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Benefits of earth observation data for conservation planning in the case of European wetland biodiversity

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SUMMARY

To evaluate the status of biodiversity and to determine how current conservation efforts can be improved, biodiversity monitoring is crucial. An important aspect of data quality lies in its spatial resolution. It is unclear how finer scale land cover and land value information might further benefit biodiversity conservation. This paper aimed to assess the impacts of scale by modelling the conservation of endangered European wetland species and their corresponding habitats. Fine-scale datasets were derived by integrating existing geographical, biophysical and economic data. A habitat allocation model, based on principles from systematic conservation planning and economic theory, was developed to estimate area requirements and opportunity costs of habitat protection in Europe. Coarse-scale and fine-scale simulations were compared by inputting both resolutions into the model. Habitat locations were restricted either only by historical species occurrence data at UTM 50 resolution or additionally by explicit wetland data at 1-km^2 resolution. Coarse country-average land rents were contrasted with spatially detailed land rent estimates at a 5′ resolution. Costs of habitat protection and area requirements for reserves may be severely underestimated when conservation planning relies only on coarse-scale data, which may result in notable shortcomings in conservation target achievement. Improvements in conservation benefits far outweigh the additional costs of acquiring fine-scale data.

Keywords: biodiversity policy, earth observation data resolution, homogenous response units, land use optimization model, mixed integer mathematical programming, spatial wetland distribution, systematic conservation planning

INTRODUCTION

Earth observation (EO) has become fundamental to achieving sustainable development (Group on Earth Observations 2005). Studies have started to examine the benefits of global earth observation (Pricewaterhouse Coopers 2006; Fritz *et al.* 2008; Trapp *et al.* 2012), however, there have been no comprehensive assessments of their economic, social and environmental benefits to date. The development of a high-quality, timely and comprehensive global earth observation system of systems (GEOSS), to include a global biodiversity observation system, would create a mechanism to integrate biodiversity data with other observations more effectively, leverage investments in local to national research and observation projects, and provide networks for global analysis and modelling. To evaluate the status of biodiversity and to determine how current conservation efforts can be improved, biodiversity monitoring is crucial (Balmford *et al.* 2005; Muchoney 2008). For example, there are proposals to establish global biodiversity monitoring systems (Pereira & Cooper 2006; Scholes *et al.* 2008) that include, harmonize and expand on current monitoring activities (Henry *et al.* 2008). Herold *et al.* (2008) and Muchoney and Williams (2010) identified global land-cover observations as being of high importance for biodiversity conservation.

This study contributes to the benefit assessment of EO in the realm of biodiversity and ecosystems. We specifically investigated conservation plans for European freshwater wetlands. Systematic conservation planning provides tools to identify optimally located priority areas for conservation (Margules & Pressey 2000; Possingham *et al.* 2000). However, efficient land allocation is only possible when these tools are used with adequate and reliable data.

An important element of data quality relates to spatial resolution. Several empirical studies have evaluated the effects of the spatial scale of databases on conservation plans (Andelman & Willig 2002; Warman *et al.* 2004; Arponen *et al.* 2012; Hermoso & Kennard 2012). However, the nature and severity of impacts of data quality on conservation outcomes are still not well understood (Grand *et al.* 2007; Hermoso & Kennard 2012). Arponen *et al.* (2012) concluded that fine-resolution analyses at large spatial extents were computationally feasible and gave more flexibility to the implementation of reserve networks. In this study, we focused on two data categories that are important for wetland biodiversity conservation planning. These were (1) data on the distribution of existing and potential wetland habitat areas and (2) land rent data. We found there were significant limitations in the available and widely used datasets on these topics. We found that no consistent adequately-resolved records of the geographical distribution of wetland areas in Europe existed. The spatial characteristics of European wetlands were only well known for selected large wetland

