that land is used efficiently taking into account socio-economic as well as ecological perspectives (Harms & Opdam 1990, Haber 1990). Thereby, conflicts between management objectives can arise and have to be identified. For example, there can be conflicts between ecological and economic objectives, but also among different ecological objectives. For example, management actions to support one endangered species may have negative effects on other species with contrasting habitat requirements or other important landscape functions. The major task of landscape planners is to find trade-offs between different conflicting management objectives and to develop management plans that support neglected landscape functions.

A variety of computer-based methods are used to support landscape planning by evaluating landscape states and assessing the impacts of planned interventions with respect to different landscape functions. Decision-support in landscape planning can be provided by different types of computer models (e.g. static models, dynamic models, model systems or optimisation models). Habitat suitability models are one example for static models that can be used to support planning (Guisan & Zimmermann 2000, Austin 2002, Elith et al. 2006). They evaluate a landscape state from the perspective of a certain species and can predict impacts of changes in static scenarios (Fielding & Haworth 1995). Dynamic models and model systems are often used to investigate systems' responses to changes. Model systems integrate models of different components, often becoming very complex (e.g. Kliskey et al. 1999, Dragan et al. 2003, Hill et al. 2005, Berlekamp et al. 2007). These decision-support tools can generate alternative simulation scenarios according to different assumptions about intervening measures. By comparing these scenarios, it is decided which scenario is most favourable with respect to the management goals. Thus, simulation scenario analyses can help to quantify trade-offs and find the best combination of options in a multifunctional context (Opdam et al. 2002, Rudner et al. 2007). Another promising possibility to achieve this goal is to apply spatial optimisation, which allows for the derivation of target-driven optimisation scenarios that can be defined by one or more management goals. Therefore, optimum trade-off solutions between conflicting management objectives can be identified. Static and/or dynamic models can be integrated into an optimisation model to evaluate the management goal. In this thesis, the potentials of spatial optimisation for supporting species conservation management in intensively used landscapes are investigated.

1.3 State-of-the-art of spatial optimisation for decision support

So far, spatial optimisation decision support tools have mainly been applied for reserve selection and forest management planning. The scope of a typical reserve selection application is to identify the minimum set of reserves that satisfies the defined conservation targets in a certain landscape subset. C-Plan (Pressey et al. 1994), SITES (Andelman et al. 1999) and MARXAN (Possingham et al. 2000, Stewart & Possingham 2005) are examples for decision-support tools developed for identifying optimum allocations for reserves. Applications of spatial optimisation for reserve selection were presented by Pressey et al. (1996), Haight & Travis (1997), Hof & Raphael (1997), Clark & Slusher (2000), Moilanen & Cabeza (2002), Hof et al. (2002), Haight et al. 2002, Nicholson et al. (2006), Crossman & Bryan (2006), Crossman et al. (2007) and many others.

In the field of forest management, spatial optimisation has often been applied for optimising harvesting schedules to maximise profit. FORPLAN (Johnson & Stuart 1987) and WOODSTOCK (Walters 1993) are decision-support tools designed for this purpose. In the last years, more and more authors considered not only economic, but also species conservation aspects in forest management (Baskent & Keles 2005). For example, Bevers & Hof (1999), Loehle (2000), Moore et al. (2000), Calkin et al. (2002) and Venema et al. (2005) considered the impact of timber harvest on habitat functions and species survival. Öhman & Lämås (2003) applied optimisation to cluster harvest activities and thus minimise the impact on biodiversity. Turner et al. (2002) considered habitat core-areas for a forest-dwelling species, water quantity and sediment yields in order to address ecologically sustainable forest management.

However, all these optimisation applications for reserve selection and forest management consider habitat to be a fixed category (e.g. forest). It is not taken into account that habitat suitability can be affected by the availability of different landscape features and a combination of resources within the species' activity radius. Only few reserve site selection applications have used explicit models of species-habitat relations (Van Langevelde et al. 2000, Newbold & Eadie 2004). However, like all approaches dealing with reserve site selection these works consider only one management option per site.

In human-dominated and densely populated landscapes it is usually not sufficient to consider only one management option per site, as conservation can not be restricted to reserves. Instead, planning has to deal with the whole landscape mosaic with its multiple land uses and functions to maintain conservation in a working landscape (Polasky et al. 2005). Thus, management actions are often multifarious. A planning problem in these landscapes could for example be to identify the optimum allocation of land-use changes (e.g. forest, grass- and cropland) or certain management practices (e.g. fertiliser/pesticide application or mowing) to satisfy a multi-objective management goal. Thus, multiple goals and management options need to be integrated into the spatial optimisation. Nevo & Garcia (1996) optimise land cover composition with respect to habitat suitabilities on a zone level, but their approach is not spatially explicit and can thus not take into account that the landscape is continuous and that the spatial configuration of landscape features might have important effects on habitat suitability (e.g. compact core habitats, specific edge habitats or connections between open fields for foraging and groves or forests for nesting). Seppelt & Voinov (2003) perform a spatially explicit optimisation of agricultural land-use patterns, but they do not consider habitat functions and neighbourhood dependencies are neglected in their approach.

For supporting species conservation planning in an intensively used multi-functional landscape such as an agricultural landscape, an adequate optimisation approach is still missing. A spatial optimisation framework is required that allows for optimising the spatial allocation of multiple management options with respect to multiple management goals. Neighbourhood dependencies need to be explicitly considered in a continuous landscape because the spatial configuration of resources in a landscape is known to be relevant for many species' habitat functions. As the high complexity of spatial optimisation problems in working landscapes is a main reason for the rarity of spatial optimisation applications dealing with the land-use impacts on species (Eppink et al. 2004), it remains a major challenge to find efficient methods to handle such problems.

1.4 Research objectives

The main research questions addressed in this thesis can be summarised as follows:

- How can we efficiently optimise complex spatial land-use patterns in real landscapes?
- What can spatial optimisation results tell us about possible conflicts and trade-offs between multiple spatially referenced habitat functions and the economic usage of an agricultural landscape?
- Which potentials and limitations does spatial optimisation have to support planning and decision-making?

An efficient spatially explicit land-use pattern optimisation framework is developed, which is applicable for planning problems dealing with the optimum allocation of multiple management options in multi-functional landscapes and allows for considering spatial interactions. Three target species are chosen to represent important habitat types in a study area and habitat suitability models are derived to quantify the effects of landscape pattern on species occurrences on the species' home range scale. The optimisation framework is applied in connection with these species distribution models to investigate possibilities to enhance habitat suitability through changes in land-use pattern. Additionally, an economic function is incorporated into the optimisation to investigate the cost-effectiveness of species conservation management measures (see Fig. 1.1 for an overview of the presented approach).

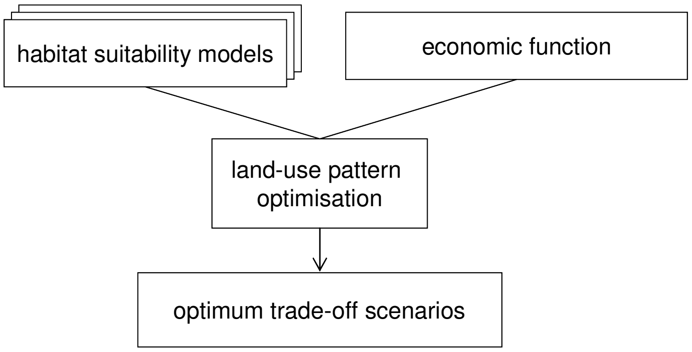


Figure 1.1: Overview of presented approach.

1.5 Overview

In the following chapter, the developed spatial optimisation framework is presented (Chapter 2). Chapter 3 gives a short introduction to the two case studies that apply the developed optimisation framework to solve optimisation problems with multiple objectives. In the first case study (Chapter 4), the optimisation algorithm is applied to investigate conflicts between habitat requirements of three target species and to find optimum trade-off solutions for all three species. The second case study (Chapter 5) deals with the possibilities for improving habitat suitabilities taking into account the economic value of the landscape usage. The optimisation is applied to analyse the cost-effectiveness of species conservation management actions on a regional scale. In a general discussion (Chapter 6), the research objectives introduced here (Section 1.4) are discussed in connection to the findings of Chapters 2, 4 and 5 and perspectives for further work are given. Major conclusions are drawn at the end of this work (Chapter 7).

Chapter 2

A generic tool for optimising land-use patterns and landscape structures

An edited version of Holzkämper & Seppelt 2007. *Environmental Modelling & Software*, accepted.

Abstract

We present a flexible and easy to use genetic algorithm-based library for optimising the spatial configurations of land-use. LUPOlib, the Land-Use Pattern Optimisation-library, can be applied to a variety of spatial planning problems to derive target-driven scenarios that identify trade-offs between conflicting objectives and solve optimum allocation problems (e.g. allocation of reserve sites or management actions). A major novelty is that spatial changes are performed according to a patch topology that allows to simultaneously integrate changes of different landscape elements (e.g. in agricultural fields and linear changes along corridors). The objective function evaluation is based on a grid representation of the landscape where neighbourhood dependencies like lateral flows or the landscape pattern can explicitly be considered. A parameter file allows the user to control the optimisation, the modelled land-use changes, objective weightings and constraints as well as input data. Only the case study-specific objective function needs to be specified in the source code. LUPOlib has been applied so far in two case studies to find optimum trade-offs between habitat requirements of three different bird species and to analyse cost-effectiveness of management actions for species conservation. The results suggest that LUPOlib can be a useful tool to support management decisions. It could be used as an extension to a GIS and for spatially explicit decision support tools.

2.1 Introduction

In the last few decades the potentials of spatial optimisation in the field of conservation management were discovered. Various software packages have been developed that apply spatial optimisation for finding optimum allocations for reserve sites (e.g. SITES / SPOT / MARXAN (Ball & Possingham 2000), C-Plan by Pressey, Ferrier and Watts (Finkel 1998)). In this paper, we present LUPOlib (Land-Use Pattern Optimisation library), a generic library for grid-based optimisation of spatial landscape configurations with respect to a user-defined optimisation goal. LUPOlib can be applied to a variety of spatial planning problems (e.g. finding trade-off between ecological and economic objectives, optimum allocation of management actions, reserve sites or roads). Like most programs dealing with complex spatial optimisation problems LUPOlib utilises a meta-heuristic search algorithm – a genetic algorithm by Wall (1996). This optimisation algorithm approaches a global optimum solution in an iterative directed search (Goldberg 1989). LUPOlib utilises a steady-state genetic algorithm with one-point crossover and flip-mutation as genetic operators. One innovative feature is that changes are performed based on a user-defined patch topology that allows an integration of two different types of land-use changes (e.g. areal and linear). Land use in designated patches (of areas or lines) is changeable, whereas the remaining landscape persists. Within the optimisation the patch topology is represented by two one-dimensional integer arrays (one for areal patches and one for line patches). However, for evaluating the goal function the landscape representation is transformed to a two-dimensional grid. This allows to explicitly consider neighbourhood-dependencies (e.g. for evaluating habitat suitability, landscape metrics or lateral flows of water and nutrients). The objective function needs to be specified by the user to solve a designated spatial optimisation problem. Up to now, the library was applied in two case studies to find optimum land-use patterns with respect to different bird species in parallel and to analyse cost-effectiveness of management actions for species conservation.

2.2 Description of LUPOlib

LUPOlib is a C/C++ library for the spatial optimisation of spatial land-use patterns (available at: http://www.ufz.de/index.php?en=4302). It integrates the C++ library for genetic algorithms GALib (Wall 1996) and provides an interface between the genetic algorithm and the subject of the optimisation, the spatially explicit landscape. LUPOlib includes functions for reading and writing raster maps, the definition of the landscape representation, algorithms for deriving a user-defined patch topology, for calculating landscape metrics, query functions and a function for applying the optimisation. It operates based on a regular grid G.

$$G = \{(x, y) | x_{\min} < x < x_{\max}, y_{\min} < y < y_{\max}; x_{\min}, x, x_{\max}, y_{\min}, y, y_{\max} \in \mathrm{IN}\}$$

Each grid cell may have different attributes z that either depend on its location (x,y) i.e. $z = f(x, y)$ or on the characteristics of neighbouring cells $N_{x',y'}$ i.e. $z = f(N_{x',y'})$, $N_{x',y'} \subset G$. For example, z_L denotes the land use at location (x,y) in the raster land-use map M. To decrease the computational effort and consider that land-use changes are made in certain decision units (e.g. agricultural fields), LUPOlib transforms the grid into a patch topology. Land-use patches that are potentially subject to change are defined as area units; line units are defined as potential locations for linear land-use changes (e.g. planting of hedges). Linear changes might be relevant to support certain landscape functions (e.g. habitat suitability, erosion, biocontrol). Grid cells of area and line units are changed *en bloc*, as they are assumed to be managed as entire units. Area and line units are identified by unique ID's (Fig. 2.1). LUPOlib allows deriving ID-maps from M according to user-specified parameters.

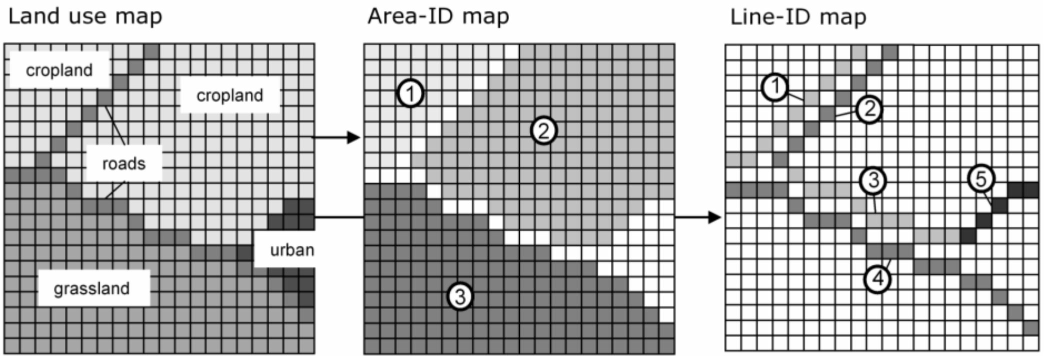


Figure 2.1: LUPOlib patch topology: Area units and line units are identified in an area- and line-ID map, respectively: Patches of crop- and grassland are assigned to area units; urban areas and roads are excluded from land-use changes. Edge cells of crop- and grassland are assigned to five different line units according to the bordering land-use types.

The general optimisation task of LUPOlib is to maximise an objective value J by finding an optimum land-use pattern for the units that are modifiable. Thus, M should be identified such that $J(M) \rightarrow \max$. Interactions between neighbouring cells can be considered making J dependent on z that itself dependents on $N_{x',y'}$. The objective function can consist of several objectives that may be weighted to integrate objectives with different units and to specify the relevance of each of the objectives (e.g. habitat suitabilities for different species, costs for changes). One or more constraints can be set (e.g. a budget that limits admissible changes). The objective function allows the incorporation of functions provided by LUPOlib, user-defined functions and even system calls for external programs can be integrated to allow a coupling to existing models.

2.3 Application of LUPOlib

Input data

A land-use map *M* is needed as input map in Arc ASCII raster-format. ID-maps that identify decision units for the optimisation can either be derived from *M* by LUPOlib or read in as pre-processed ASCII raster-files (e.g. to exclude protected areas from changes). Likewise, further input maps that are needed to evaluate the objective function can be read in.

Parameter file

A parameter file allows the user to control the genetic algorithm, the possibilities and constraints for land-use change and the derivation of area and line units. Furthermore, input maps are identified and weightings and constraints for the goal function can be defined (Table 2.1).

Table 2.1: Parameter file description (* see Wall (1996) for documentation of GA parameters).

Parameters	Values	Description
pAU	0.5	probability for random initialisation of area units
pLU	0.1	probability for random initialisation of line units
popSize	20	population size*
pCross	0.6	crossover probability*
pMut	0.01	mutation probability*
pRepl	0.25	probability of replacement*
nGen	100	maximum number of generations*
pConv	0.99	convergence criterion*
nConv	100	convergence parameter*
alleleset_area	4 9 10;	changeable land-use types
alleleset_line	7;	linear changes can be made to these types
area_change_except	4 10;	no changes are performed to these types
line_change_except	8 9;	no linear changes on these types
line_edge_except	8 9;	no linear changes bordering to these types
AREA_IDMAP	create	create area-ID map
areaID_cat	4 10;	assign ID's to patches of these land-use types
neighbourhood	4	consider 4 nearest neighbours
min_area	1600	exclude area units < 1600m^2
LINE_IDMAP	line_Idmap	filename of preprocessed line-ID map
lineID_cat	;	derive line-ID's for edge-cells of these categories
lineID_except	;	no line-ID's for cells bordering to these categories
min_length	0	exclude line units < 0m
weightings	0.5;	weightings for objective function evaluation
constraints	800;	constraints for objective function evaluation
landusemap	landuse	filename of input land-use map
inputmaps	forest_age	filename of input map for objective evaluation

Definition of the objective function

The definition of the objective function sets the optimisation goal. It is problem-specific and thus to be coded by the user. After modification of the objective function the program has to be recompiled. The pseudo-code below shows an example of an objective function to maximise timber harvest profit, while minimising habitat fragmentation given a maximum harvest area defined in a constraint. A weighting is incorporated to allow for an integration of the two objectives (`obj1`, `obj2`). It applies a user-defined function (`getHarvestProfit()`) and two functions provided by LUPOlib (`getArea()`, `getEdgeDensity()`).

```
float
objective(landusemap, inputmap, weighting, constraint){
  float J = 0.000; //objective function value
  float obj1 = 0.000;
  float obj2 = 0.000;
  float con = 0.000;
  con = getArea(landusemap, harvest); //harvested area in landusemap
  if(con <= constraint){
    //harvest profit in landusemap calculated based on
    //inputmap “forest_age” (see Table 2.1)
    obj1 = getHarvestProfit(landusemap, inputmap);
    //fragmentation of habitat in landusemap:
    obj2 = getEdgeDensity(landusemap, habitat);
    //maximise harvest profit, while minimising habitat fragmentation:
    J = weighting*obj1 - obj2;
  }
  return(J);
}
```

A variety of other functions is provided in LUPOlib for calculating different landscape metrics for the whole landscape subset and within a certain radius around a grid cell (e.g. edge density, patch cohesion, largest patch index). All landscape metrics are calculated according to McGarigal et al. (2002). They can be useful, when the optimisation task is to minimise fragmentation or to maximise habitat suitability for species that respond to landscape structure on a territorial scale (Holzkämper et al. 2006).

Output data

The optimisation algorithm terminates either if the specified convergence criterion or the maximum number of iterations is reached. As model output LUPOlib stores the optimised land-use map in Arc ASCII raster format and a text file with the highest objective values in all processed iterations. ID-maps derived by LUPOlib are also stored with output data.

2.4 Case studies

LUPOlib has been applied in two different studies so far (Holzkämper et al. 2006, Holzkämper & Seppelt 2007). The first one dealt with optimising land-use patterns with respect to habitat suitability for three bird species with contrasting habitat requirements. It was investigated where habitat requirements oppose, where they coincide and which management actions improve habitat suitability for all three species. In a second study, LUPOlib was applied with an ecological-economic goal function to analyse cost-effectiveness of conservation management actions for different bird species on a regional scale by deriving general patterns of Pareto-optimality. These examples demonstrate that LUPOlib can be used to find trade-offs between conflicting management objectives and cost-effective opportunities for ecological improvement.

2.5 Conclusions and recommendations

Applying a patch topology within the optimisation produced reasonable land-use patterns, as the units of change correspond to the land-use parcels on which decisions are made in reality. LUPOlib can be a useful tool to support conservation management decisions. The library is very flexible and could easily be applied for analysing a variety of other management actions (e.g. concerning land-use intensity or cultivation methods) on different spatial scales with different spatially referenced goal functions (e.g. biodiversity, erosion, leaching of nutrients). Thus, integrated models for decision support, like the ones of Berlekamp et al. (2007) and Dragan et al. (2003) that usually apply scenario analysis could be extended by LUPOlib to create target-driven scenarios. Furthermore, the library might also be incorporated in a GIS such as GRASS. The possibility to integrate areal and linear changes is a major advantage as it allows for optimising the pattern of different landscape elements simultaneously. The program reads and writes maps in Arc ASCII raster format, which is supported by many GIS (e.g. ArcGIS/ArcView, GRASS). It is interoperable, running under Windows and Linux and can easily be used in batch mode.

Acknowledgements

The software presented in this paper uses the GAlib genetic algorithm package by Wall (1996) as well as a routine for patch derivation from Michael Müller, UFZ Leipzig-Halle.

Chapter 3

The case studies

The developed optimisation framework is applied in two case studies to test the performance of the optimisation model and to investigate possible trade-offs between multiple spatially referenced habitat functions and the economic usage of an intensively used agricultural landscape.