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areas or wetlands of special ecological interest (Merot *et al.* 2003). Furthermore, country statistics differ in spatial accuracy, reliability, acquisition method and class definition. At present, CORINE (Coordination of Information on the Environment; EEA [European Environment Agency] 2000) is the most detailed land cover database for the European Union. However, wetland areas are not aggregated within a single class, but are integrated within various different classes, such as 'forests', 'moors and heathland', 'inland marshes' or 'natural grassland'. Identification of wetlands within these classes is only possible with further analyses (see Schleupner 2010). The digital map of the potential natural vegetation of Europe (Bohn & Neuhäusel *et al*. 2003) shows a detailed classification and potential distribution of wetland vegetation types across Europe, however this distribution does not account for human influences such as river regulation, peat extraction or urbanization, which may substantially impair wetland restoration. Given these limitations, a necessary step is to develop fine-scale wetland data representing the current situation of Europe's wetlands. Accurate data on land rents are also required to estimate the cost of habitat protection. Spatial aspects of economic data seldom receive the same attention in conservation planning as the spatial scale of biodiversity data. Andelman and Willig (2002) analysed the effects of the scale of species occurrence data on reserve selection, however they set all site costs to a value of one. In a similar study on the effect of species' data resolution on conservation outputs, Hermoso and Kennard (2012) used constant costs across all planning units. Grantham *et al.* (2008) evaluated the benefits of additional biodiversity data by analysing the return on investment. They acknowledged that not only biodiversity, but also economic data were likely to be highly variable across planning units, but yet assumed uniform costs across their study area. Richardson *et al.* (2006) were the first to explicitly consider the issue of socioeconomic data resolution in reserve design. They showed that the implementation of fine-scale economic data in marine conservation planning substantially reduced the monetary losses of fisherfolk. Bode *et al*. (2008) showed that conservation outcomes were sensitive to uncertainty in land cost data, claiming that better data on conservation costs would lead to rapid improvements in the efficiency of conservation spending. European statistics (such as Eurostat, see epp.eurostat.ec.europa.eu/) and models such as the Global Trade Analysis Project (GTAP) model (Lee *et al.* 2009) provide comprehensive data on land rents. However, these data are not spatially explicit. To establish geographically more accurate land rent data, we used productivity differences at homogenous response units (HRU; Skalsky *et al.* 2008).

Obtaining finer scale EO data is costly, and questions arise over whether conservation planning will benefit from the availability of better data. Fritz *et al.* (2008) introduced the benefit-chain-approach to address this issue. A meta-analysis of the return on investment of EO data by Trapp *et al.* (2012) concluded that the overall expected financial benefits were about four times larger than the associated increased costs produced by using higher resolution spatial data and their infrastructures.

In this study of European wetlands, we consider the impact of data and methodology on land allocation efficiency for biodiversity conservation. We developed specific high-resolution data on European wetland habitats and land rents to replace the coarse spatial datasets frequently used in conservation planning processes, and employed a conservation planning tool that was able to analyse the impacts of differently resolved datasets; we call this the Habitat model. We discuss the different degrees of errors that may result from employing coarse-scale data, and thereby assess the benefits of EO data. We assessed 72 wetland species present across the entire European continent to model the conservation of European wetland biodiversity. To foster their use and further development by the scientific community, the fine-scale datasets we derived are available for download from the internet (see http://www.wetlandresearch.de).

METHODS

Structure of the study

To analyse possible benefits of a finer resolution of EO data in the context of conservation planning in Europe, we chose a specific study setup. The spatial prioritization tool we used for this analysis was the Habitat model (Jantke & Schneider 2011). Data on the geographical distribution and spatial extent of valuable habitat types were one important input parameter. A second major external dataset included information on the costs of land to set aside for conservation purposes.

Both datasets were inserted into the Habitat model in coarse-scale and fine-scale versions. The low-quality coarse-scale dataset on habitat data included all land areas except for urban and other sealed off (artificial surface) areas. The Habitat model may allocate all these land areas to species' reserves, provided that historical records of the respective species existed. The coarse-scale land rent data were taken from the GTAP model (Lee *et al.* 2009). These data differ only between countries, not within them. The fine-scale datasets were developed exclusively for this study. We produced spatially explicit wetland habitat areas at 1-km^2 resolution and fine-scale land rent data at a resolution of 5′ for the European continent.