3.1 Study area

The case studies are carried out in the administrative district of Leipzig in north-west Saxony, Germany (Fig. 3.1). The study area spans ~441.000 ha and borders to the federal state of Saxony-Anhalt in the North and West, to Brandenburg in the North-East and in the South-West to Thuringia. Topography is relatively flat with altitudes around 100 m a.s.l. in the North-West (*Leipziger Land*). Elevation rises towards the increasingly hilly South-East of the study area to about 250-300 m a.s.l. (*Nordsächsisches Platten- und Hügelland*). These hills are formed through the basement. In the northern part of the study area push moraines form slight hills (*Düben-Dahlener Heide*) (Bernhardt et al. 1986).

At the soil surface mainly glacial and periglacial depositions are to be found, overlain by limnogenous and fluvigenous depositions along rivers. Surface substrates are dominantly loamy loess depositions in the lowlands around Leipzig, silty loess in the hilly south-east and sandy melt water sediments dominate in the old moraine area in the North-East. South and also north of Leipzig, opencast mining has extensively altered the topography by introducing deep mining pits and waste heaps. In these areas soils were relocated under anthropogenic influence (Bernhardt et al. 1986).

On the sandy substrates in the old moraine area in the North-East soil types with relatively low fertility like brown soils, brown podsols and podsols are to be found. At sites under groundwater influence gley soils have formed. Para-brown earth and pale leached soil are predominantly found in the fertile loess areas that cover the major southern part of the study area (Mannsfeld & Richter 1995).

Climatic conditions in the study area are mainly driven by topography. Mean annual temperature decreases from ~8 °C in the South-East to ~9 °C in the North-West. Conversely, mean annual precipitation increases from ~500-550 mm in the North-West to ~600-650 mm in the South-East (Mannsfeld & Richter 1995).

Three major rivers and their affluxes characterise the surface water structure in the administrative district of Leipzig. The Weiße Elster, which flows through Leipzig from South to North, the Mulde, crossing the central study area from South to North and the Elbe, which flows through the administrative district of Leipzig in the North-East (Regionaler Planungsverband Westsachsen 1999).

The study area is dominated by agricultural land use as soil fertility is generally high in the study area. Agricultural areas cover about 66% of the study area, whereas forests are scarce and cover only about 15% and 11% are covered by urban and traffic areas (Regionaler Planungsverband Westsachsen 2002).

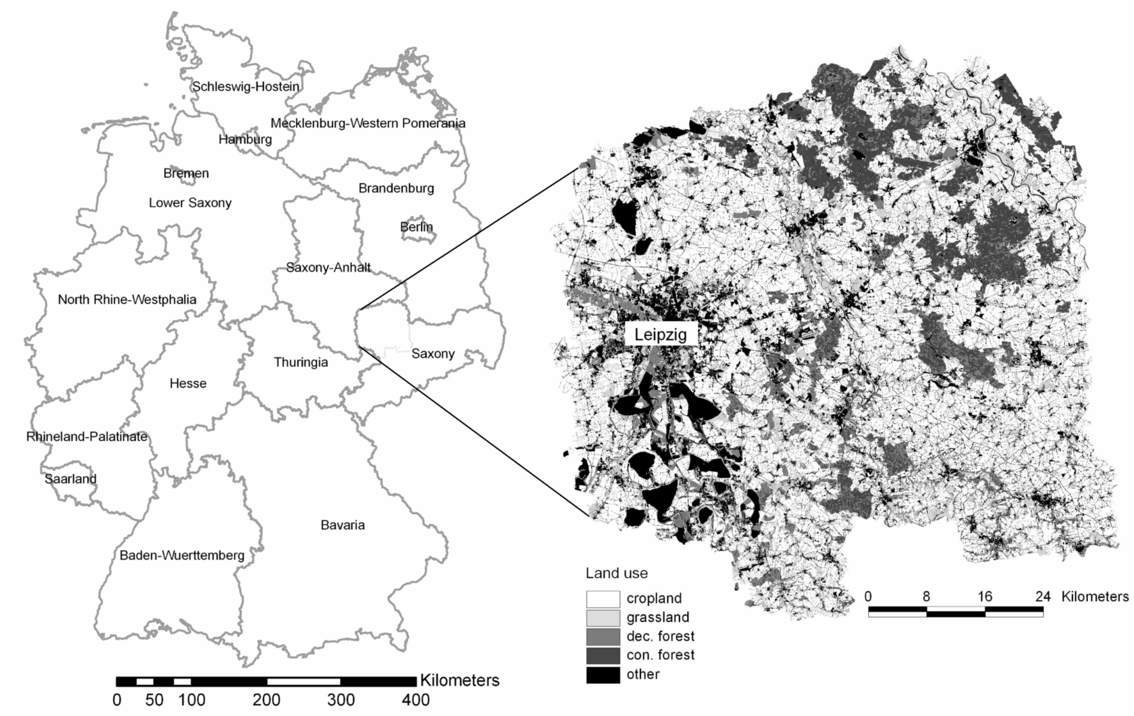


Figure 3.1: The administrative district of Leipzig with its main land-use types and its location in Germany (land-use data source: Küster 2003).

As in all federal states of the former GDR, farmland collectivisation, starting in the 1950s, has extensively changed the agricultural land-use pattern (Van der Ploeg & Schweigert 2001). Fields were merged and accompanied to that, many small biotopes like woodlots, hedgerows and field verges disappeared (Duhme et al. 1997). The homogenisation and intensification in Eastern German agricultural landscapes has led to an even stronger reduction of biodiversity than in Western Germany (Van der Ploeg & Schweigert 2001). This makes the administrative district of Leipzig an appropriate study area for investigating the possibilities to enhance habitat functions through changes in land-use patterns.

3.2 Species selection

Three bird species are chosen to represent important habitat types and associated species in the study area (Fig. 3.2). Birds are often used as biodiversity indicators because they represent important components of overall biodiversity. Furthermore, they are very appealing to the public and often good databases on bird distributions exist.

Middle-Spotted Woodpecker (*Dendrocopus medius*)	Wood Lark (*Lullula arborea*)	Red-Backed Shrike (*Lanius collurio*)
		
Habitat characteristics: extensive old-growth deciduous forests (preferably Oaks) Species conservation status: Red List species 3 (endangered)	Habitat characteristics: half-open landscapes and coniferous forests on dry, sandy sites Species conservation status: Red List species 2 (highly endangered)	Habitat characteristics: half-open landscapes, hedges, forest-edges in agricultural areas Species conservation status: no Red List species in Saxony

Figure 3.2: The target species, their habitat characteristics (Steffens et al. 1998) and conservation status in Saxony (Rau et al. 1999); (Photos: Kerihuel 2005, Jahn 2005, Granitza 1999).

The three chosen bird species are generally threatened through loss of natural habitats and land-use intensification. The Middle-Spotted Woodpecker is mainly endangered through deforestation and conversions of deciduous to coniferous forests, the Red-Backed Shrike is threatened through agricultural land-use intensification and associated loss of small landscape elements like hedges, and groves and the Wood Lark is at risk due to deforestation and land-use intensification (Glutz von Blotzheim 1999).

By considering these three species, it is taken into account that management actions to support one species might have negative effects on other species with contrasting habitat requirements.

Habitat amount and quality are assumed to be important key factors for species survival. Thus, habitat suitability is used as a proxy for the capacity of the landscape to retain a species. Habitat suitability models are derived for the three species to quantify the relationship between environmental parameters and species' occurrences in the administrative district of Leipzig and to predict effects of environmental changes on species' habitats. Environmental parameters that are considered in this context are elevation, climate variables, soil texture and aspects of land-use pattern within the species' home ranges (see Table 3.1 for an overview of spatial data used in this thesis).

3.3 Specific research questions

The two case studies presented in the following chapters apply the optimisation framework in connection to habitat suitability models and an economic function in the study area to investigate the specific research questions:

- Where do species' habitat requirements of the target species oppose and where do they coincide?
- Is landscape composition or configuration more relevant for species' habitat functions?
- Can habitat functions be improved for all three species simultaneously?
- Where are land-use changes to enhance habitat functions for the three species most cost-effective?

Table 3.1: **Summary of spatial data of the administrative district of Leipzig used in this thesis.**

Theme	Units	Resolution	Date	Source	Data preparation
Counties ("Kreise")	Polygons	Counties	2004	Regional planning bureau (Regionale Planungsstelle)	
Municipalities ("Gemeinden")	Polygons	Municipalities	2004	Regional planning bureau (Regionale Planungsstelle)	
Elevation	m	20m	2002	Landesvermessungsamt Sachsen (2002)	
Mean annual temperature	°C	1000m	1961-1990	German meteorological service (DWD)	
Mean annual precipitation	mm	1000m	1961-1990	German meteorological service (DWD)	
Annual sunshine duration	h	1000m	1961-1990	German meteorological service (DWD)	
Land use	20 categories	10m	1965, 1984, 1994	UFZ, Department of Computational Landscape Ecology	Visual interpretation of data from different sources (satellite imagery, aerial photographs, topographic maps, land-use mapping) (Küster 2003)
Soil map	11 categories	1:25 000	1970-1990	UFZ, Department of Computational Landscape Ecology	Intersection of MMK 25 (Medium-Scaled Agricultural Site Mapping) and WBK (Forest Soil Map) of the Saxonian Federal Bureau of Environment and Geology (Bomhard 2002)
Soil texture	% sand/silt/clay in soil	1:25 000	1970-1990	UFZ, Department of Computational Landscape Ecology	Derived from soil map based on AG Boden (1994)
Soil fertility ("Ackerzahlen")	10 (very infertile) - 100 (very fertile)	Municipalities	1930s	"Reichsbodenschätzung" carried out by governmental institutions	Discretised based on municipalies 2004
Mean crop profits	€/ha	Municipalities	2005	UFZ, Department of Computational Landscape Ecology	Estimated based on land-use profits derived from crop statistics of Saxonian State Office for Agriculture in the year 2005 (http://www.smul.sachsen.de/BPSPlan/); discretisation according to distribution of crop types on municipality level (Statistisches Landesamt des Freistaates Sachsen 2003) and soil fertility scores
Mean grassland profits	€/ha	Municipalities	2005	UFZ, Department of Computational Landscape Ecology	Estimated based on profit margins for grassland and pasture derived from crop statistics of Saxonian State Office for Agriculture in the year 2005 (http://www.smul.sachsen.de/BPSPlan/); discretisation according to distribution of grassland types / stock farming on municipality level (Statistisches Landesamt des Freistaates Sachsen 2003) and soil fertility scores; 75% of all grassland was assumed to be pasture
Mean deciduous and coniferous forest profits	€/ha	Municipalities	1996	UFZ, Department of Computational Landscape Ecology	Estimated based on information from Mixdorf (1996) and soil fertility
Bird breeding occurences	Presences	Occurence points	1963-1996	National Bureau of Environment (Staatliches Umweltfachamt Leipzig) and Natural History Museum Leipzig	dgitised at the UFZ, Department of Computational Landscape Ecology by Küster (2003)

Chapter 4

Optimising landscape configuration to enhance habitat suitability for species with contrasting habitat requirements

An edited version of Holzkämper et al. 2006. *Ecological Modelling*, published.

Abstract

Heterogeneity of agricultural landscapes is supposed to be of significant importance for species diversity in agroecosystems. However, land-use-pattern changes may lead to an increase in suitable habitat for some species, but to habitat deterioration for other species with opposing habitat requirements. To investigate the effects of land-use changes on different species' habitat suitabilities and to allow a trade-off between management objectives, we applied a spatial optimisation model. In this paper we present a new approach that integrates a neighbourhood dependent multi-species evaluation of land-use patterns into an optimisation framework for generating goal-driven scenarios. It is implemented using a genetic algorithm approach that aims at maximising habitat suitability of three selected bird species (Middle-Spotted Woodpecker, Wood Lark, Red-Backed Shrike) by identifying optimum agricultural land-use patterns. The evaluation of habitat suitability is based on landscape metrics calculated within the species' home ranges to incorporate the effects of species responses to landscape pattern on a coarser scale. The main focus of this study is to explore the potential of this approach for conservation management on the basis of a case study. We investigate where habitat requirements oppose, where they coincide and how a landscape optimised simultaneously for all target species should be characterised. We found that all species would benefit from an increase of deciduous and coniferous forest, a decrease of cropland and grassland in the study area and more heterogeneous land-use patterns (smaller patches, more diversity of land-use types). Habitat requirements of

Red-Backed Shrike contrast most to those of the other two species with respect to landscape composition and configuration.

4.1 Introduction

Landscape structure is thought to have important influences on various ecosystem functions (e.g. biodiversity (Weber et al. 2001, Weibull et al. 2003), nutrient cycles (Seppelt & Voinov 2002, Lenhart et al. 2003), and water balance (Bormann et al. 1999, Bellot et al. 2001)). In this paper, we focus on the impacts of landscape structure on habitat suitability for different bird species. As species habitat requirements differ, changes may have positive effects on some species and negative effects on other species. For example, some species like the Middle-Spotted Woodpecker prefer core habitats, while other species such as the Red-Backed Shrike depend on boundary structures like forest edges or hedges (Latus et al. 2004). Furthermore, some species may use different habitat types for different activities such as breeding and foraging. Land-use changes may therefore lead to an increase in suitable habitat for one species, but to habitat loss and fragmentation for another species with opposing habitat requirements. As bird species are known to respond to habitat factors at coarser spatial scales, land-use patterns within a certain radius need to be considered for evaluating habitat suitability (Freemark & Merriam 1986, Graf et al. 2005). Scenario analysis can be applied to analyse the effects of land-use changes on habitats for different species. However, to methodically approximate an optimum landscape pattern with respect to a certain goal, a spatially explicit optimisation approach must be employed. This technique allows one to incorporate trade-offs between different management objectives. Spatial optimisation methods have mostly been used in the field of timber and wildlife management (Thompson et al. 1973, Nevo & Garcia 1996, Bevers et al. 1997, Church et al. 2000, Loehle 2000, Hof et al. 2002), for selecting wildlife reserves (Pressey et al. 1995, Polansky et al. 2000, Cabeza & Moilanen 2003, Strange et al. 2006) or for optimising crop yields given ecological constraints (Seppelt 2000, Seppelt & Voinov 2002). Many applications of optimisation approaches are spatially explicit, but only a few of them take into account neighbourhood dependencies. Bevers & Hof (1999) optimise habitat configuration resulting from forest management with respect to wildlife edge effects. A similar approach was used by Moore et al. (2000), where population viability was optimised over ten decision periods based on a very simple landscape. Likewise, Loehle (2000) minimises the impact of timber harvest on edge-sensitive bird species while maximising timber harvest. This study is also based on a very simple grid landscape. Venema et al. (2005) optimise forest structures with respect to certain landscape metrics.

In this paper, we present a new approach that integrates a neighbourhood dependent multi-species evaluation of land-use patterns into an optimisation framework for generating goal-driven scenarios. We need to incorporate neighbourhood effects due to the dependencies of species' habitat quality on the characteristics of surrounding habitat. Thus, we chose to implement our model using a genetic algorithm, which is known to be capable of handling very complex optimisation problems. Our optimisation model aims to maximise habitat suitability for three selected bird species by identifying optimum agricultural land-use patterns. Bird species with contrasting habitat requirements and preferences in habitat structure were chosen as target species to investigate the different effects of land-use changes. In contrast to the approach of Venema et al. (2005), where landscape-level metrics define the optimisation goal, our model uses cumulative habitat suitabilities estimated for the study area to determine the optimisation goal. The evaluation of these habitat suitabilities is based on static variables like soil types or climate factors and land-use patterns quantified by landscape metrics (McGarigal et al. 2002). These metrics are estimated within the species' home ranges. Thus land-use patterns are optimised for the three species on a territorial scale. The optimisation model approach allows us to analyse how weighting for selected species affects the composition and configuration of optimised landscapes. The main focus of this paper is to explore the potential of this approach for conservation management on the basis of a case study. To do this, we investigate where species habitat requirements oppose and where they coincide, and how a landscape optimised for all target species should be characterised.

4.2 Methodological concept

Our optimisation model is designed to implement trade-offs between different management objectives, taking into account spatial configurations of landscape elements. It was used to detect optimum landscape patterns for several species with contrasting habitat requirements. With this approach, we want to analyse how an improvement of habitat suitability for one species affects other species' habitat suitability. Thus the optimisation task is to maximise the weighted sum of habitat suitabilities of all species in the study area by identifying optimum spatial configurations of agricultural land-use patterns. As this is quite a complex combinatorial problem, we apply a genetic algorithm approach, which is known to be a robust method for gradient-free optimisation (Goldberg 1989). We utilised the C++ genetic algorithm library GALib 2.4.6 by Wall (1996). The results of logistic regression habitat suitability modelling are fed into the optimisation model to evaluate the optimisation goal. To minimise the computational effort and avoid unrealistic land-use patterns we defined model units as contiguous cells of identical land use. These model units correspond to patches of agricultural fields, grassland and forest that are assumed to be managed as entire units. Within the model units all grid cell values are changed *en bloc*.

Habitat suitability modelling procedure

Statistical habitat suitability models were developed using logistic regression based on grid data of the study area with 40 m resolution. As only presence point data was available for the target species, random sets of pseudo-absence data were generated that were of equivalent size to those in the actual presence data set. This method was chosen as it results in coefficients for all variables that can be used for predicting habitat suitability under changed conditions in the optimisation model. To avoid bias through spatial autocorrelation we excluded all presence points where the home ranges overlapped. The selection of pseudo-absence data had to be done several times because different samples could result in different models. To prevent pseudo-absence points from overlapping with presence points, the selection was restricted by a mask layer, where species' occurrences buffered with the home range radius were excluded. For all data points (presence and pseudo-absence), the local values of static habitat variables (e.g. elevation, slope, proportion of soil texture, precipitation, sunshine duration, temperature) were stored. To test the effects of structural landscape aspects on habitat suitability, landscape metrics (McGarigal et al. 2002) were calculated for each of these points within a radius that corresponds to the species' home ranges. We incorporated the metrics largest patch index on the landscape level as well as class area and edge density on class level in the habitat suitability modelling. We chose these rather simple metrics as they have relatively high explanatory power and interpretability (Tischendorf 2001). The largest patch index quantifies landscape homogeneity. Edge density is given by the class length of edge segments (m) per hectare, while class area is simply the area of a certain class per hectare. Furthermore, we used the patch cohesion metric at the class level, as this metric incorporates class area and class fragmentation (Schumaker 1996). Patch cohesion approaches zero as class area decreases and becomes increasingly subdivided and it increases monotonically as class area increases until an asymptote is reached near the percolation threshold (McGarigal et al. 2002). We also introduced an edge sum metric, which is the sum of edge cells of one land-use type bordering a certain other land-use type, to include the effects of edges between two specific land-use classes.

In the analysis, a set of uncorrelated potential habitat variables was chosen for each species. As class area and patch cohesion of one land-use class are necessarily highly correlated, we tested the relevance of each in separate analyses. One thousand pseudo-absence samples were drawn and based on the presence data and multiple pseudo-absence data sets, 1000 logistic regression models were calculated for each species by using a stepwise variable selection procedure (forward and backward variable selection; Harrell 2001; Reineking & Schröder 2006). The step-function selects a model according to the AIC (Akaike's Information Criterion), which corresponds to a penalisation term, of 2 which is equivalent to an α-level of 0.157 (Reineking & Schröder 2006).

To allow a direct interpretation of model coefficients, all independent variables were scaled. The coefficients of the most frequently occurring model were chosen and averaged to result in the model used for predicting habitat suitabilities in the optimisation. Standard deviations for the coefficients are standard errors of averaged estimates. To evaluate the averaged model, AUC (area under the ROC-curve) was evaluated based on the 1000 samples. For model predictions, the variable values were scaled with the averaged mean and the averaged standard deviation derived from the data sets of the source models.

Model formulation of optimisation problem

As genetic algorithms (GA) are based on the principles of evolution, we need to perform the following steps for coding an optimisation procedure with a GA:

a) Definition of 'genome': The subject of the optimisation needs a representation of a certain data structure within the genetic algorithm. This representation is called a 'genome' or 'individual' in this context. Evolution acts on a 'population' of 'genomes', where each 'genome' has slightly different characteristics. These characteristics are equivalent to the 'genes' in a 'genome'. The 'allele' set describes the possible states of 'genes'.

b) Definition of 'genetic operators' (crossover, mutation): To allow changes in the 'population' and thus make 'evolution' possible, operators for 'crossover' and 'mutation' need to be defined. The 'crossover' operator specifies the procedure of generating new 'genomes' by recombining 'genes' of selected 'parent genomes'. 'Mutation' is applied to each 'child genome' after 'crossover' and randomly alters each 'gene' with a low probability. Thus, 'mutation' provides a small amount of random search and helps insure that no point in the search space has a zero probability of being examined (Beasley et al. 1993). For example, if only part of the 'allele' set is represented in the current 'population', other 'alleles' could still be introduced through 'mutation'.

c) Definition of objective function: Within the objective function we specify our optimisation goal. It returns 'fitness' scores for each 'genome' that are used to select 'genomes' for 'crossover' and for resizing the 'population' after 'crossover'. The term 'objective function' is synonymous to the terms 'goal function' and 'performance criterion'. 'Fitness' scores are also called objective values.

In this paper, we use the terms ‘population’, ‘individual’, ‘genome’, ‘gene’, ‘crossover’, ‘mutation’ and ‘generation’ only in the context of genetic algorithms. Figure 4.1 illustrates the procedure of our optimisation model.

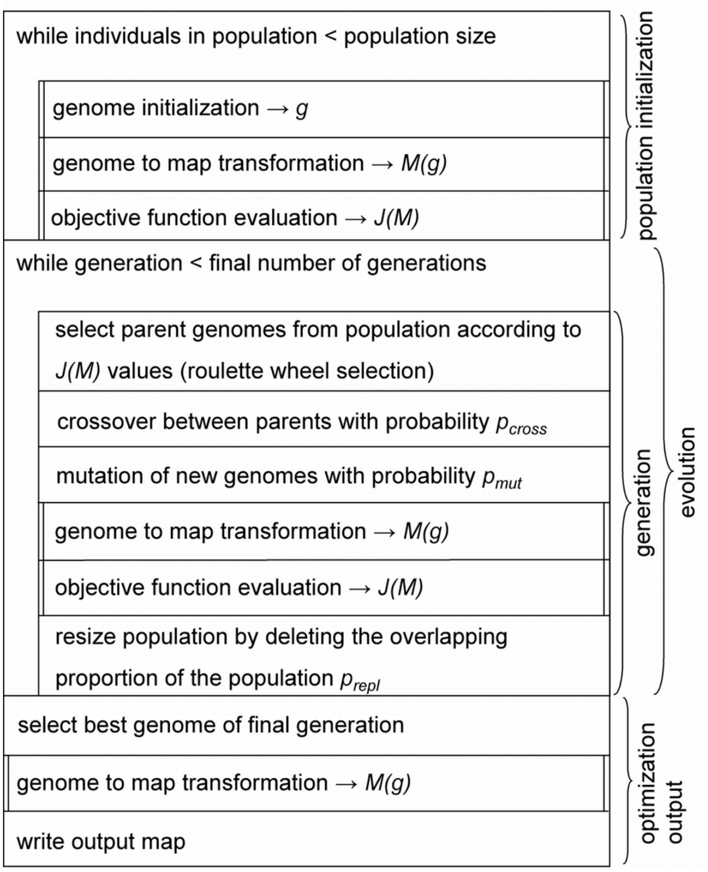


Figure 4.1: Diagram illustrating the optimisation routine; for more detailed illustrations of the processes of genome initialisation, genome to map transformation and objective function evaluation see also Figures 4.2 and 4.3.

The optimisation model is based on a discrete grid *G*. This grid represents the study area and it is denoted by

$$G = \{(x, y) | x_{\min} < x < x_{\max}, y_{\min} < y < y_{\max}; x_{\min}, x, x_{\max}, y_{\min}, y, y_{\max} \in \mathrm{IN}\}.$$

Each grid cell has several attributes that are derived from different raster maps such as the land-use category *l* and site conditions (height above see level *he*, proportion of sand *psa,* mean annual sunshine duration *ssd*, mean annual temperature *tm* and mean annual precipitation *pr*).

$l : G \rightarrow M = \{1, \ldots, 20\}$,

$ssd : G \rightarrow \mathrm{SSD} \in [1384, 1487]$ (h),

$he : G \rightarrow \mathrm{HE} \in [127, 312]$ (m),

$tm : G \rightarrow \mathrm{TM} \in [8.1, 9.9]$ (C°),

$psa : G \rightarrow \mathrm{PSA} \in [0, 100]$ (%),

$pr : G \rightarrow \mathrm{PR} \in [502, 763]$ (mm)

Further attributes are landscape metrics like edge density ed_l, patch cohesion coh_l, number of edge cells between two classes $es_{l,m}$ and largest patch index lpi on the landscape level, which are calculated for each grid cell within the radius that corresponds to the species' home range. The values derived from this moving window analysis serve as neighbourhood-dependent habitat variables. For the calculation of these metrics (equation 4.1-4.4) we introduce indices to describe the radius (r) that corresponds to the species' home range as well as the affiliation to patches (p) and land-use types (l, m).

lpi: $G \rightarrow \mathrm{LPI} \in [0, 100]$ (%), coh_l: $G \rightarrow \mathrm{COH_l} \in [0, 100]$ (%),

ed_l: $G \rightarrow \mathrm{ED_l} \geq 0$ (m/ha), $es_{l,m}$: $G \rightarrow \mathrm{ES_{l,m}} \geq 0$ (-)

The metrics are calculated as follows:

$$lpi = \frac{1}{A_r} \max_{p.l}\left(a_{p,l}\right) * 100 \tag{4.1}$$

$$ed_l = \frac{1}{A_r} \sum_{p=1}^{n} e_{p,l} * 10000 \tag{4.2}$$

$$coh_l = \left[1 - \frac{\sum_{p=1}^{n} p_{p,l}}{\sum_{p=1}^{n} p_{p,l}\sqrt{c_{p,l}}}\right]\left[1 - \frac{1}{\sqrt{C_r}}\right]^{-1} * 100 \tag{4.3}$$

$$es_{l,m} = \sum_{p=1}^{n} ec_{p,l,m} \tag{4.4}$$

where

$a_{p,l}$ = area (m²) of patch p with land use l

A_r = total area within radius r (m²)

$e_{p,l}$ = total length (m) of edge of patch p with land use l

$p_{p,l}$ = perimeter of patch p with land use l in terms of number of cell surfaces

$c_{p,l}$ = area of patch p with land use l in terms of number of cells

C_r = total number of cells in the radius r

$ec_{p,l,m}$ = number of edge cells of patch p with land use l bordering land use m

For the definition of edge cells in all metrics we used the von Neumann neighbourhood (4 nearest cells). We summarised all n attributes ($l, he, psa, ssd, tm, pr, lpi, ed_l, coh_l, es_{l,m}$) by parameters v_k

and the corresponding grids by R: $v_k : G \rightarrow \mathrm{R}; \quad k = 1,\dots, n$

While the attribute land use l is subject to changes in the genetic algorithm, all other attributes are used as static habitat variables to quantify habitat suitability. To decrease the computational effort and obtain realistic results with the genetic algorithm, we switch from a land-use grid to a patch topology. All cells that have an equal land cover type l and have at least one common edge define a model unit u and are identified by a unique identifier id (Fig. 4.2). The variable m denotes the number of modifiable model units.

$u : G \rightarrow id=1,2,3\dots\,, \quad u(x, y) = id = 1,2,3...,m,$

with its inverse function providing a connecting set of cells in G

$$u^*(id) = \{(x, y) | l(x, y) = \text{const., connecting set}\} \subset \mathrm{G}$$

In our model, the initial 'population' consists of 'genomes' derived from the initial landscape. The two-dimensional grid representation of the landscape is transformed into a one-dimensional array of all model units with land-use categories of the 'allele' set L_g (Fig. 4.2). The 'allele' set consists of the choice variables 'grassland', 'cropland', 'deciduous forest' and 'coniferous forest' and is denoted by L_g = {grassland, deciduous forest, coniferous forest, cropland}$\in M$. It is possible to exclude certain land-use patches from changes by not assigning them to model units (Fig. 4.2). Some stochasticity was introduced to obtain an initial 'population' of slightly different 'individuals'. For this purpose, each 'gene' – representing a land-use patch – is randomly changed with a low probability of p_{init} to any of the possible 'genes' defined in the 'allele' set (Fig. 4.2).

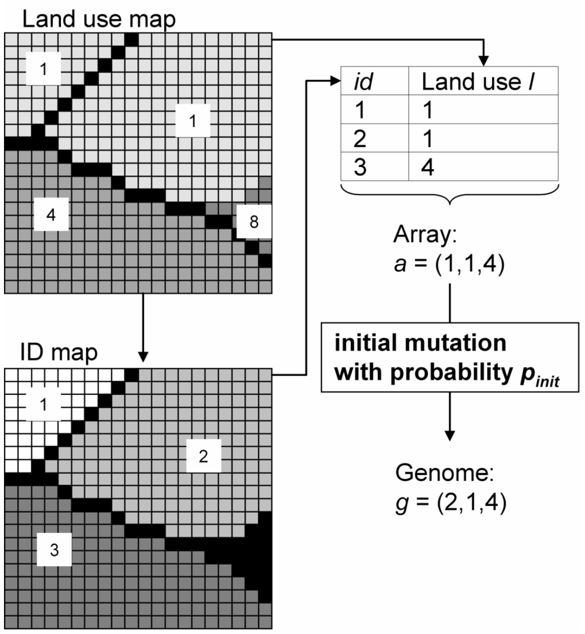


Figure 4.2: 'Genome' initialisation: grid landscape is transformed into 1D-array-representation based on the land-use map and ID map (black grid cells represent roads that separate patches, patch with land-use type 8 is excluded from changes by not assigning an ID); initial mutation introduces variability into the 1D-genome.

Thus, p_{init} can be understood as an initial 'mutation' rate. A 'genome' g represents a modified landscape and is defined as a one-dimensional array of model units: $g = (l_i)_{i=1,\dots m}$ with $l_i \in L_g$.

We chose the 'one-point crossover operator' (Wall 1996) to accomplish 'crossover'. In this case, with a probability p_{cross}, the 'parent genome' strings are cut at some random position to produce two 'head' and two 'tail' segments. The 'tail' segments are swapped to produce two new 'genomes'. For 'parent' selection the roulette wheel selection method is used (Goldberg 1989), where the likelihood of selection is proportionate to the 'fitness' score given by the performance criterion (Equation 4.6). The size of the section in the roulette wheel is proportional to the value of the 'fitness' function of every 'individual'. The 'mutation' operator that is applied to the new 'genomes' changes each 'gene' to any of the possible 'allele' values with a probability of p_{mut}. After 'crossover' and 'mutation', the 'individuals' with the lowest 'fitness' scores are removed to resize the 'population'. In our study, we apply a 'steady-state genetic algorithm'. This algorithm uses overlapping 'populations', where only a user-specified proportion of the 'population' p_{repl} is replaced each 'generation'.

The optimisation task is to maximise the weighted sum of the cumulative habitat suitability values for the three target species by finding an optimum configuration of land-use classes $l_i \in L_g$ for the units that are modifiable. Thus, for a given triplet of species weightings (w_1, w_2, w_3), g^* should be identified such that $J(M(g^*)) > J(M(g))$ for all admissible g (Equation 4.6).

The objective function is evaluated based on map M which was derived from genome g (Fig. 4.3).

$$M(g) = \left\{ id_i(l_i) \;\middle|\; i = 1,2,\dots,m;\, g = (l_i)_{i=1,\dots,m} \right\}, \text{ where } i \text{ is the patch ID.} \tag{4.5}$$

It is then defined by

$$J(M) = \sum_{s=1}^{3} w_s HSI_s(M) \quad \text{with} \sum_{s=1}^{3} w_s = 1 \tag{4.6}$$

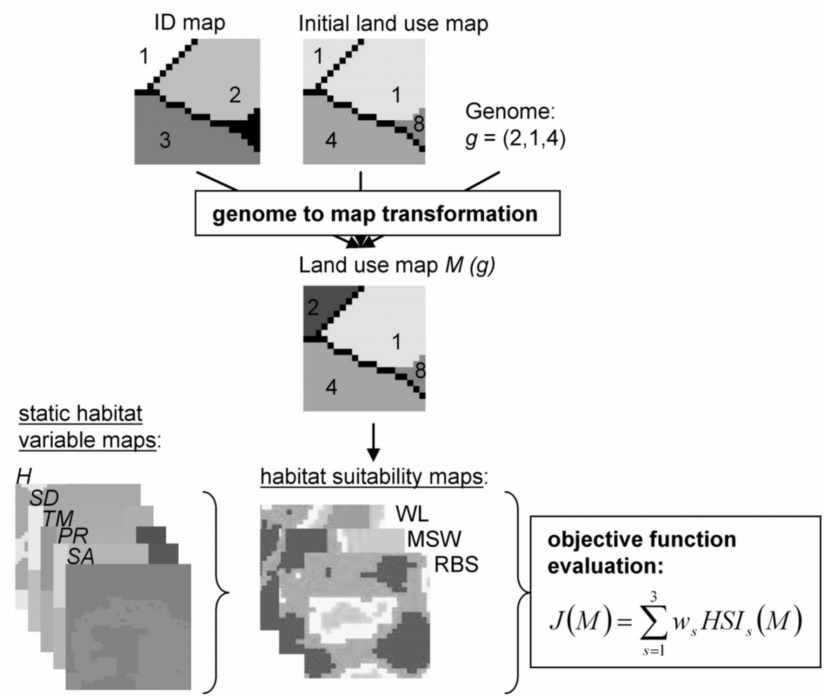
where HSI_s is the cumulative habitat suitability of species s summed over the entire study area:

$$HSI_s(M) = \sum_{x}^{x_{\max}} \sum_{y}^{y_{\max}} hsi_s(M(x,y)) \tag{4.7}$$

Logistic regression habitat suitability models of species s use model estimates b (b_0 = intercept; b_k = coefficients) and n parameters v_k (habitat variables) at location (x,y) to derive values of local habitat suitability hsi: $G \rightarrow (0,1)$:

$$hsi_s(x,y) = \exp\left(b_{s,0} + \sum_{k=1}^{n} b_{s,k} v_k(x,y)\right)\left[1 + \exp\left(b_{s,0} + \sum_{k=1}^{n} b_{s,k} v_k(x,y)\right)\right]^{-1} \tag{4.8}$$

with v_k specific site conditions of the study area (e.g. height) or landscape metrics (e.g. largest patch index, class area, edge density) within the species' home ranges around location (*x,y*). As v_k are spatially referenced and depend on a given land-use map *M*, the spatial dependency can be identified through $hsi_s(x,y) = hsi_s(M(x,y))$.



$$J(M) = \sum_{s=1}^{3} w_s HSI_s(M)$$

Figure 4.3: 'Genome' to map transformation and objective function evaluation: weighted sum of cumulative habitat suitabilities is evaluated based on the land-use map derived from the 'genome' and the static variable maps.

4.3 Model application

Study area and data base

The study was carried out in the administrative district of Leipzig in Northwest Saxony, Germany (Fig. 4.4). It covers an area of ~ 441.000 ha. The main land use in this region is agriculture. During the period 1949-89, an industrialisation of agriculture was promoted. Fields were merged to increase the efficiency of cultivation. Fields sizes in our study area range up to 30 ha. The elevation 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. In the South Eastern area, where the relief is increasingly hilly, the landscape is more fragmented and agricultural fields are smaller.

Land-use data including 13 categories was available for this region at a resolution of 10 m for three time steps (1965, 1984 and 1994; Fig. 4.4). The study was mainly based on land-use data from 1994. Land-use data from the other two time steps was only used for modelling habitat suitability where species data from one time step was not sufficient. The land-use categorisation is the result of a visual interpretation of data from different sources (satellite imagery, aerial photographs, topographic maps and land-use mappings). A digital elevation model with a resolution of 20 m was available from the Landesvermessungsamt Sachsen (2002). The digital soil type map generated at the Department of Computational Landscape Ecology, UFZ Leipzig-Halle GmbH by intersecting the MMK 25 (Medium-scaled Agricultural Site Mapping) and the WBK 25 (Forest Soil Map) of the Saxonian Federal Bureau of Environment and Geology was used. Information on the proportion of soil texture was derived from the mapped soil types based on AG Boden (1994). Climate data including mean annual sunshine duration, mean annual temperature and mean annual precipitation (between 1961 and 1990) were available from the German National Meteorological Service (DWD) with a resolution of 1000 m. Point data on the model species' breeding occurrences between 1963 and 1996 were provided by the local environmental administration (National Bureau of Environment) and digitised at the UFZ. We chose the Middle-Spotted Woodpecker (*Dendrocopos medius*), the Woodlark (*Lullula arborea*) and the Red-Backed Shrike (*Lanius collurio*) as target species. The Middle-Spotted Woodpecker and the Wood Lark are protected as red-list species (Flade 1994). The Red-Backed Shrike was chosen due to its association to edge habitats. All species are representatives for different habitat types, thus their conservation serves to protect species with similar habitat requirements. The Middle-Spotted Woodpecker utilises large core areas of deciduous forests. The Woodlark can be found in coniferous heath forests with dry and sandy soils. The Red-Backed Shrike prefers open and half open areas with boundary structures. For all three species, we assumed home range sizes of ~ 10 ha, which correspond to rounded radiuses of 200 m (Flade 1994).

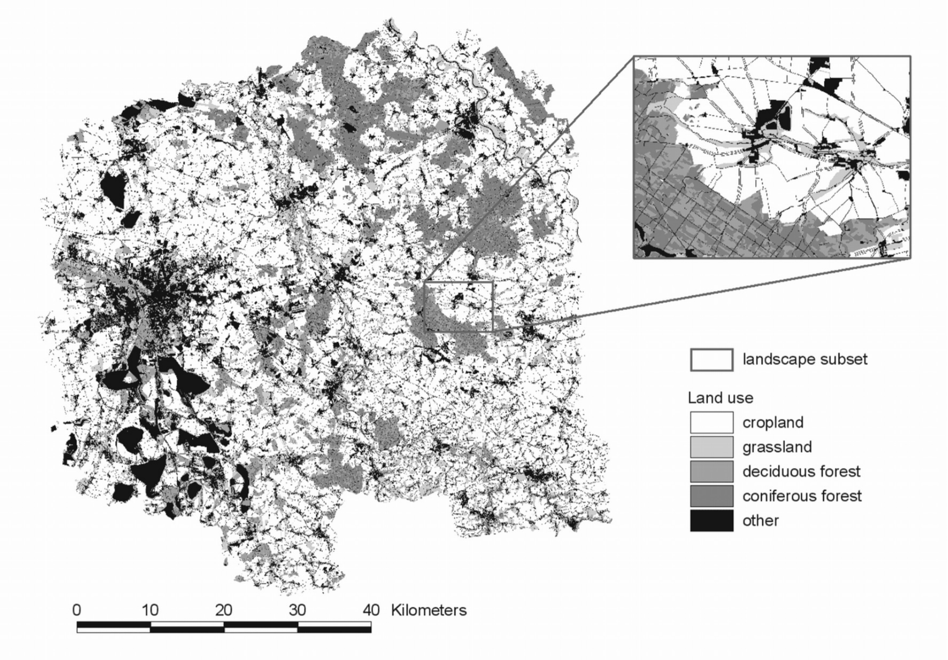


Figure 4.4: Land-use map of the study area from 1994; whole area (~441.000 ha) used as input for habitat suitability modelling, subset (6.256 ha) used as input for optimisation (source: Küster 2003).

Habitat suitability models

For the Red-Backed Shrike and the Wood Lark presence data between 1993 and 1995 were correlated to the land-use structures from 1994. The data sets included 61 occurrence points of the Wood Lark and 730 occurrence points of the Red-Backed Shrike. For the Middle-Spotted Woodpecker presence data were very limited and thus presence data from three periods (1963-65, 1979-80, 1993-95) were used and correlated to the land-use structure of 1965, 1984 and 1994, respectively. There were 28 occurrence points between 1963 and 1965, 11 between 1979 and 1980 and 28 between 1993 and 1995. The datasets of these three time periods were then combined into one dataset for calculating the habitat suitability models.

For the Middle-Spotted Woodpecker, the Wood Lark and the Red-Backed Shrike the predictive models were averaged based on 394, 207 and 292 models, respectively. The best model fit is achieved for the Middle-Spotted Woodpecker (AUC: 0.97) (s. Table 4.1). This model includes the independent variables elevation, mean annual sunshine duration and the patch cohesion of deciduous forest within the species' home range. The most important factor is patch cohesion of deciduous forest. The model fit of the Wood Lark model is also very good (AUC: 0.93). This model identifies a positive impact of the patch cohesion of coniferous forest and also deciduous forest within a 200 m radius, but the influence of coniferous forest is much stronger. Furthermore, the proportion of sand at the specific location has a significant positive effect on habitat suitability for the Wood Lark. With an AUC of 0.76 the Red-Backed Shrike model is acceptable. It includes negative effects of the habitat variables largest patch index, mean annual precipitation and edge density of build-up area. The most important positive factor in this model is the edge density of cropland, followed by mean annual temperature, number of edge cells of deciduous forest to cropland, edge density of groves and single trees, patch cohesion of grassland, edge density of hedges and tree rows and number of edge cells of coniferous forest to cropland. In summary, it can be ascertained that the Red-Backed Shrike prefers warm and dry conditions in heterogeneous agricultural landscapes with a high edge density of forest, groves and hedges.

Table 4.1: Habitat suitability models for the target species (COH = landscape metric "patch cohesion" calculated within 200m-radius, ED = landscape metric "edge density" calculated within 200m-radius).