To compare the impacts of these differing datasets, we applied four conservation planning scenarios (Table 1). In the 'non-GEOSS' scenario, we used coarse habitat and coarse land rent data, the input data for this setup being available without advances in the field of EO. In the 'habitat-data' scenario, we included fine-scale wetland habitat data, but land rents remained uniform within each country. The 'cost-data' scenario examined the implementation of fine-scale land rent data alone, with habitat data implemented at the coarse scale. Finally, the 'GEOSS' scenario included fine-scale datasets for both land rents and habitat areas.

Table 1 Quality of habitat and rent data for each model scenario. Coarse-scale habitat data included all land areas (except for urban and other artificial surface areas) without differentiation of habitat types. Coarse-scale land rent data differed only between countries, not within them. Fine-scale habitat data comprised wetland areas at 1-km^2 resolution, distinguishing wet forests, wet grasslands, peatlands, water courses and water bodies. Fine-scale land rent data were specific for each country and each HRU at a resolution of 5′.

Scenario	*Habitat area data*	*Land rent data*
Non-GEOSS scenario	Coarse scale	Coarse scale
Habitat-data scenario	Fine scale	Coarse scale
Cost-data scenario	Coarse scale	Fine scale
GEOSS scenario	Fine scale	Fine scale

The Habitat conservation planning model

Model characteristics and input data

Habitat is a deterministic, spatially-explicit mathematical optimization model programmed in general algebraic modelling system (GAMS), solved with a mixed integer programming algorithm from CPLEX version 12.1.

Conceptually, the Habitat model depicts the set-covering problem from systematic conservation planning. Its objective is to minimize total resource expenditure, subject to the constraint that all biodiversity features meet exogenously given conservation targets (Possingham *et al.* 2000; McDonnell *et al.* 2002). In our model, conservation targets account for the two principal conditions of systematic conservation planning: representation and persistence of the biodiversity features (Margules & Pressey 2000; Sarkar *et al.* 2006). Each representation of a species corresponds to one minimum viable population (MVP) of that species. The land area necessary to sustain a MVP is allocated to habitat types required by that species. In this application of the Habitat model, 10 conservation targets were analysed. Conservation target 10, for example, stands for the cost-effective representation of 10 viable populations of each considered species in a reserve system.

The Habitat model contains many planning units of varying shape and size. The potential habitat area to be selected was specified for each planning unit. There were two possible conservation states indicating whether a planning unit was used as a species' reserve (1) or not (0). Assigning a planning unit as a species reserve was only possible if this species was historically observed in a planning unit or in its close proximity. Parts of planning units necessary to fulfil conservation targets were selected as reserves. If species' area requirements could not be fulfilled within a single planning unit, further habitat was selected in adjacent planning units.

Seventy-two wetland vertebrate species of European conservation concern mainly listed in the Birds Directive (79/409/EEC, see URL http://ec.europa.eu/environment/nature/legislation/birdsdirective/index_en.htm) and the Habitats Directive (European Community Directive on the Conservation of Natural Habitats and of Wild Fauna and Flora 92/43/EEC, see URL http://ec.europa.eu/environment/nature/legislation/habitatsdirective/index_en.htm) served as surrogates for biodiversity in our model. The species assemblage included 16 amphibians, four reptiles, 43 breeding birds and nine mammals. Recorded occurrences from species atlases (Gasc *et al.* 1997; Hagemeijer & Blair 1997; Mitchell-Jones *et al.* 1999) identified their European distributions. The atlas data were provided in the universal transverse mercator (UTM) projection with grid squares of about 50 × 50 km. The non-marine parts of 2725 grid squares encompassing the whole European continent served as planning units in our model. Cyprus, Malta, and the Portuguese and Spanish islands in the Atlantic Ocean were excluded from the analysis due to data deficiencies.

Population density data for all 72 species were equal to the maximum observed densities from a comprehensive literature review. In addition, we used the proposed standards for minimum population sizes from Verboom *et al.* (2001) as proxies for MVP size. We distinguished five broad wetland habitat types, namely peatlands, wet forests, wet grasslands, water courses and water bodies. Information on species' habitat type requirements resulted from literature review (Appendix 1, Table S1, see supplementary material at Journals.cambridge.org/ENC).