	Estimates	Standard errors
Red-Backed Shrike		
intercept	-0.0201	0.0082
largest patch index	-0.4437	0.0555
mean annual temperature	0.2804	0.0654
mean annual precipitation	-0.3026	0.0653
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	0.1630	0.0378
AUC:	**0.7607**	**0.0093**
Middle-Spotted Woodpecker		
intercept	-0.4581	0.1301
elevation	-1.1355	0.2782
COH deciduous forest	2.5704	0.2608
mean annual sunshine duration	-1.4966	0.3711
AUC:	**0.9717**	**0.0082**
Wood Lark		
intercept	-0.1084	0.0567
COH deciduous forest	0.7219	0.1996
COH coniferous forest	1.7470	0.2116
proportion of sand	0.7084	0.1546
AUC:	**0.9287**	**0.0201**

Optimisation model

The optimisation model was applied to a small subset of the land-use map from 1994 (6.8 x 9.2 km). This subset is located in the Eastern part of the region (s. Fig. 4.4). The model units were identified based on the original data with a resolution of 10 meters. An ID map was generated, where each patch of the four selected land-use types was assigned a unique ID. To reduce the computational effort, the optimisation was performed based on input grids resampled to 40 m. Thus the genome was derived from the resampled ID map and the land-use map in 40 m resolution. The genetic algorithm was set up with the parameters shown in Table 4.2. We constrained our choice of parameters based on previous applications of genetic algorithms (Goldberg 1989, Seppelt & Voinov 2002, Venema et al. 2005).

Table 4.2: Parameters of genetic algorithm application (p_{init} = probability of random disturbance in initial population, p_{cross} = probability of crossover, p_{mut} = probability of mutation, p_{repl} = proportion of population overlap).

population size	10
p_{init}	0.03
p_{cross}	0.6
p_{mut}	0.01
number of generations	1500
p_{repl} [%]	0.25

To analyse how composition and configuration vary with the weightings for the selected species for which habitat suitability is maximised, we carried out a sensitivity analysis with variable species' weightings. The optimisation was performed for all possible combinations of weightings with increments of 0.1 (66 combinations = possible number of weighting combinations where weightings add up to one). The resulting optimal landscapes were analysed using a set of landscape metrics to describe various aspects of land-use pattern and habitat suitability for the target species. In detail, we used the metrics number of patches (NP), edge density (ED), largest patch index (LPI), Shannon's diversity index (SHDI) and contagion index (CONTAG) on landscape level, and class area (CA) and patch cohesion (COH) of the four changeable land-use types. In contrast to the metrics used in the habitat suitability models, these metrics were not calculated by using a moving window analysis. Landscape metrics at landscape level describe fragmentation (NP and ED), landscape homogeneity (LPI), diversity of land-use types (SHDI) and aggregation of land-use classes (CONTAG). Class areas of the changeable land-use types show changes in landscape composition, while patch cohesion also quantifies the connectedness of these land-use types. For the comparison of the optimisation results with the initial landscape, the same metrics were used as for the comparisons among the optimisation results. As the species weights add up to one, the optimisation results can be presented in ternary plots, where the three axes represent the ratios of species weightings. The plots are read considering the intersections of the parallels to each of the three axes.

To investigate the effects of landscape configuration separately, constraints were introduced into the performance criterion to keep landscape composition relatively constant (Equation 4.9). As model units are of different sizes, it would be difficult to realise changes in configuration while keeping the initial landscape composition. Thus we allowed a deviation of up to 1 % for each changeable land-use class (Equation 4.10). With these constraints incorporated, the evolutions of habitat suitability values were recorded for the three optimisation runs for the three discrete species and compared to the unconstrained runs.

$$J_{con} = \left(J\left(M\right)\right) \cdot f_{con} \tag{4.9}$$

$$f_{con} = \begin{cases} 1 & \text{if } \frac{1}{C}\left|c_l(M_0) - c_l(M(g))\right| < 0.01 \quad \text{for } l = 1,2,3,4 \\ 0 & \text{else} \end{cases} \tag{4.10}$$

where

M_0 = initial state of land-use map

C = total number of cells

c_l = number of cells of class l

l = land-use type $\in L_g$

If all species were equally weighted, the improvement would be towards the optimum for the species with the highest sensitivity to changes in the genetic algorithm, and genes that could improve habitat suitability for other species might get lost. To enhance habitat suitability for all three target species in equal measure, we need to weight the species according to their sensitivity to land-use changes. Thus, habitat suitability values derived from the optimised landscapes were normalised for each species by division through the maximum habitat suitability. The maximum sum of normalised habitat suitabilities for the three species was determined and the species' weightings were derived accordingly.

4.4 Results

Do species habitat requirements contrast or coincide?

Habitat suitabilities (HSI) for all three target species improved during almost all optimisation runs, except for the runs optimising habitat suitability for the Wood Lark and the Middle-Spotted Woodpecker, where Red-Backed Shrike habitat suitability decreased. We also observed a slight decrease of habitat suitability for Wood Lark in the runs optimising habitat suitability for Middle-Spotted Woodpecker and Red-Backed Shrike (Fig. 4.5). The highest mean habitat suitability values were reached for the Middle-Spotted Woodpecker (mean HSI between 0.52 and 0.95). In almost all optimisation runs, mean HSI for the Middle-Spotted Woodpecker exceeded those of the other species. The optimisation was least successful for the Red-Backed Shrike (mean HSI between 0.30 and 0.54). For the Wood Lark, the mean habitat suitability varies between 0.28 and 0.74. As the initial mean habitat suitability index was 0.40 for the Middle-Spotted Woodpecker, 0.30 for the Wood Lark and 0.32 for the Red-Backed Shrike, the improvement was best for the Middle-Spotted Woodpecker and worst for the Red-Backed Shrike. The minimum values of habitat suitability of the Middle-Spotted Woodpecker and the Wood Lark are reached when the weight for Red-Backed Shrike is high (0.9). Before that habitat suitabilities for the Middle-

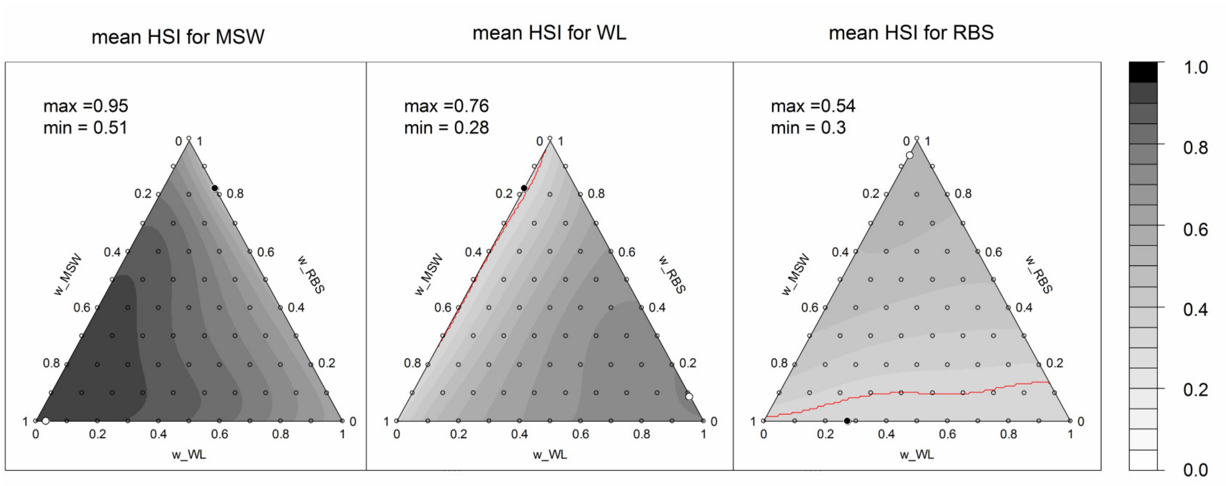


Figure 4.5: Mean habitat suitability indices (HSI) of the target species (MSW = Middle-Spotted Woodpecker, WL = Wood Lark, RBS = Red-Backed Shrike) depending on species' weightings (w_MSW = weight for Middle-Spotted Woodpecker, w_WL = weight for Wood Lark, w_RBS = weight for Red-Backed Shrike); white dots indicate maximum values; black dots indicate minimum values; lines indicate mean HSI values derived from the initial landscape; for MSW the initial value is below the values in the plot.

Spotted Woodpecker and the Wood Lark decrease more slightly when the weight for Red-Backed Shrike is increased. The lowest values of the Red-Backed Shrike habitat suitability are found when the weight for the Wood Lark is highest.

How do landscape composition and configuration differ in landscapes optimised for each of the three target species?

Figure 4.6 shows the effects of species weightings on landscape configuration at the landscape level. Landscapes optimised for the Middle-Spotted Woodpecker show the most homogenous and least diverse pattern. The Red-Backed Shrike prefers the most diverse and fragmented landscapes, while landscapes optimised for the Wood Lark are intermediate. Landscape homogeneity was much higher in the initial landscape than in those optimised for the Red-Backed Shrike and the Wood Lark, but lower than in the landscape optimised for the Middle-Spotted Woodpecker. The contagion index is lower in the initial landscape than in those optimised for the Middle-Spotted Woodpecker and the Wood Lark, but it is slightly higher than in the landscape optimised for the Red-Backed Shrike. Likewise, landscape diversity is higher in the landscape optimised for the Red-Backed Shrike than in the initial landscape and much lower in the landscapes optimised for Wood Lark and Middle-Spotted Woodpecker.

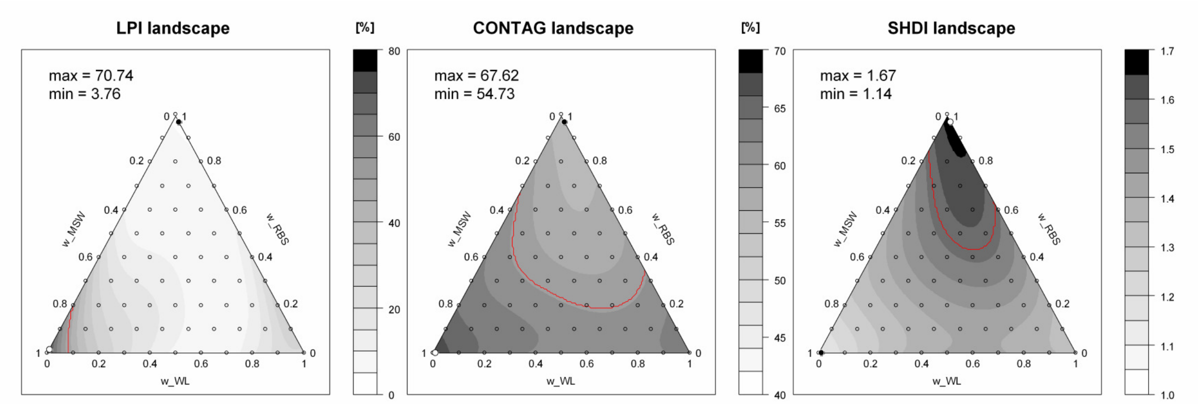


Figure 4.6: Landscape metrics largest patch index (LPI), contagion index (CONTAG) and Shannon diversity index (SHDI) on landscape level depending on species' weightings (w_MSW = weight for Middle-Spotted Woodpecker, w_WL = weight for Wood Lark, w_RBS = weight for Red-Backed Shrike); white dots indicate maximum values; black dots indicate minimum values; lines indicate values of initial landscape. The metric largest patch index (LPI) equals the percent of the landscape that the largest patch comprises. The contagion index (CONTAG) shows the aggregation of land-use classes in the landscape and the Shannon diversity index (SHDI) indicates the diversity of patch types in the landscape.

Results of the analysis of landscape composition depending on the combination of species' weightings correspond to the habitat suitability models, but they also show the effects of contrasting habitat requirements. The Middle-Spotted Woodpecker prefers deciduous forest, the Wood Lark prefers coniferous forest and the Red-Backed Shrike favours cropland and grassland (Fig. 4.7). The proportion of cropland is lowest in the runs optimised for the Wood Lark. This indicates that the Wood Lark avoids cropland more than the Middle-Spotted Woodpecker does, which explains why the habitat requirements of the Red-Backed Shrike contrast more sharply with those of the Wood Lark than those of the Middle-Spotted Woodpecker (see Figure 4.5). The contrast in habitat requirements of Middle-Spotted Woodpecker can be explained by the proportion of deciduous forest. To a certain extent, the Red-Backed Shrike is more tolerant to the proportion of deciduous forest than the Wood Lark, but when the weight for the Red-Backed Shrike exceeds 0.6, deciduous forest is increasingly avoided.

The Wood Lark avoids grass- and cropland and to a certain extent also deciduous forest, but habitat suitability for the Wood Lark is not well-characterised by the proportion of coniferous forest alone. Deciduous forest also has a positive effect, but the positive effect of coniferous forest is higher (Table 4.1).

When we compare the initial landscape composition to those of the optimisation results, we see that the proportion of cropland has decreased during all optimisation runs. Also, the proportion of grassland decreased compared to the initial landscape, except for the optimisation with respect to the Red-Backed Shrike, where an increase occurred. Compared to the initial landscape, the proportion of deciduous forest is higher in all optimisation runs. The proportion of coniferous forest has increased in the optimisations for the Wood Lark and decreased in those for the Middle-Spotted Woodpecker and the Red-Backed Shrike.

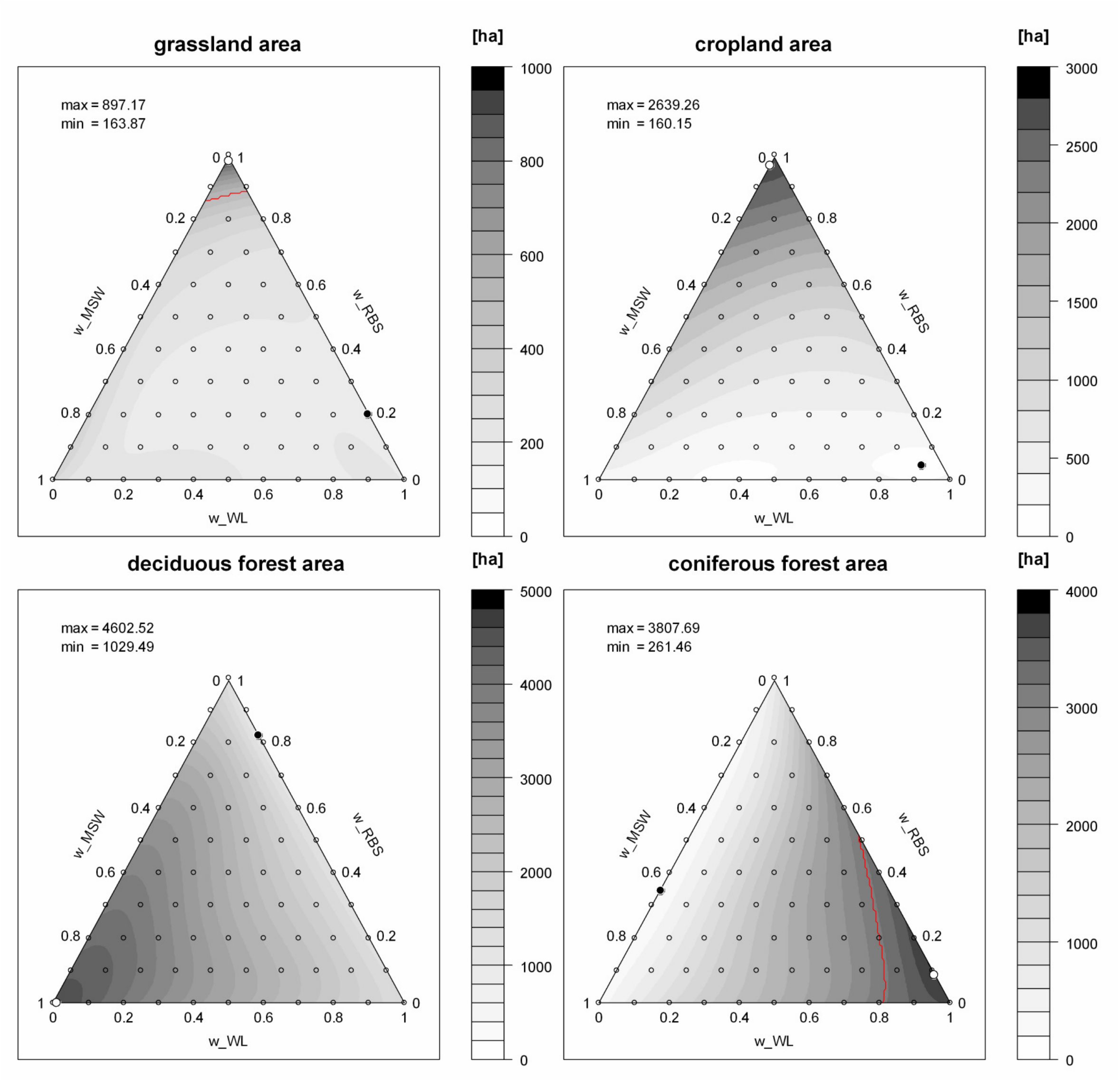


Figure 4.7: Area of the four changeable classes depending on species' weightings (w_MSW = weight for Middle-Spotted Woodpecker, w_WL = weight for Wood Lark, w_RBS = weight for Red-Backed Shrike); white dots indicate maximum values; black dots indicate minimum values; lines indicate values of initial landscape.

How do landscape composition and configuration contribute to an improvement of habitat suitability?

Figure 4.8 shows the dependence of the evolution of the mean habitat suitability on the optimisation criterion for all three target species. By maximising habitat suitability for the Middle-Spotted Woodpecker, the habitat suitabilities for the Wood Lark and the Red-Backed Shrike are also slightly increased initially, but after about 800 evaluations they decrease and, in the end, habitat suitability for the Red-Backed Shrike falls below the initial value. The increase in habitat suitability for the Wood Lark within the first 800 evaluations is due to an increase in deciduous forest. Thereafter, habitat suitability for the Wood Lark decreases as the proportion of coniferous forest decreases in favour of the proportion of deciduous forest.

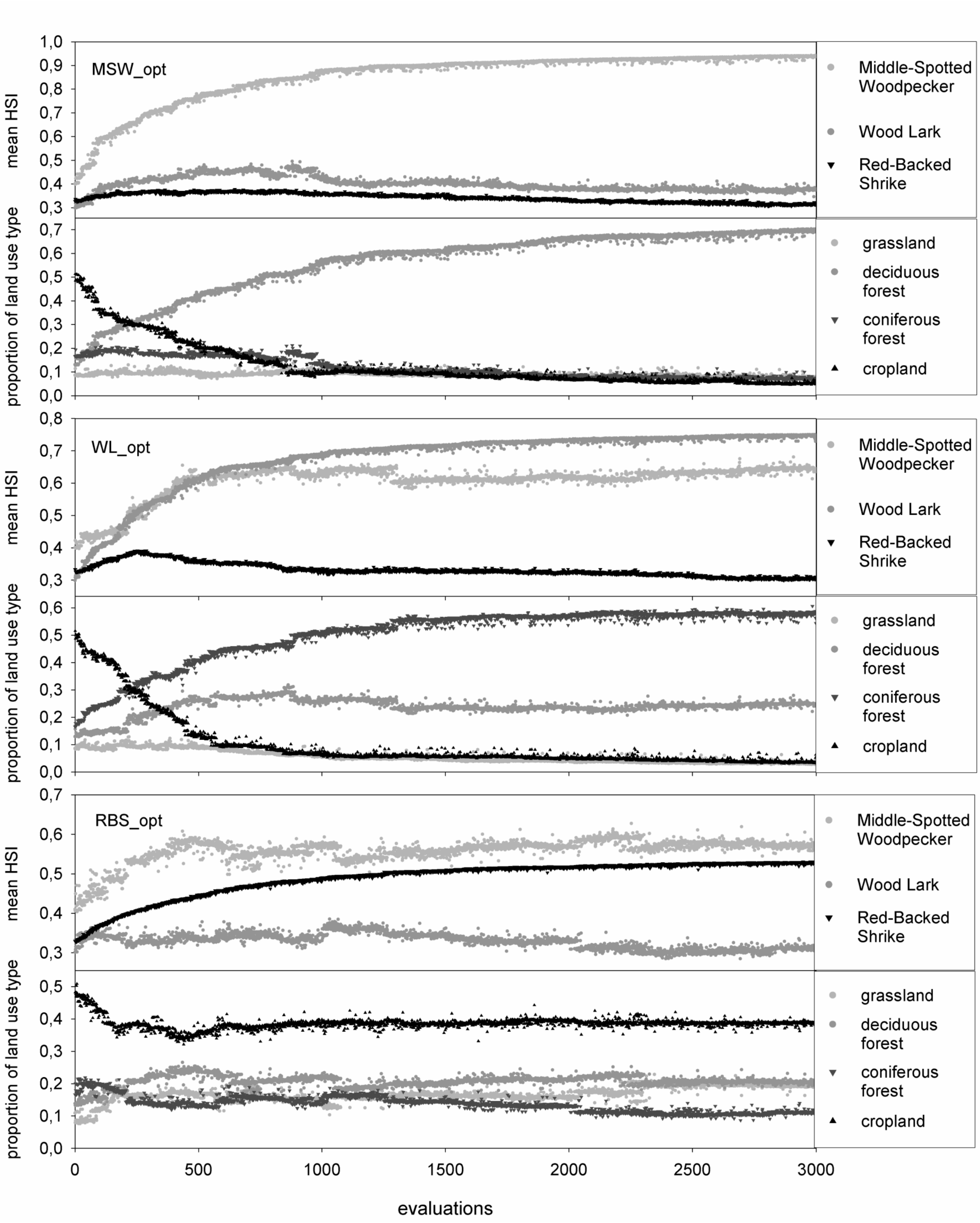


Figure 4.8: Dependence of the evolution of mean habitat suitability for target species and the proportions of changeable land-use types on the optimisation criterion (MSW_opt = maximise habitat suitability for MSW, WL_opt = maximise habitat suitability for WL, RBS_opt = maximise habitat suitability for RBS).

Maximising habitat suitability for the Wood Lark slightly decreases habitat suitability for the Red-Backed Shrike after the first 250 evaluations and leads to an unsteady increase in habitat suitability for the Middle-Spotted Woodpecker.

Optimising for the Red-Backed Shrike also increases habitat suitability for the Middle-Spotted Woodpecker, which achieves even higher mean habitat suitability values by the end of the optimisation. Mean habitat suitability for the Wood Lark increases within the first 200 evaluations, but slightly decreases afterwards until it finally reaches its initial value.

When we compare the evolution of habitat suitabilities to the proportions of changeable land-use types, we see that changes in habitat suitability for the Middle-Spotted Woodpecker are essentially driven by the proportion of deciduous forest. Changes in habitat suitability for the Wood Lark are mainly driven by the proportion of coniferous forest and, to a certain extent, by changes in the proportion of deciduous forest. The changes in habitat suitability for the Red-Backed Shrike are not driven by single land-use types. The Red-Backed Shrike benefits from a decrease of cropland to about 40% in favour of an increase of deciduous forest (Fig. 4.8). It is striking that within the first evaluations habitat suitabilities are increased in all optimisation runs.

To investigate the effects of landscape configuration, the optimisation was performed for all three species while keeping landscape composition constant. The results of the constrained optimisation, shown in Figure 4.9 and Table 4.3, indicate that the possibilities for an improvement of habitat suitability are limited when only changes in landscape configuration are allowed. The best improvement is achieved for the Red-Backed Shrike, the worst for the Wood Lark. However, there seem to be no considerable contrasts between the species' habitat requirements with respect to landscape configuration (Figure 4.9). The optimisations for the Middle-Spotted Woodpecker and the Wood Lark increase habitat suitabilities for all three species, but changes in habitat suitability for the Red-Backed Shrike have hardly any effect on habitat suitabilities for the other two species. Habitat configuration requirements of the Red-Backed Shrike differ from those of the other two species. For this species, the improvement of habitat suitability through changes in landscape configuration was almost as good as through changes in landscape composition and configuration. The landscape configuration optimised for the Red-Backed Shrike is the most heterogeneous (highest number of patches and edge density, lowest largest patch index value on the landscape level) as connectivities (patch cohesion) of cropland, deciduous forest and coniferous forest are the lowest (Table 4.3). The optimisation for the Middle-Spotted Woodpecker led to the most homogeneous land-use pattern (highest largest patch index and number of patches, lowest edge density on landscape level). In this run, patch cohesion of deciduous forest is higher than in the runs optimised for the Wood Lark and the Red-Backed Shrike. Likewise, patch cohesion of coniferous forest is highest in the run optimised for the Wood Lark. However, in the initial landscape, values of both patch cohesion of deciduous and coniferous forest are higher. This can be explained by the fact that the habitat variables "patch cohesion of deciduous/coniferous forest" are calculated within the species' home ranges, whereas for the comparison of optimisation results the same metrics were calculated for the whole landscape subset.

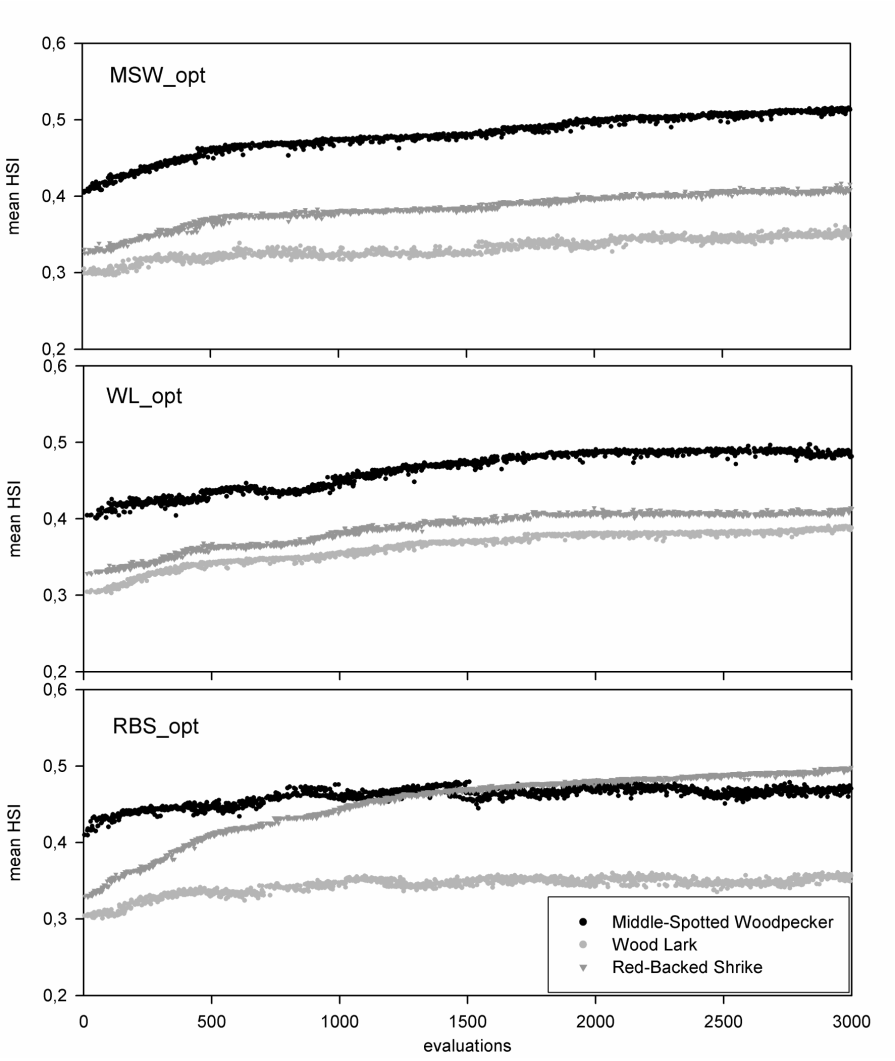


Figure 4.9: Dependence of the evolution of mean habitat suitabilities for target species with constant landscape composition depending on the optimisation criterion (MSW_opt = maximise habitat suitability for MSW, WL_opt = maximise habitat suitability for WL, RBS_opt = maximise habitat suitability for RBS).

What characterises a landscape optimised for all three target species?

The sums of the normalised mean habitat suitabilities for all species are shown in Figure 4.10. The white dot indicates the maximum of the normalised mean habitat suitabilities, which is reached with species' weightings of 0.23 (Middle-Spotted Woodpecker), 0.32 (Wood Lark) and 0.45 (Red-Backed Shrike).

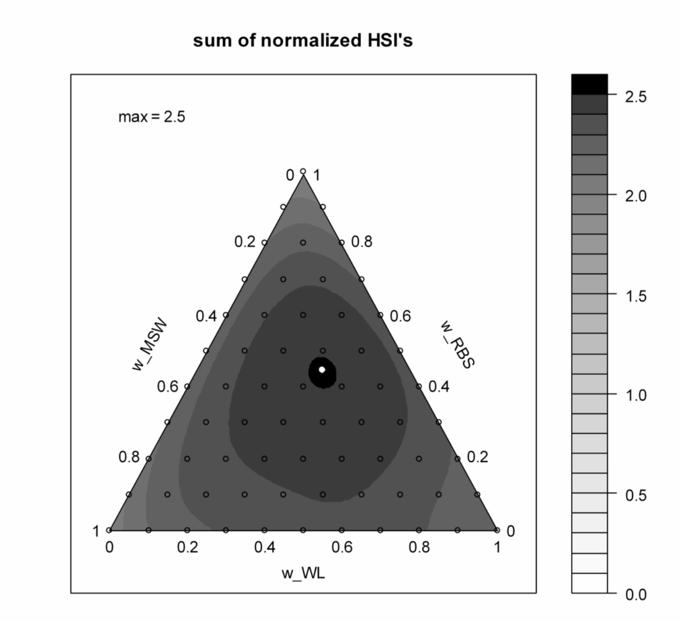


Figure 4.10: Sums of normalised mean habitat suitabilities (HSI) of target species depending on species' weightings; white dot shows maximum sum.

Figure 4.11 shows the landscape pattern optimised for all three species according to the species' weightings derived from Figure 4.10. Compared to the initial landscape, the optimisation result is characterised by a lower proportion of grassland and cropland and a higher proportion of deciduous and coniferous forest (Fig. 4.11, Table 4.3). Landscape configuration is less compact and aggregated and the pattern is slightly more diverse in the optimised landscape (Fig. 4.11, Table 4.3). Cropland is concentrated in the South-Western part of the landscape subset, where model units are small. Larger model units are occupied by deciduous or coniferous forest. Mean habitat suitability for the Middle-Spotted Woodpecker and the Wood Lark increased by 0.36. The increase in mean habitat suitability for the Red-Backed Shrike was only 0.12.

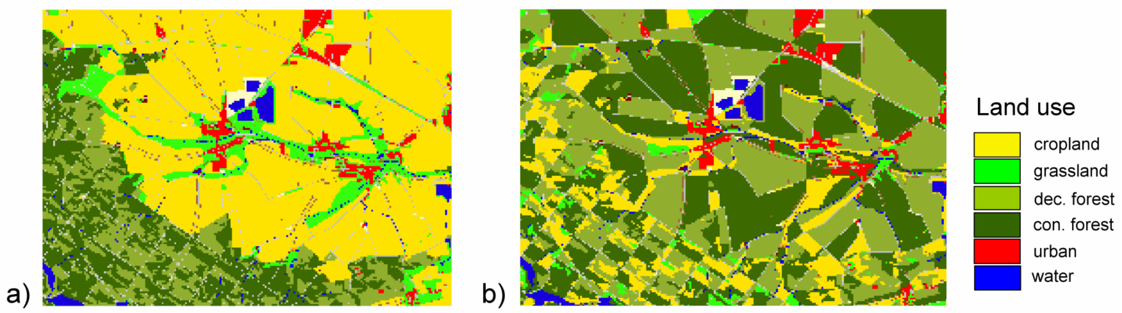


Figure 4.11: Initial landscape (a) and result (b) of optimisation for all three target species according to species' weightings 0.23 (MSW), 0.32 (WL) and 0.45 (RBS).

Table 4.3: Landscape configuration and composition of initial landscape, results of constrained and unconstrained optimisation runs for target species (MSW = Middle-Spotted Woodpecker, WL = Wood Lark, RBS = Red-Backed Shrike, NP = number of patches, ED = edge density, LPI = largest patch index, CONTAG = contagion index, SHDI = Shannon's diversity index, COH = patch cohesion) depending on the optimisation criterion (MSW_opt = maximise habitat suitability for MSW, WL_opt = maximise habitat suitability for WL, RBS_opt = maximise habitat suitability for RBS) and result of optimisation for all three target species (HSI_max) according to species' weightings 0.23 (MSW), 0.32 (WL) and 0.45 (RBS).

		initial landscape	unconstrained optimization			constrained optimization			HSI_max
			MSW_opt	WL_opt	RBS_opt	MSW_opt	WL_opt	RBS_opt	
mean HSI	MSW	0.40	0.95	0.64	0.57	0.52	0.49	0.47	0.76
	WL	0.30	0.34	0.75	0.31	0.35	0.39	0.36	0.66
	RBS	0.32	0.31	0.31	0.54	0.41	0.41	0.50	0.44
NP		2427	2397	2462	2633	2522	2549	2606	2586
ED [m/ha]		98.34	87.32	95.95	105.00	99.11	100.21	102.75	103.51
LPI [%]		48.94	72.52	20.77	3.95	35.78	27.58	8.45	4.22
CONTAG [%]		59.84	67.96	62.17	54.55	57.25	57.92	57.71	56.65
SHDI		1.57	1.14	1.35	1.68	1.58	1.59	1.57	1.58
COH grassland		89.13	77.37	75.18	92.41	86.79	86.17	86.04	74.06
COH cropland		99.70	80.94	77.17	94.83	98.54	99.05	97.18	87.04
COH dec. forest		91.45	99.86	92.36	91.21	90.14	89.93	88.89	94.13
COH con. forest		96.00	78.60	98.35	86.96	91.40	92.81	89.88	94.39
grassland area [ha]		511.36	324.64	196.64	1044.96	531.04	540.16	488.00	203.36
cropland area [ha]		3170.88	320.00	222.08	2570.40	3108.96	3146.72	3163.84	873.44
dec. forest area [ha]		822.72	4596.16	1555.68	1302.40	870.24	868.16	860.16	2197.60
con. forest area [ha]		1049.28	314.56	3581.12	637.76	1044.80	1000.48	1043.36	2281.12

4.5 Discussion

The results of the sensitivity analysis reflect the habitat requirements of the different species and show where habitat requirements contrast between species. The ternary plots of mean habitat suitabilities for the three species indicate that habitat requirements of the Red-Backed Shrike differ most from those of the other two species (Fig. 4.5). Thereby, Red-Backed Shrike habitat requirements contrast more to those of the Wood Lark than to those of the Middle-Spotted Woodpecker. The differences in habitat suitabilities are mainly due to changes in landscape composition (Fig. 4.7, Fig. 4.8). Habitat suitability for the Middle-Spotted Woodpecker increases with the proportion of deciduous forest, habitat suitability for the Wood Lark increases with the proportion of coniferous and also deciduous forest and habitat suitability for the Red-Backed Shrike is driven by the proportion of cropland relative to deciduous forest, coniferous forest and grassland. The evolution of habitat suitabilities shown in Figure 4.9 indicates that contrasts between habitat requirements of different species only emerge when certain thresholds of landscape composition are exceeded; below these thresholds, the habitat requirements of all three species coincide. This demonstrates that there is potential for improving habitat suitability for all three species. However, differences in habitat requirements also show up with respect to landscape configuration (Fig. 4.6, Fig. 4.9). Again, landscapes optimised for the Red-Backed Shrike contrast most to those of the other two species. The landscape pattern is most homogeneous in the landscapes optimised for the Middle-Spotted Woodpecker and most heterogeneous in the landscapes optimised for the Red-Backed Shrike (Fig. 4.6). The results shown in Figure 4.9 and Table 4.3 suggest that this is not only due to simultaneous changes in landscape composition, where landscape homogeneity is increased with the proportion of a certain land-use type, but also to changes in landscape configuration. The improvement of habitat suitability for the Middle-Spotted Woodpecker and the Wood Lark is low when landscape composition is kept constant. Habitat requirements of the Wood Lark and the Middle-Spotted Woodpecker coincide with respect to landscape configuration. This might be due to the fact that the configuration of deciduous forest is important for both species. For the Red-Backed Shrike, changes in landscape configuration alone can improve habitat suitability almost as much as changes in landscape composition and configuration. This reflects Red-Backed Shrike's strong dependence on complex habitat structures. The fact that the habitat suitability for the Middle-Spotted Woodpecker is highest in all runs with a non-zero weighting for the Middle-Spotted Woodpecker can be explained by the high sensitivity of this habitat model towards alternations in the genetic algorithm. The most important reason for the high sensitivity towards the genetic algorithm is the simplicity of the habitat model. Patch cohesion of deciduous forest is the only habitat variable that can be influenced and has the highest model coefficient. Thus, changes in the genetic algorithm cause great changes in habitat suitability and therefore habitat suitability can be improved to a greater extent. The Wood Lark model contains two variables that can be influenced. As in the Middle-Spotted Woodpecker model, these variables are the ones with the highest coefficients, but still the sensitivity of the Wood Lark habitat model is lower. This can be explained by the fact that an increase in two land-use types is needed instead of just one in the Middle-Spotted Woodpecker model. The model with the most variables is the Red-Backed Shrike model, thus it shows the lowest sensitivity towards changes in the genetic algorithm. Additionally, the most important factor is the edge density of build-up area within the species' home range, which is not a modifiable variable. The influences of the changeable variables (edge density of cropland, edge cells of deciduous and coniferous forest to cropland and patch cohesion of grassland) are comparatively low and, thus, the algorithm converges at a much lower level. These findings need to be taken into account when optimising landscape configuration with respect to all three target species. If all species were equally weighted, the optimisation would favour the Middle-Spotted Woodpecker more than the other two species because Middle-Spotted Woodpecker is most sensitive to the modelled changes and, therefore, genes that could improve habitat suitability for other species could get lost. Therefore, the mean habitat suitabilities of all runs were normalised and summed up to find the weighting combination where the best trade-off between all species can be achieved (Fig. 4.10). At this ideal trade-off point, the highest weight is given to the Red-Backed Shrike – the species with the lowest sensitivity towards changes in the genetic algorithm – and the lowest to Middle-Spotted Woodpecker, which is most sensitive. The comparison of the initial landscape to the landscape optimised for all three species showed that an increase in deciduous and coniferous forest and a decrease of crop- and grassland could improve habitat suitability for all three species. Furthermore, all species benefit from an increase in landscape heterogeneity, landscape diversity and a disaggregation of land-use classes (Fig. 4.11, Table 4.3). Still, the increase in habitat suitability for the Red-Backed Shrike is smaller than for the two other species. This indicates that other management actions need to be taken into consideration to improve habitat suitability for this species.

4.6 Conclusions

The approach outlined in this paper shows promise as a tool for analysing the effects of land-use changes on different species and for detecting conflicts between species.

We investigated the effects of different land-use changes on habitat suitability for three target species. An increase of deciduous and coniferous forest and a decrease of cropland and grassland in the landscape subset have positive effects on all target species. Middle-Spotted Woodpecker habitat suitability depends mainly on the proportion of deciduous forest. An increase of coniferous forest has a positive effect on habitat suitability for the Wood Lark, whereas for the Red-Backed Shrike juxtaposing patches of cropland, groves and deciduous forest is optimal. This species is highly depended on landscape configuration and its habitat requirements contrast most with those of the other two target species. However, land-use changes between cropland, grassland, deciduous and coniferous forest do not allow an improvement of habitat suitabilities for all three model species in equal measure.

The methodology presented and applied in this study could be a useful tool to support conservation management decisions, even though there are some clear improvement opportunities. The optimisation approach is very flexible and could easily incorporate other spatially-referenced conservation objectives. It can detect trade-offs between different management objectives and identify the solution space where all objectives are improved. In a conservation application, species' weightings could be assigned according to conservation status. Using patch topology within the optimisation produced reasonable land-use patterns, as the units of change correspond to the land-use parcels on which decisions are made. However, at this point the approach could be improved by incorporating linear land-use changes like the introduction of hedges along field edges. This could be interesting when considering functions or processes that are affected by linear landscape elements (e.g. Red-Backed Shrike habitat suitability, erosion). As the model results of this case study are not realistic, further constraints need to be considered to enhance usability for conservation planning. Thus, we plan to include economic considerations into the performance criterion to take into account cost effectiveness of land-use changes in a future study.

Acknowledgements

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Chapter 5

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

An edited version of Holzkämper & Seppelt 2007. *Biological Conservation*, published.

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 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 extent 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 extent 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 for a large spatial extent. 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.

5.1 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 & Kirk 2001, Tilman et al. 2001) resulting in migration or even local extinction (Woinarski & 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 & Raphael 1997, Moilanen & Cabeza 2002, Nalle et al. 2004, Polasky et al. 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 & 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 & 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 extent with a multitude of decision units is considered (Seppelt & Voinov 2002). Thus, the application of spatial optimisation approaches to real landscapes for a large spatial extent 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 for a large spatial extent. 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 for a large spatial extent. 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.

5.2 Method

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) F evaluated over M. 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:

$$J(M) = \lambda E(M) - F(M) \tag{5.1}$$

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).

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 $F(M)$. 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. 5.1). Within the optimisation identified patches and patch boundaries are subject to changes.

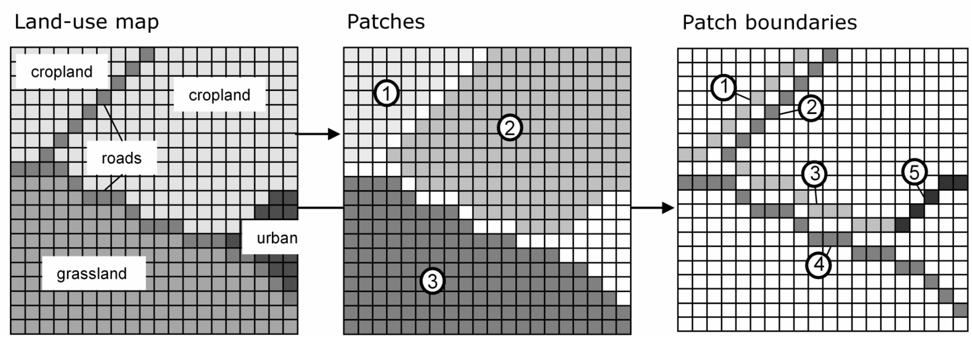

Figure 5.1: Representation of the grid landscape within the optimisation: Patches of class 'cropland' and 'grassland' are potential locations for areal land-use change; urban area is excluded from land-use change simulations. Edge cells of 'crop'- and 'grassland' are assigned to five different patch boundaries according to the adjacent land-use types.

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 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 for a large extent 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 & 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 $F(M) = 0$ in equation (5.1)) 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 for a large spatial extent 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 $F = 0$ for each study site and can thus be interpreted as cost-effectiveness of management actions *eff* [1/€/ha] for a certain ecological goal.

$$eff = \left.\frac{dE_{opt}(F)}{dF}\right|_{F=0} \qquad (5.2)$$

5.3 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.

Study area and species selection

The administrative district of Leipzig is an area of about 441.000 ha (Fig. 5.2). 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 5.1 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

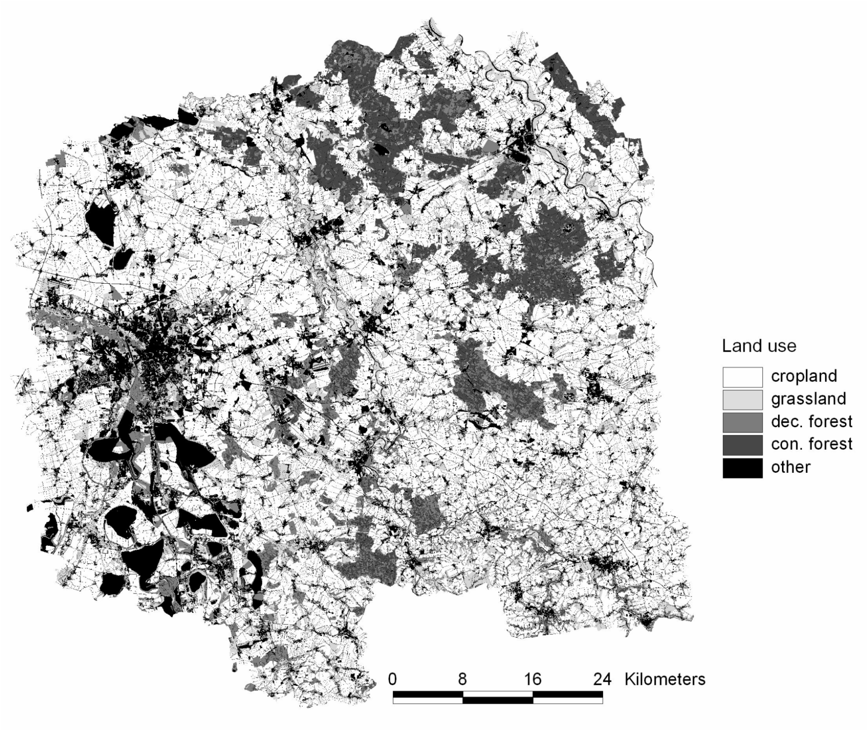

Figure 5.2: Study area with main land-use categories (land-use map 1994).

Table 5.1: 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) (Küster 2003)
Elevation	meters	20 m	2002	Landesvermessungsamt Sachsen (2002)
Soil map*	categories	1 : 25 000	1970-1990	Saxonian Federal Bureau of Environment and Geology
Annual sunshine duration	hours	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	1930's	“Reichsbodenschätzung” carried out by governmental institutions

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

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 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.

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* (equation (5.1)) was specified as follows:

$$E(M) = HSI(M)$$

$$F(M) = P(M)$$

$$J(M) = \lambda HSI(M) - P(M) \tag{5.3}$$

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 km², 150x150 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 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. 5.3). For the Red-Backed Shrike 13 sample study sites were chosen, 24 for the Middle-Spotted Woodpecker and 35 for the Wood Lark.

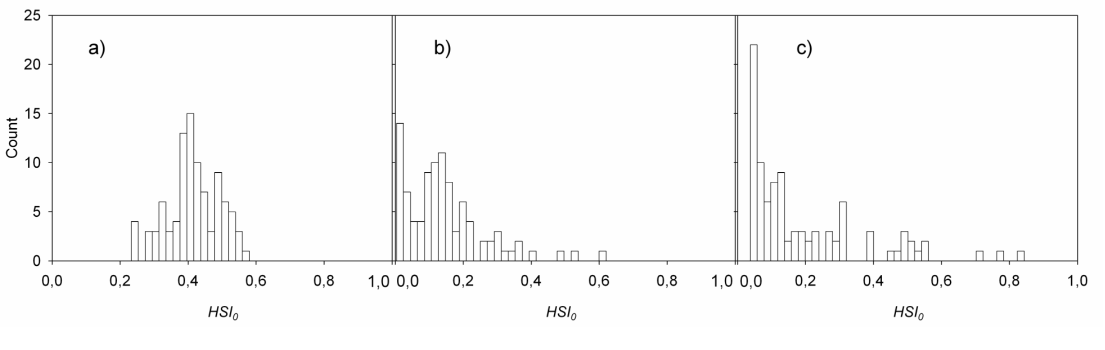

Figure 5.3: Distributions of initial habitat suitabilities for Red-Backed Shrike (a), Middle-Spotted Woodpecker (b) and Wood Lark (c) in the 95 study sites of the study area.

For each of the three target species, the spatial optimisation model was applied to the chosen sample study sites with objective function (5.3) 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 3x3 km² (75x75 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 equation (5.2).

Quantification of habitat suitability

The first part of the objective function (Equation (5.3)), $HSI(M)$, was quantified based on statistical habitat suitability models for the three target species as presented in Holzkämper et al. (2006) (Chapter 4, Table 4.1). 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 b (b_0 = intercept; b_k = coefficients) and n species-specific habitat variables v_k at location (x,y), where $hsi \in [0,1]$:

$$hsi(x,y) = \exp\left(b_0 + \sum_{k=1}^{n} b_k v_k(x,y)\right)\left[1 + \exp\left(b_0 + \sum_{k=1}^{n} b_k v_k(x,y)\right)\right]^{-1}$$

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 territorial 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.

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:

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

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 5.2). 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 (Statistisches Landesamt des Freistaates Sachsen 2003) and soil fertility scores (see Table 5.1), 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 5.2 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 5.2 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.

Table 5.2: Estimated profits from land use per year (see Table 5.1 for description of soil fertility scores).

Soil fertility score	Cropland (€/ha)	Grassland (€/ha)	Dec. forest (€/ha)	Con. 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

5.4 Results

Cost-benefit relationships

Optimisation results showed that the cost-benefit relationships differed not only between the species, but also between study sites (see Fig. 5.4, 5.5). The relations between $HSI(M^*)$ and $P(M^*)$ for each of the three target species could be described by three exponential saturation functions (equations (5.4)-(5.6)). 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.

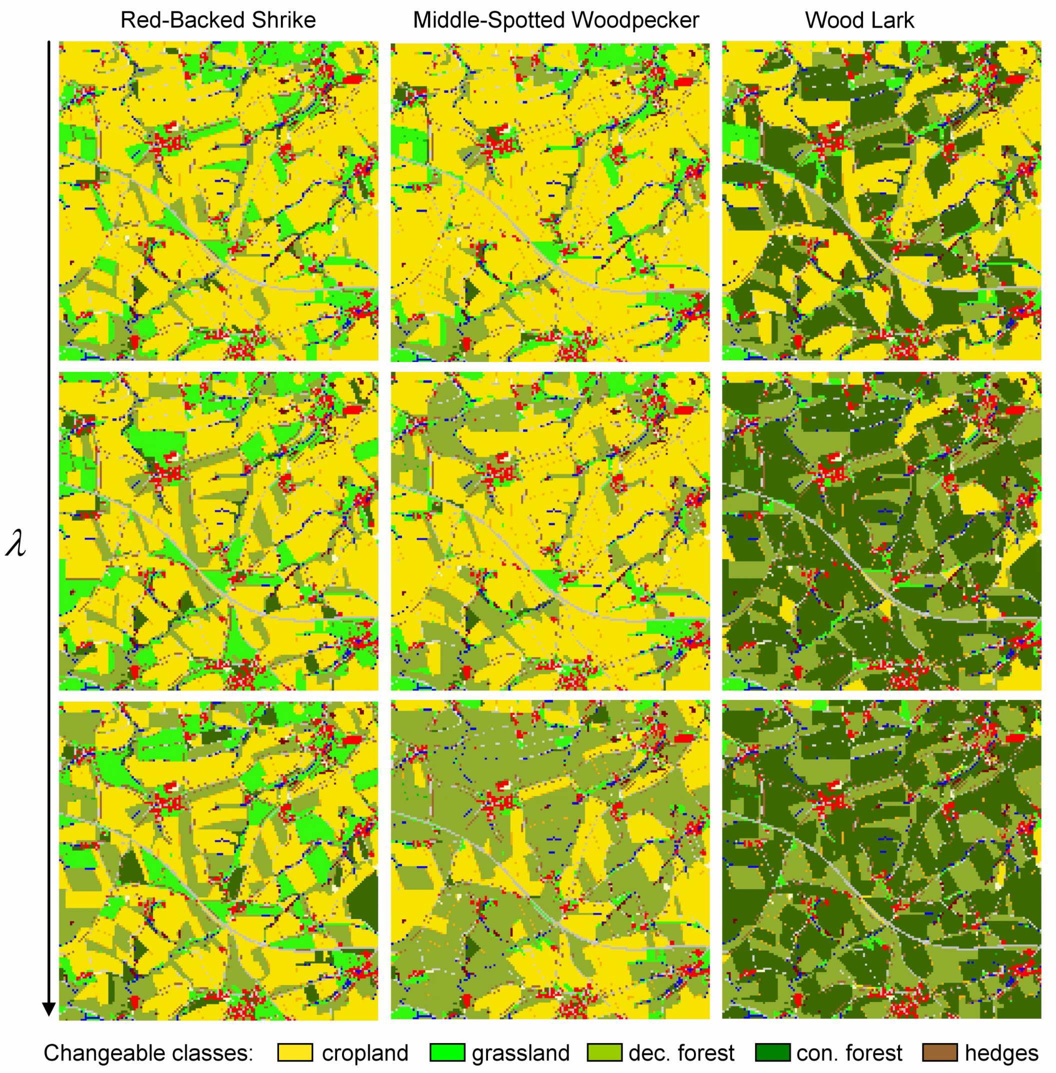

Figure 5.4: Exemplary set of optimum trade-off solutions for the three species given different values for λ.

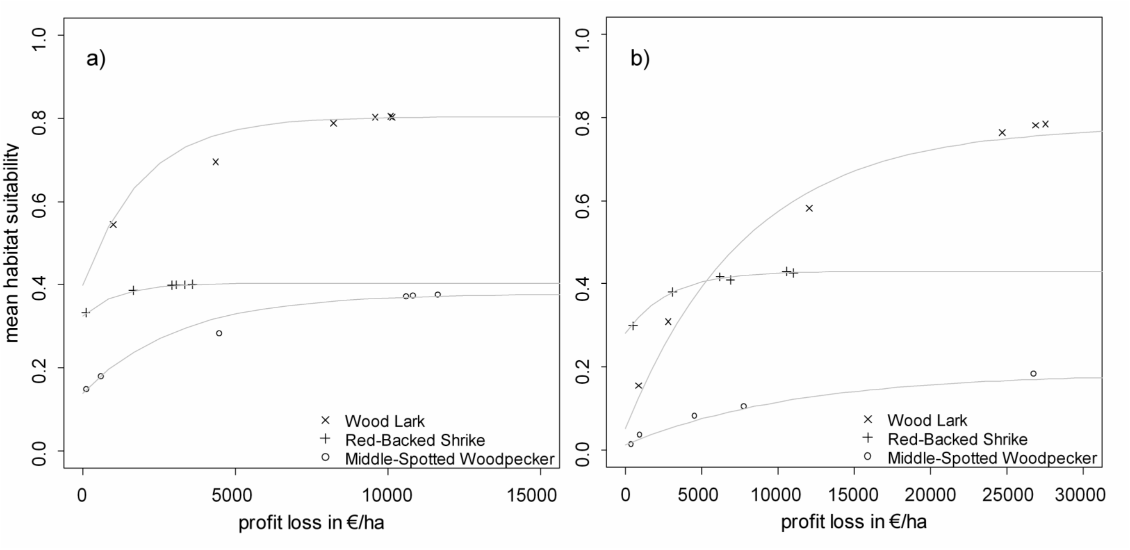

Figure 5.5: Optimisation results for all three species in two different study sites a) and b) with n=18 for each study site (mean soil fertility score = 48.2 in site a), 71.4 in site b)); lines show predictions of equations 5.4-5.6.

In equations (5.4)-(5.6) 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 5.3-5.5.

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} (equation 5.4). Table 5.3 shows the estimated coefficients of this non-linear regression model.

$$HSI_{opt}(P, HSI_{\max}, HSI_0, fs) = \Delta HSI \cdot \left(1 - e^{-k \cdot P \cdot (1-\Delta HSI) \cdot (a-fs)}\right) + HSI_0 \tag{5.4}$$

Table 5.3: Estimated coefficients for non-linear regression function (5.4).

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 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.0045 on 76 degrees of freedom
Adjusted R² = 0.99

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:

$$HSI_{opt}(P, HSI_{\max}, HSI_0, fs, h, sd) = \Delta HSI \cdot \left(1 - e^{-k \cdot P \cdot (1-\Delta HSI) \cdot (a-fs) \cdot (b-h) \cdot (c-sd)}\right) + HSI_0 \tag{5.5}$$

Coefficient *b* determines the relevance of variable height *h* incorporated in function (5.5) and coefficient *c* defines the relevance of variable mean annual sunshine duration *sd* (see Table 5.4 for estimated coefficients).

Table 5.4: Estimated coefficients for non-linear regression function (5.5).

Coefficient	Estimate	Std. 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 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 0.0239 on 213 degrees of freedom				
Adjusted R² = 0.99				

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

$$HSI_{opt}(P, HSI_{\max}, HSI_0, fs, sa) = \Delta HSI \cdot \left(1 - e^{-k\cdot(1-\Delta HSI)\cdot P\cdot(a-fs)\cdot(d+sa)}\right) + HSI_0 \tag{5.6}$$

Coefficient d defines the relevance of variable mean proportion of sand sa, which is incorporated in function (5.6) to predict optimised Wood Lark habitat suitability (see Table 5.5 for estimated coefficients).

Table 5.5: Estimated coefficients for non-linear regression function (5.6).

Coefficient	Estimate	Std. 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 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 0.0359 on 277 degrees of freedom				
Adjusted R²= 0.97				

Figure 5.6 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.

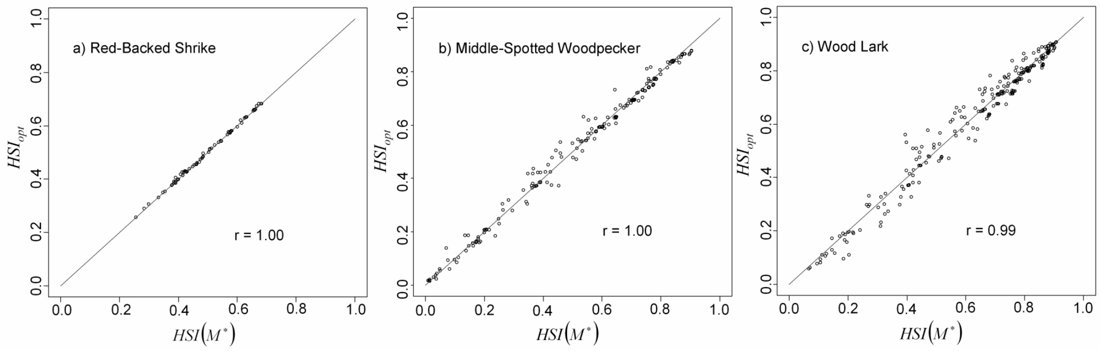

Figure 5.6: Correlations between optimised mean habitat suitabilities and mean habitat suitabilities predicted based on the fitted non-linear regressions for the three target species in the chosen training study sites; n = 78 for a), n = 144 for b), n = 210 for c); r = Pearsons's product moment correlation coefficient.

Regionalisation

The results of the independent validation with study sites of 3x3 km² shown in Figure 5.7 indicate that the fitted non-linear regression functions predicted HSI_{opt} also fairly well for the smaller study sites. As it is shown in Figure 5.8, correlations between predicted HSI_{opt} and optimisation results do not significantly differ between study site sizes.

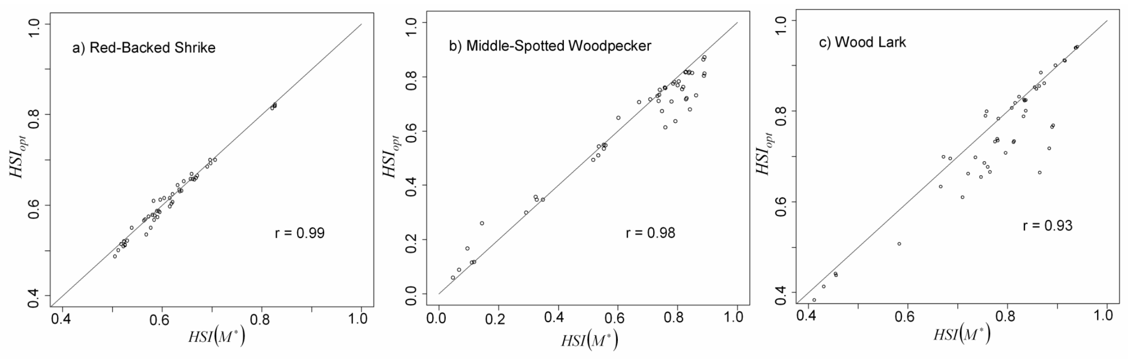

Figure 5.7: Correlations between optimised mean habitat suitabilities for randomly chosen study sites (3x3 km²) and mean habitat suitabilities predicted based on the non-linear regressions for the three target species fitted with results of larger study sites (6x6 km²); n = 48 for a), b) and c); r = Pearsons's product moment correlation coefficient.

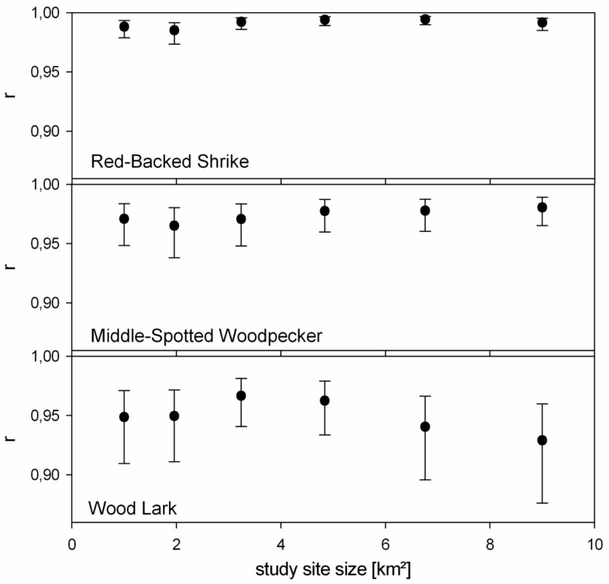

Figure 5.8: Pearsons's product moment correlation coefficient with 95%-confidence intervals for correlations between predicted optimised mean habitat suitabilities and optimisation results for the three target species for different study sites sizes (n=48 for each study site size).

Based on equation (5.2) we calculated cost-effectiveness of management actions *eff* for each of the three target species in all study sites (Fig. 5.9). Thus, we can identify areas where habitat improvement for the three target 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

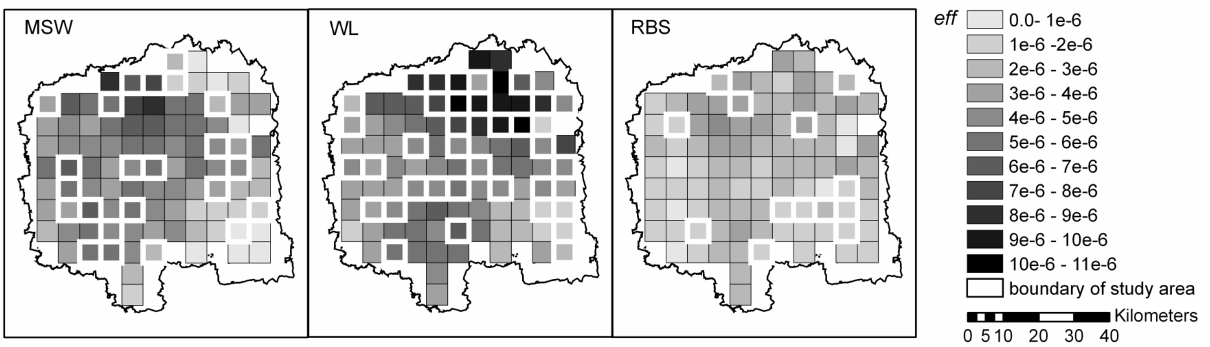

Figure 5.9: Regional distributions of *eff* for the three target species (MSW = Middle-Spotted Woodpecker, RBS = Red-Backed Shrike, WL = Wood Lark); training study sites marked with white frames.

values (Fig. 5.9). For all three species the highest *eff* were found in the Northern part of the study area. However, the distributions 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 5.6 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 equations (5.4)-(5.6). Temperature and precipitation were correlated to *eff* for the Red-Backed Shrike even though these variables were not included in equation (5.4).

Table 5.6: Pearsons's product moment correlation coefficients explaining *eff* for the three target 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 ***	0.60 ***	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** ***

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

5.5 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 target 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.

The distributions of regionalised *eff* were mainly driven by soil fertility (Fig. 5.9, Table 5.6). 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 5.6). 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 & 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 & Voinov (2003) our approach did not aim at predicting optimum land-use compositions for a large spatial extent. However, the spatial optimisation model can be applied to a small extent 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 species with the lowest spatial habitat variability. The validation based on a set of independent study sites of smaller extents 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.

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.

5.6 Conclusions

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

The results of our case study are promising and indicate that the approach can be useful 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 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 for a smaller extent.

Acknowledgements

We would like to 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 (R Development Core Team 2005) was used for fitting the nonlinear regression.

Chapter 6

Discussion & Perspectives

In the following, the three main research questions stated in the introduction (Section 1.4) are taken up. Based on the insights gained from the development of the optimisation framework (Chapter 2) and the two case studies (Chapters 4-5) it is discussed how complex spatial land-use patterns can be efficiently optimised and what optimisation results can tell us about conflicts and trade-offs between multiple spatially referenced habitat functions and the economic usage of the landscape. Furthermore, the potentials and limitations of spatial optimisation to support planning and decision making are discussed and finally, perspectives for further work are given.

6.1 Optimisation of complex spatial land-use patterns

The choice of the optimisation method

The optimisation problems addressed in this thesis are consistently very complex combinatorial problems. The case studies deal with the optimum allocation of multiple land-use options with respect to multiple goals. With such optimisation problems, complexity exponentially increases with the number of decision units in a real landscape, the number of land-use options considered per decision unit, the number of objectives and the expansion of considered neighbourhood-dependencies. Classical optimisation techniques are often insufficient for solving combinatorial optimisation problems with very high complexity. Linear programming was one of the first methods used to support management decisions (Thompson et al. 1973). However, it assumes that the optimisation problem is linear and neighbourhood interactions can be ignored, which makes the method unsuitable for solving the spatial optimisation problems addressed in this thesis. Other approaches such as integer- and mixed integer-programming can be applied to solve combinatorial problems (e.g. Bevers & Hof 1999). However, these approaches can only handle problems of limited size and complexity and are not sufficient for the integration of complex spatial dependencies as encountered here.

Approaches that overcome these restrictions and that are able to solve highly complex problems are heuristic techniques such as tabu search (Glover & Laguna 1997), simulated annealing (Kirkpatrick et al. 1983) and genetic algorithms (Goldberg 1989). This group of optimisation algorithms was found to perform well in solving complex spatial planning problems (e.g. Lookwood & Moore 1993, Bettinger et al. 1997, Moore et al. 2000, Baskent & Jordan 2002, Venema et al. 2005). Heuristic methods aim at producing high quality solutions in short amounts of time to problems with non-linearities or combinatorial relationships (Bettinger et al. 2002). They do not explore all possible solutions, but perform a directed search through the solution space. Thus, there is no proof that the global optimum is reached after the algorithm terminates (De Jong 1993), but the identified solution can be seen as an approximation to the global optimum. However, as long as computational power restricts the applicability of classical optimisation methods, heuristic optimisation methods present the only feasible way to counter very complex combinatorial problems which are often involved in spatial planning.

In this thesis, a genetic algorithm (GA) was applied for optimisation – a heuristic method, which approaches a global optimum solution based on a concept that adopts the principle of genetic evolution (Goldberg 1989). It has been shown that genetic algorithms perform better than other heuristic techniques, such as simulated annealing, for solving very difficult spatial planning problems (Stewart et al. 2004, Pukkala & Kurttila 2005). In a genetic algorithm a pool of alternative solutions evolves from one iteration step to the next (multidirectional search), whereas in simulated annealing only one solution is altered in each step (unidirectional search). Therefore, in some cases simulated annealing converges faster than a genetic algorithm because evaluating only one solution per iteration step can save a lot of computation time (Bettinger et al. 2002, Liu et al. 2006). However, for complex spatial planning problems it is beneficial when the method performs more complicated moves than selecting one of the neighbouring solutions as it is done in simulated annealing (Pukkala & Kurttila 2005). Genetic algorithms can be more powerful if the solution surface has many local optima as is the case in the presented applications.

Genetic algorithm specification and performance

A large number of different genetic algorithms (GA) exists. Different types of genetic algorithms are: the ‘simple GA’, which uses non-overlapping ‘populations’, the ‘steady state GA’, which uses over-lapping ‘generations’, the ‘incremental GA’, in which each ‘generation’ consists of one or two ‘children’ and the ‘deme GA’, which evolves multiple ‘populations’ in parallel (Wall 1996). In each of these approaches, many modifications are possible that potentially affect the subsequent optimisation performance. For example, different GA-functions for GA-crossover, -mutation, -selection and -genome representation can be chosen and customised, and different settings of GA-parameters (GA-population size, crossover probability, mutation probability, convergence criterion/number of iterations) can be adjusted to enhance optimisation performance.

The large number of possible modifications offers great opportunities to optimise performance, but also makes the finding of robust and optimal GA configurations difficult (Pereira et al. 2005). Hardly any general rule exists to guide parameter adjustment. It seems reasonable that for problems with many local optima in the solution surface a larger population size is required (Deb & Agrawal 1998), but the precise optimum parameter configuration will always be specific to the optimisation problem. To identify the optimum parameter configuration a ‘GA-within-GA’ optimisation or Latin hypercube sampling could be used. However, in spatial planning applications this was mostly omitted due to the extensive computation times such analyses would require. Instead, most authors chose their GA specification subjectively, relying on guidance from previous studies (e.g. Moore et al. 2000) and preliminary experimentations (Venema et al. 2005).

In this thesis, parameter configuration was not systematically optimised, but rather derived based on similar previous applications (Goldberg 1989, Seppelt & Voinov 2002, Venema et al. 2005). Results of the case studies indicate that the genetic algorithm performed well in optimising land-use patterns with respect to multiple spatially depending objectives. The algorithm converged after a moderate number of iterations and the variance of optimisation results between different optimisation runs was relatively low (Tab. 6.1).

Table 6.1: Results of ten replications of an optimisation with equal species weightings over 1000 generations (MSW = Middle-Spotted Woodpecker, WL = Wood Lark, RBS = Red-Backed Shrike, LPI = largest patch index, SHDI = Shannon diversity index, CONTAG = contagion index).

	mean habitat suitability			land use proportions [%]				landscape metrics		
	MSW	WL	RBS	grassl.	dec.f.	con.f.	cropl.	LPI	SHDI	CONTAG
mean	0.9056	0.5769	0.4467	0.0304	0.6475	0.2337	0.0823	60.6501	0.9698	71.2355
standard deviation	0.0055	0.0134	0.0136	0.0026	0.0118	0.0173	0.0123	1.4760	0.0187	0.6708
variance	0.0000	0.0002	0.0002	0.0000	0.0001	0.0003	0.0002	2.1786	0.0003	0.4500

Specific methods to reduce complexity

In some cases, even the solvability with a heuristic method like the genetic algorithm can be limited by computational power. In this thesis, problem complexity and thus the computational effort was reduced by performing land-use changes based on a patch topology of clustered decision units. As the patch topology can be defined by the user, the optimisation framework allows the user to modify problem complexity. Another method to counter high problem complexity due to a large landscape extent with a high number of decision units is presented in the second case study (Chapter 5). Here, optimisation results of smaller subsets are used to derive problem- and site-specific Pareto functions that can then be used for regionalising the optimisation results. The regionalisation method is potentially transferable to other optimisation problems, provided that the objective can be evaluated in smaller subsets independently. Based on this regionalisation sub-areas for further investigations can be identified and the optimisation can then be applied in this specific area.

6.2 Optimisation with respect to multiple habitat functions

Habitat suitability models for the three target species

The three target species were chosen to represent important habitat types in the study area. It is probable that co-occurring species would also benefit from habitat improvements for these three species. Comparisons of habitat suitability model predictions to occurrences of further bird species, conducted according to Bonn & Schröder (2001), showed that especially the Middle-Spotted Woodpecker and the Red-Backed Shrike have detectable 'umbrella effects' on other bird species in the study area (Tab. 6.2). However, some species 'under the umbrella' are inevitably limited by ecological factors that are not relevant to the chosen target species (Noss et al. 1997, Basset et al. 2001, Hess & King 2002). In this respect, each of the chosen species might rather be seen as a conservation target on its own than an umbrella species representing all co-occurring species.

Table 6.2: 'Umbrella effects' of the Middle-Spotted Woodpecker (MSW), Wood Lark (WL) and Red-Backed Shrike (RBS) quantified through AUC (area under the ROC curve = discrimination); bold AUC-values indicate acceptable model fits.

	AUC with MSW model mean (stddev)	**AUC with WL model** mean (stddev)	**AUC with RSB model** mean (stddev)
Ortolan bunting (*Emberiza hortulana*)	0.57 (0.04)	0.62 (0.03)	**0.76 (0.02)**
Hobby (*Falco subbuteo*)	**0.77 (0.03)**	0.63 (0.04)	0.63 (0.04)
Corn bunting (*Emberiza calandra*)	0.57 (0.03)	0.43 (0.02)	**0.73 (0.02)**
Great grey shrike (*Lanius excubitor*)	0.66 (0.02)	0.58 (0.02)	**0.74 (0.02)**
Long-tailed tit (*Aegithalos caudatus*)	**0.85 (0.02)**	**0.76 (0.03)**	0.64 (0.03)
Long-eared owl (*Asio otus*)	**0.77 (0.02)**	0.61 (0.02)	0.62 (0.02)
Honey buzzard (*Pernis apivorus*)	**0.85 (0.02)**	0.70 (0.03)	0.65 (0.03)

Logistic regression was chosen to quantify the habitat functions of the three target species. This method had proven to be robust for modelling species distributions in many previous studies (e.g. Fielding & Haworth 1995, Kleyer et al. 1999/2000, Manel et al. 2001, Graf et al. 2006). A great advantage of logistic regression is that it provides a straightforward habitat suitability function, which can easily be applied for evaluating impacts of changes in the optimisation routine.

However, it has to be noted that habitat suitability model predictions are subject to uncertainties arising from the quality and quantity of data, from constraints to the modelling technique and from the assumptions stated about underlying processes. For example, important variables might have been neglected in the habitat suitability models. Between the environmental variables and species occurrences linear relationships were assumed. Other types of relationships, for example unimodal relationships, might be more realistic, but such relationships could not be confirmed by the data. This might be due to the fact that rages of habitat variables in the study area are limited and only parts of the hump-shaped relationships are present. Another source of uncertainty might be that all habitat variables unrelated to land use are probably indirect variables that have no direct relevance for the species, but rather replace a combination of different resources and direct variables (Guisan & Zimmermann 2000). The relationship between the indirect variable and the replaced direct habitat factors is not necessarily causal, but can also be specific to the conditions in the study area. This might introduce uncertainty in the optimisation scenarios because the ability of the habitat suitability models to predict occurrence probabilities for any combination of site characteristics could not be tested. Data-related uncertainty might arise from the fact that the habitat suitability models are derived based on data collected at a certain point in time. Thereby, a quasi-equilibrium between the organism and the environment is assumed, given the change is expected to be slow relative to the lifespan of the species (Kleyer et al. 1999/2000, Guisan & Zimmermann 2000, Austin 2002). This quasi-equilibrium assumption is largely justified in the habitat suitability models because changes of environment variables such as elevation, soil texture and long-time climatic variables are slow in relation to species' lifespans. However, the assumption can be violated as land-use variables might change within species' lifespans. Another possible source of uncertainty could be that species occurrence data were not systematically collected, but are rather a collection of sightings by different ornithologists. Determination errors might have occurred in data acquisition and investigated sites might not be uniformly distributed in the study area; they might for example be biased due to differences in accessibility. Furthermore, no information on species absences was available. Instead, the models were built based on randomly drawn pseudo-absences, which are assumed to represent true species absences. Finally, data on environmental variables is uncertain due to inaccuracies in data collection.

However, the good model fits of all three presented habitat suitability models proved that logistic regression performed well in describing species occurrences based on the available data. The derived models are plausible and agree with the general descriptions of the three species' habitats found in the literature (Flade 1994, Steffens et al. 1998, Glutz von Blotzheim 1999). The best model fit was achieved for the Middle-Spotted Woodpecker because its habitats are clumped and sharply silhouetted against the remaining landscape. In contrast, the Red-Backed Shrike habitat is relatively evenly distributed in the study area, which complicates model predictions, as the suitable habitat is harder to distinguish from the unsuitable habitat. This is in the line with the findings of Seoane et al. (2005) and Betts et al. (2006).

Optimisation scenarios

By incorporating the statistical habitat suitability models for the three target species in the optimisation model, contrasting habitat requirements of species are investigated. Conflicts between species habitat requirements and economic demands to the landscape are analysed through the further integration of an economic function.

Results of the two presented case studies can be used to support species conservation management in the study area. It has been shown that there are good possibilities to avoid conflicts between conservation goals for the three chosen species in the administrative district of Leipzig. In the representative landscape subset analysed in the first case study (Chapter 4), an increase in forest area and increased landscape heterogeneity would benefit all three species. These results are transferable to the whole study area. Cost-effectiveness of management actions to enhance habitat suitability was generally found to be highest where land is less valuable (low, soil fertility), and where site conditions are most favourable for habitat quality. In areas where cost-effectiveness of management actions is high for more than one species, habitat suitability can either be improved for all species (optimum trade-off solution) or priority can be given to management actions that are most cost-intensive or that enhance habitat quality for the most endangered species in the area. For example, the areas of highest cost-effectiveness for Middle-Spotted Woodpecker and Wood Lark partly overlap in the northern part of the administrative district of Leipzig (Fig. 6.1). Management actions to enhance habitat suitability for the Middle-Spotted Woodpecker are the most expensive. Thus, priority could be given to management actions for this species where they are most cost-effective. Wood Lark habitat enhancement could then be conducted in areas where cost-effectiveness of habitat enhancement is low for the Middle-Spotted Woodpecker, but high for the Wood Lark (Fig. 6.1).

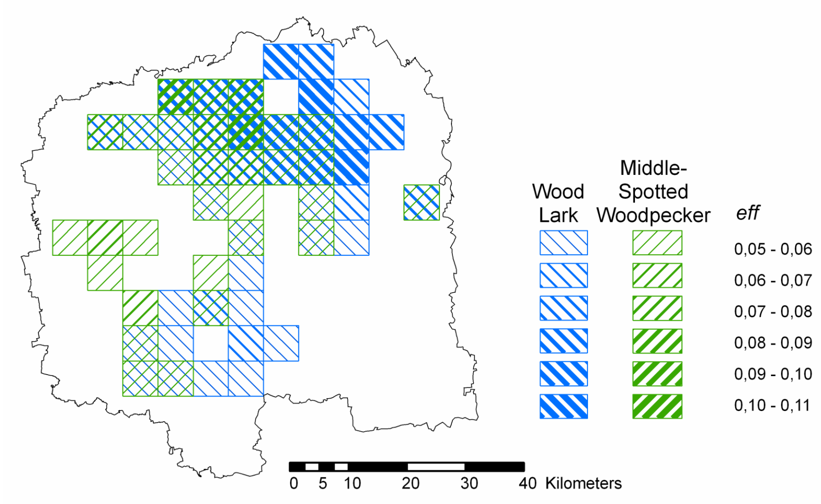

Figure 6.1: Overlap between highest cost-effectiveness values *eff* of management actions for Wood Lark and Middle-Spotted Woodpecker in the 6x6km² study sites in the administrative district of Leipzig (areas without hatching have *eff*-values < 0.05).

It has to be noted that the derived optimisation scenarios assume stationarity, as do the evaluation functions. For building the habitat suitability models no information on dynamic stages was available. Thus, newly introduced forest areas are assumed to be in the same successional stage as the current forests are. For example, it is neglected that, in reality, it would take several decades to establish a forest that is a suitable habitat for species like the Middle-Spotted Woodpecker. The economic function derives profit losses from a comparison of annual profits between different land-use types. Costs for maintenance, which would be higher for reforestation and the introduction of hedges than for conversions to grassland, are neglected. However, if long-term costs were considered, the ranking between costs for the different conservation types would largely stay the same. The utilised economic function does not quantify the real cost values for management actions, but can rather be seen as a proxy for the real costs.

Habitat suitability was assumed to be an indicator for species survival in the study area. Habitat quality and habitat amount are clearly major factors that influence species survival in a landscape. However, it has to be noted that the effects of habitat configuration on species' populations are neglected in the habitat suitability models. Habitat configuration becomes relevant on the population and meta-population level, when habitat becomes scarce and habitat patches are too small to support viable populations, or when fragmentation of habitat confines interchange between populations (Fahrig 2003, Bennett et al. 2006).

If optimisation scenarios are used to support management decisions, one needs to be aware of the associated assumptions and uncertainties arising from stochastic variations of optimisation results and uncertain evaluation functions. Uncertainty increases if the regionalisation approach is applied because also the Pareto-frontier function fitted based on landscape subsets is subject to uncertainty. This uncertainty is higher if spatial variability of the driving parameters is high in the study area.

6.3 Potentials and limitations of spatial optimisation for decision-support

Spatial optimisation, as it was performed with the developed optimisation framework LUPOlib (Land-Use Pattern Optimisation library) in this study, has much potential to support cost-effective and defensible planning decisions concerned with the optimum allocation of management options. It provides the opportunity to derive target-driven scenarios. This is a great advantage over scenario analysis with simulation models where only a limited number of alternatives are explored. A spatial land-use optimisation application for enhancing habitat suitability for selected target species in Western Canada showed that optimisation scenarios were superior to expert-based scenarios in terms of habitat enhancement (Environment Canada 2006). A similar study was recently conducted by Westphal et al. (*in press*) where optimal sites for habitat reconstruction with respect to multiple species were identified using simulated annealing. Groot et al. (2007) applied spatial land-use optimisation to provide insights into the trade-offs between different management objectives in a working landscape. The outcomes of these recent publications and the results of this thesis demonstrate the great value of spatial land-use optimisation for supporting spatial planning decisions that deal with landscape multifunctionality. Conflicts between different management objectives can be analysed and optimum trade-off solutions can be identified. Knowledge from different disciplines can be integrated in the goal function evaluation. Hence, multi-objective spatial optimisation can support objective decision-making.

LUPOlib provides a parameter file to facilitate user-adjustments for specific spatial allocation problems. The program structure is modular and the interaction between the user and the source code is restricted to the objective function definition. Several functions for general landscape evaluation are provided by LUPOlib to simplify the objective function definition for the user.

However, some limitations may still prevent the application of spatial optimisation in general and LUPOlib in particular for practical planning problems. Potential users of spatial decision support tools are not necessarily familiar with the underlying concepts of optimisation and may thus be sceptical about the method and its results (Stewart et al. 2004). To integrate knowledge and support communication between stakeholders with LUPOlib, all stakeholders would require a basic understanding of the optimisation routine. The appropriate choice of optimisation parameters will be difficult and confusing for users not familiar with this optimisation method. Also, it will often be difficult for stakeholders to quantify their management goals in an evaluation function. Management objectives such as overall attractiveness, for instance, are often left to expert-judgement, which is hard to be quantified in an objective function. If several objectives with differing units are involved (e.g. costs and mean habitat suitability), weighting coefficients need to be introduced to allow the intercomparison of the objectives and to quantify the relative importance of each objective. Clearly, the choice of these weightings influences the trade-off found in the optimisation scenario, but it will be largely unclear to the user how they will affect the trade-off unless the relationship is tested. Moreover, optimisation scenarios are subject to uncertainties as discussed above, which might be difficult to communicate to stakeholders (Caminiti 2004). Finally, the complexity of the objective function evaluation might increase the computing time of a particular optimisation application, possibly impeding its convergence within a reasonable amount of time. In these cases, scenario analysis may be the only suitable method for supporting planning decisions in very complex systems.

6.4 Perspectives for further work

Further work could either focus on the application and extension of LUPOlib as a scientific tool, or LUPOlib could be specified and extended to be a user-friendly and application-specific optimisation-based decision support system.

Further scientific applications

Further scientific applications of LUPOlib could integrate different objective functions and different management options. Not only land-use changes, but also management intensities or crop rotation types could be considered. Objective functions could utilise either static evaluation functions, dynamic models or even dynamic model systems. If dynamic processes are expected to have important effects on an objective function, dynamic models can be incorporated in LUPOlib to describe landscape dynamics and dynamic responses. For example, hydrological, ecological or economic functions can be affected by succession, crop rotation, growth cycles and climate. Dynamic variables (e.g. disturbance frequencies, successional stages) can be integrated into static habitat suitability models to evaluate the effects of relevant dynamic processes (cf. Kliskey et al. 1999, Larson et al. 2004, Rudner et al. 2007). To take into account that species survival not only depends on habitat quality and amount, but also on the distribution of habitat and on demographic processes, dynamic (meta-) population models (Hanski 1994, Schumaker 1998, Akçakaya 2002) could be coupled to the optimisation framework in addition to habitat suitability models. Dynamic population models could provide a direct measure of species' responses to landscape changes. However, the parameterisation of spatially explicit population models is not trivial and often requires a lot of data that are not readily available (e.g. demographic data or data on movement behaviour; cf. Rudner et al. 2007, Westphal et al. *in press*).

The integration of a hydrological model into LUPOlib could allow for the consideration of hydrology-related landscape functions that are affected by land use. Important landscape functions and processes related to hydrology are, for example, nutrient leaching, water quality, water availability or flood regulation. First investigations on the effects of land use on hydrology-related landscape functions were carried out with a regionalised version of the conceptual hydrological model HBV (Lautenbach et al. 2006) in the catchment of the Parthe – an afflux of the Weiße Elster – south-east of Leipzig (Fig. 6.2). Preliminary results of this investigation indicate that the annual runoff-volume is strongly affected by land-use composition (~60% changes), while land-use configuration has only minor effects (~4% changes). First optimisation results for the flood year 1994 in the Parthe catchment showed that increased proportions of grassland and forest and decreased proportions of cropland and sealed area could reduce flood risk (quantified based on runoff-volume) by ~25% given an economic constraint (profit loss < 1.000.000 €) (Fig. 6.2). Further work could investigate trade-offs between different (possibly contrasting) hydrology-related landscape functions (e.g. flood regulation, water availability and water quality), ecological and economic functions in a catchment.

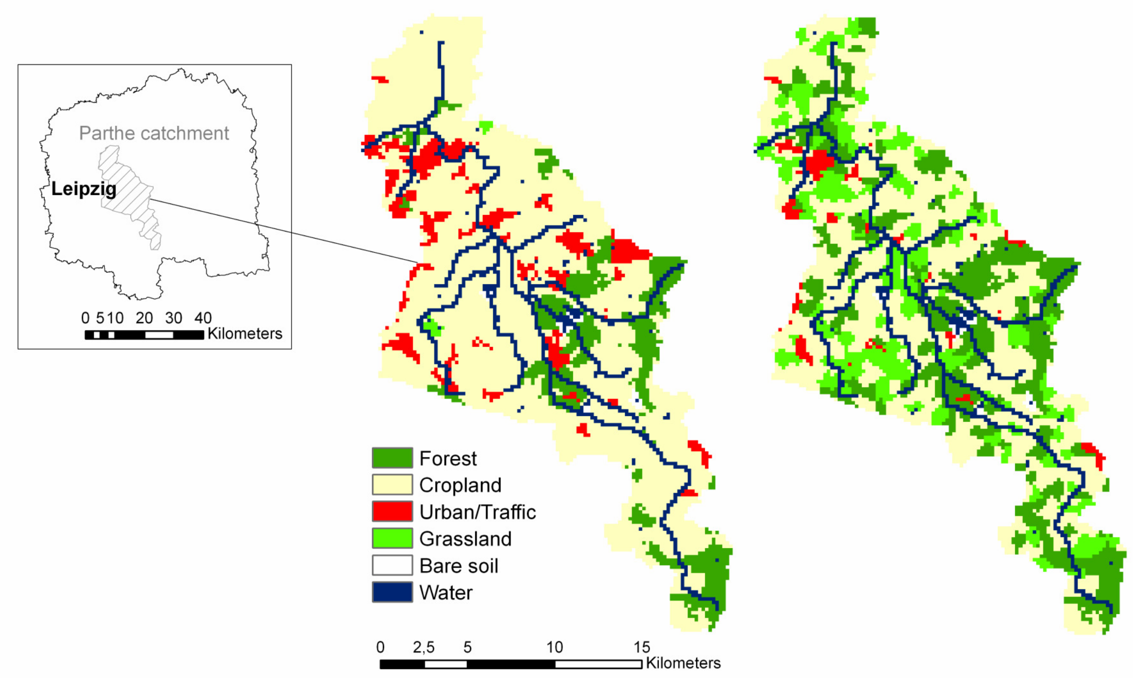

Figure 6.2: Parthe catchment in the administrative district of Leipzig: original land-use pattern (left) and land-use pattern optimised for flood regulation function subject to an economic constraint (right) using LUPOlib in combination with a regionalised version of HBV (see Table 6.3 for information on spatial data used).

In sophisticated dynamic models, such as population models or hydrological models, many assumptions about underlying processes are required resulting in an increased uncertainty in the model results. In this respect, a major task is to quantify uncertainty in the optimisation scenarios. To do this, optimisation could be applied based on different evaluation functions (e.g. different modelling approaches, different model specifications and different runs of stochastic models). The range of optimisation results could then give an indication of scenario uncertainty with respect to the objective.

Finally, the potential of enhanced optimisation performance of LUPOlib could be investigated by applying a different genetic algorithm (GA)-specification (e.g. ‘crossover’-function, ‘mutation’-function, GA parameter configuration). Also, an alternative optimisation method or a combination between different methods could enhance optimisation performance.

Table 6.3: Summary of spatial data of the Parthe catchment used for preliminary investigations presented in the outlook of this thesis.

Theme	Units	Resolution	Date	Source	Data preparation
Land use	7 categories	200m	2000	Corine landcover data, http://www.corine.dfd.dlr.de/data_de.html	Reclassification
Elevation	m	20m	2002	Landesvermessungsamt Sachsen (2002)	resampled to 200m cell size
Soils	5 categories	200m	1968	UFZ, Department of Computational Landscape Ecology	derived from Thomas-Lauckner (1968) by Düthmann (2005)
Daily precipitation	mm	13 gauging stations	1993-1994	Governmental service for environmental data (UBG = Umweltbetriebsgesellschaft)	
Daily mean temperature	°C	1 gauging station	1993-1994	Governmental service for environmental data (UBG = Umweltbetriebsgesellschaft)	
Daily catchment runoff	mm	1 gauging station	1993-1994	Governmental service for environmental data (UBG = Umweltbetriebsgesellschaft)	
Daily water withdrawal	mm	2 water works	1993-1994	Water works Naunhof I + II	
Catchment border	1 category	200m	2001	UFZ, Department of Computational Landscape Ecology	derived from elevation map in 200m resolution in a GIS by Lautenbach
Flow direction map	8 categories	200m	2001	UFZ, Department of Computational Landscape Ecology	derived from elevation map in 200m resolution in a GIS by Lautenbach
Stream network	1 category	200m	2001	UFZ, Department of Computational Landscape Ecology	derived from flow direction grid in a GIS by Lautenbach

Development of an optimisation-based decision-support system

To make LUPOlib applicable for users, who are not familiar with programming and optimisation techniques, various refinements could be made to bridge the gap between multi-disciplinary expert-knowledge and knowledge application. A more user-friendly optimisation-based decision support system could guide users and counter scepticism of planners about the method of spatial optimisation. A user-interface for a guided objective function definition could be a major step towards integrating expert knowledge into the optimisation framework. Thereby, rule-based approaches like fuzzy logic (Bárdossy & Duckstein 1995) or Bayesian (Ghazoul & McAllister 2003) methods could be useful to quantify expert knowledge and its uncertainties. The interface could provide a query for the user to answer, which is then integrated into an assessment function (cf. Janssen et al. 2005). Apart from that, a choice of basic functions for spatial evaluation (e.g. landscape metrics, as already integrated in LUPOlib) could be provided to specify a management goal. Furthermore, the decision support system could use a fixed parameter specification, which was previously tested and found to produce robust results for the problem type under investigation. This would save the user the trouble of adjusting optimisation parameters. A challenging task is to provide methods for quantifying and communicating uncertainties in the optimisation scenarios. If uncertainties are explicitly considered, the system can be used to support the development of management strategies that are robust to uncertainties (Borchers 2005, Schlüter & Rüger 2007). To allow users to gain insights into the interrelations in the system under study and to inform discussions between stakeholders, the possibility to explore static or simulation scenarios could be integrated besides the optimisation functionality. Hence, the decision support system could efficiently combine the advantages of both, spatial optimisation and scenario analysis. In order to enhance comprehensibility and support communication between stakeholders in the planning process, a tighter GIS-coupling with enhanced capabilities for visualisation and spatial analysis would be very useful. A user-oriented decision-support system, as suggested here, could best be developed in a participatory process to suit the needs of potential users. However, the tailored system would then most likely be specific to a certain problem or problem class and usability would be increased at the expense of flexibility.

Chapter 7

Conclusions

In this thesis, an approach for efficiently optimising complex spatial land-use patterns was developed and applied for investigating trade-offs between multiple species' habitat requirements and the economic usage of a landscape.

It was found that heuristic optimisation methods, like the genetic algorithm used in the developed framework, provide the only suitable tools for solving very complex spatial planning problems. A genetic algorithm is especially useful if the solution surface has many local optima as is the case in the presented applications. The performance of the genetic algorithm approach applied here was satisfactory, but modifications of the genetic algorithm-specification might still increase optimisation performance.

The developed framework applies a patch-based spatial optimisation instead of a pixel-based optimisation to reduce problem complexity. Thereby, the number of spatial decision units is decreased by merging single pixels to patches. In cases where the study area is too large and has still too many decision units to apply a spatial optimisation successfully, optimisation results of small extent landscape subsets can be used for deriving target- and site-specific Pareto frontier functions that can then be used for regionalisation. The application of the regionalisation approach helps to identify areas for management actions or further investigations.

Logistic regression habitat suitability models can easily be integrated into the developed optimisation framework for addressing species conservation management issues. By considering multiple species, it can be taken into account that changes benefiting one species can have negative effects on other species with contrasting habitat requirements. A spatial optimisation model applied in connection with multiple spatially referenced habitat suitability models and an economic function provides great potentials for supporting decision making in conservation management. Conflicts between competing management goals can be analysed and optimum trade-off solutions can be found. However, it has to be recognised that the optimisation scenarios are subject to uncertainties arising from the stochastic variability of optimisation results and from uncertainties in the objective function evaluation. Uncertainty further increases if the regionalisation approach is applied.

The developed optimisation framework is the first freely available spatial optimisation tool that can be adapted to various spatial planning problems dealing with the optimum allocation of multiple management options in working landscapes. It provides great flexibility and is therefore a suitable and promising tool for scientific analyses and advanced decision support. Apart from the applications presented in this thesis it could be applied to a variety of further spatial allocation problems considering the multifunctionality of a landscape. Moreover, it could serve as a basis for user-friendly and application-specific decision support systems.

Summary

In landscapes, where exploitation pressure is high, the ecological implications of land-use changes can be extensive. For example, in intensively used agricultural landscapes biodiversity is often threatened through the loss of natural habitats and land-use intensification. Landscape planning has to regulate the different socio-economic and ecological demands on a landscape. Thereby, various computer-based tools can assist planners in developing effective management strategies. Spatial optimisation is a very promising approach, which has frequently been applied for supporting decisions in forest management and reserve site selection. However, in working landscapes, planning often has to deal with multiple management options because conservation can not be restricted to reserves in these landscapes. Adequate optimisation approaches for spatial optimisation in working landscapes are missing so far.

The aim of this thesis was to develop a spatially explicit land-use pattern optimisation tool to investigate trade-offs between different management objectives within working landscapes. The developed optimisation framework LUPOlib (Land-Use Pattern Optimisation library) meets this claim. It utilises a heuristic search method, a genetic algorithm, for optimisation. Neighbourhood dependencies, which are known to be relevant for various important landscape functions and processes (e.g. habitat functions, species dispersal, erosion, nutrient leaching), can be explicitly taken into account. Spatial changes are accomplished based on a user-defined patch topology. In an agricultural landscape these patches or decision units can be agricultural fields that are managed as entire units. Besides areal changes also linear changes, like for example the introduction of hedges along field boundaries, can be realised. Thus, the patch-based optimisation not only allows for decreasing problem complexity, but also leads to more realistic optimisation results compared to a pixel-based optimisation. The optimisation framework is applicable for a variety of spatial planning problems dealing with the optimum allocation of multiple management options in a working landscape. A parameter file allows the user to adjust the framework to a specific problem and to control the optimisation. The program structure of LUPOlib is modular and the interaction between the user and the source code is restricted to the objective function definition.

The developed optimisation framework was successfully applied in the agricultural landscape of the administrative district of Leipzig in Germany to identify conflicts between different species conservation goals and to explore possibilities for improving land-use patterns with respect to all management objectives. For this purpose, logistic regression habitat suitability models were

derived for three representative bird species in the study area (Middle-Spotted Woodpecker, Wood Lark and Red-Backed Shrike) and these models were integrated into the optimisation. The habitat suitability models consider species' responses to landscape pattern at home range-scale. Cost-effectiveness of management actions was evaluated by further incorporating an economic function, which considers profits from land use. For analysing cost-effectiveness on a regional scale, the application of spatial optimisation is limited by computational power due to the very high number of decision units. Thus, a regionalisation approach was applied, where optimisation results of smaller landscape subsets were used to derive general target- and site-specific Pareto frontier functions that are transferable to the whole region.

Results of the spatial optimisation applications showed that the habitat requirements of the Red-Backed Shrike contrast most to those of the other two species. Middle-Spotted Woodpecker and Wood Lark are mainly influenced by landscape composition, while landscape configuration is most important for Red-Backed Shrike. Despite the identified contrasts between habitat requirements, all three species would benefit from an increase in landscape heterogeneity and increased proportions of forest. Cost-effectiveness of management actions to enhance habitat suitability is generally highest in areas, where land is less valuable. Differences in spatial distributions of cost-effectiveness with respect to the three species are due to distributions of species-relevant site characteristics.

These results can be used to support planning decisions concerned with the conservation of the three chosen species in the study area. However, if spatial optimisation is used as a decision support tool, it has to be recognised that optimisation scenarios are subject to uncertainties. These uncertainties must be considered to develop robust management strategies.

The developed optimisation framework is a suitable and flexible tool for applied scientific analyses and advanced decision support. Furthermore, it can be the basis for a more user-friendly and application-specific spatial decision-support system.

Zusammenfassung

In Landschaften, die unter hohem Nutzungsdruck stehen, können die ökologischen Folgen von Landnutzungsänderungen weit reichend sein. Zum Beispiel ist in intensiv genutzten Agrarlandschaften die Biodiversität häufig durch den Verlust naturnaher Habitate und Nutzungsintensivierung bedroht. Es ist Aufgabe der Landschaftsplanung, die unterschiedlichen sozioökonomischen und ökologischen Ansprüche an eine Landschaft zu lenken. Dabei können verschiedene computer-basierte Werkzeuge Planer bei der Entwicklung von effektiven Managementstrategien unterstützen. Die räumliche Optimierung ist ein viel versprechender Ansatz, der schon oft zur Entscheidungsunterstützung im Forstmanagement und bei der Auswahl von Schutzgebieten Verwendung fand. In vielseitig genutzten Landschaften jedoch muss die Planung oft vielfältige Managementoptionen in Betrag ziehen, weil Naturschutz in diesen Landschaften nicht auf Schutzgebiete beschränkt sein kann. Zur räumlichen Optimierung in vielseitig genutzten Landschaften fehlen bislang adäquate Optimierungsansätze.

Ziel dieser Arbeit war es, ein räumlich explizites Landnutzungs-Optimierungswerkzeug zu entwickeln, um Zielkonflikte zwischen Managementzielen in vielseitig genutzten Landschaften zu untersuchen. Das entwickelte Optimierungswerkzeug LUPOlib (Land-Use Pattern Optimisation library) erfüllt diesen Anspruch. Es verwendet ein heuristisches Verfahren, einen genetischen Algorithmus, zur Optimierung. Nachbarschaftsabhängigkeiten, welche für verschiedene wichtige Landschaftsfunktionen und -prozesse (z.B. Habitatfunktion, Artenausbreitung, Erosion, Nährstoffauswaschung) relevant sind, können darin explizit berücksichtigt werden. Räumliche Änderungen werden auf Basis einer nutzerdefinierte Patch-Topologie durchgeführt. In einer Agrarlandschaft könnten diese Patches oder Entscheidungseinheiten Ackerschlägen entsprechen, die als Einheiten bewirtschaftet werden. Neben flächenhaften Änderungen können auch linienhafte Änderungen, wie zum Beispiel Heckenanpflanzungen entlang von Feldgrenzen, realisiert werden. Damit ermöglichst es die Patch-basierte Optimierung nicht nur die Problemkomplexität zu verringern, sondern führt auch zu realistischeren Optimierungsergebnissen im Vergleich zu einer pixel-basierten Optimierung. Das Optimierungswerkzeug ist auf eine Vielzahl von räumlichen Planungsproblemen anwendbar, die sich mit der optimalen Verortung von vielfältigen Managementoptionen in multifunktionalen Landschaften beschäftigen. Ein Parameter-File ermöglicht es dem Anwender, die Optimierung für ein spezielles Problem anzupassen und zu kontrollieren. LUPOlib ist modular aufgebaut und die Interaktion zwischen dem Nutzer und dem Quellcode beschränkt sich auf die Definition der problem-spezifischen Zielfunktion.

Das entwickelte Optimierungstool wurde erfolgreich in der Agrarlandschaft des Regierungsbezirks Leipzig angewandt, um Zielkonflikte zwischen unterschiedlichen Artenschutzzielen zu identifizieren und Verbesserungsmöglichkeiten des Landnutzungsmusters in Bezug auf alle Schutzziele zu untersuchen. Zu diesem Zweck wurden mit logistischer Regression Habitateignungsmodelle für drei repräsentative Vogelarten im Untersuchungsgebiet (Mittelspecht, Heidelerche und Neuntöter) abgeleitet und diese Modelle wurden in die Optimierung integriert. Die Habitateignungsmodelle berücksichtigen, dass die Vogelarten auf das Landschaftsmuster innerhalb ihres Aktionsradius reagieren. Durch die zusätzliche Einbeziehung einer ökonomischen Funktion, die den Profit aus der Landnutzung berücksichtigt, konnte die Kosteneffektivität von Managementmaßnahmen bewertet werden. Zur Analyse der Kosteneffektivität auf regionaler Ebene wäre die Anwendung einer räumlichen Optimierung aufgrund der sehr hohen Anzahl von Entscheidungseinheiten durch die Rechenleistung beschränkt. Daher wurde ein Regionalisierungsansatz entwickelt, bei dem basierend auf Optimierungsergebnissen von kleineren Landschaftsausschnitten generelle ziel- und standortspezifische Kosten-Nutzen-Funktionen abgeleitet werden, die auf das Gesamtgebiet übertragbar sind.

Die Ergebnisse der Optimierungsanwendungen haben gezeigt, dass die Habitatansprüche des Neuntöters am stärksten von denen der anderen beiden Arten abweichen. Mittelspecht und Heidelerche sind hauptsächlich von der Landschaftskomposition beeinflusst, während die Landschaftskonfiguration für den Neuntöter die größte Bedeutung hat. Trotz der unterschiedlichen Habitatansprüche würden alle Arten von einer Zunahme an Landschaftsheterogenität und einer Zunahme von Waldflächen profitieren. Die Kosteneffektivität von Managementmaßnahmen zur Verbesserung von Habitateignung ist generell in den Bereichen am niedrigsten, in denen Land weniger wertvoll ist. Unterschiede in den räumlichen Verteilungen der Kosteneffektivitäten in Bezug auf die drei Arten resultieren aus den Verteilungen der art-relevanten Standorteigenschaften.

Diese Ergebnisse können zur Unterstützung von Planungsentscheidungen für den Schutz der drei gewählten Zielarten im Untersuchungsgebiet angewandt werden. Jedoch ist bei einer Anwendung der räumlichen Optimierung zur Unterstützung von Planungsentscheidungen zu berücksichtigen, dass die abgeleiteten Optimierungsszenarien mit Unsicherheiten belegt sind. Diese Unsicherheiten müssen berücksichtigt werden, damit robuste Managementstrategien entwickelt werden können.

Das entwickelte Optimierungswerkzeug LUPOlib ist ein geeignetes und flexibles Werkzeug für wissenschaftliche Analysen mit Anwendungsbezug und zur Entscheidungsunterstützung durch Experten. Weiterhin kann es die Basis für ein anwenderfreundlicheres und anwendungsspezifisches räumliches Entscheidungsunterstützungssystem darstellen.

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Lebenslauf

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Erklärung

Hiermit erkläre ich eidesstattlich, dass ich diese Dissertation selbstständig und nur mit den angegebenen Hilfsmitteln verfasst habe.

Leipzig, 28.03.2007

Annelie Holzkämper