Mathematical model structure

The Habitat model, with its sets, variables and exogenous data, used the following notation.

Sets and set mappings: $c = \{1,\ldots, C\}$ is the set of countries, $p = \{1,\ldots, P\}$ is the set of planning units, $t = \{1,\ldots, T\}$ is the set of habitat types, $s = \{1,\ldots, S\}$ is the set of species, $u(s, t)$ identifies the mapping between species and habitat types, and $k(s, p, t)$ represents possible existence of species and habitats in a planning unit.

Variables: O represents total opportunity costs, Z_c represents opportunity cost in country c, $Y_{p,t}$ depicts the habitat area for planning unit p and habitat type t in hectares, and $X_{s,p}$ is a binary variable array, with $X_{s,p} = 1$ indicating species s is represented in planning unit p, and $X_{s,p} = 0$ otherwise.

Exogenous data: $r_{\mathrm{c,p}}$ denotes the annual land rent per hectare in country c and planning unit p, $a_{\mathrm{p,t}}$ contains the maximum available area for planning unit p and habitat type t, d_{s} represents species-specific population density data, m_{s} is a species-specific proxy for the MVP size, $h_{\mathrm{t,s}}$ determines non-substitutable habitat requirements for habitat type t and species s, t_{s} is the desired representation target for species s, and v_{s} specifies possible deviations from the representation target based on exogenously calculated occurrence maxima.

According to the respective model scenario (Table 1), either the coarse- or the fine-scale datasets were implemented for the parameters $r_{\mathrm{c,p}}$ and $a_{\mathrm{p,t}}$.

$$\text{Minimize } O = \sum_{c} Z_c \tag{1}$$

subject to:

$$Z_c = \sum_{p,t} Y_{p,t} \cdot r_{c,p} \quad \text{for all } c \tag{2}$$

$$Y_{p,t} \leq a_{p,t} \quad \text{for all } p, t \tag{3}$$

$$\sum_{p} X_{s,p} \geq t_s - v_s \quad \text{for all } s \tag{4}$$

$$Y_{p,t} \geq h_{t,s} \cdot X_{s,p} \quad \text{for all } p, t, s \tag{5}$$

$$\sum_{t} Y_{p,t} \cdot d_s \,|_{k(s,p,t) \wedge u(s,t)} \geq m_s \cdot X_{s,p} \quad \text{for all } p, s \tag{6}$$

$$\sum_{p,t} Y_{p,t} \cdot d_s \,|_{k(s,p,t)} \geq t_s \cdot m_s \quad \text{for all } s. \tag{7}$$

The objective function (Eq. 1) minimizes total costs across all planning units. Equation (2) accounts the total conservation costs in each country as product of habitat area times land rent summed over all planning units. Constraint (3) limits habitat areas in each planning unit to given endowments. Constraint (4) implements representation targets for all species but allows deviations if the number of planning units with occurrence data is below the representation target. Constraint (5) depicts minimum requirements of non-substitutable habitat types for relevant species and planning units. Constraint (6) forces the habitat area for the conservation of a particular species to be large enough to support viable populations of that species. The summation over habitat types depicts the choice between possible habitat alternatives. Constraint (7) ensures that the total population size equals at least the representation target times the MVP size. This constraint was especially relevant for cases where the representation target was higher than the number of available planning units for conservation. For example, a representation target of ten viable populations with possible species occurrences in only nine planning units would thus require one or more planning units to establish enough habitat for more than one viable population. Further versions of this habitat allocation model can be found in Jantke and Schneider (2010), Jantke *et al.* (2011), and Jantke and Schneider (2011).

Spatially explicit data on European wetlands

This study applied data from the empirical wetland distribution model SWEDI (Spatial Wetland Distribution; Schleupner 2009, 2010), which is based on a geographic information system (GIS) and relies on multiple spatial relationships of existing geographical data. Developed as an extraction tool, it denotes wetland allocations in 37 European countries at resolution of 1 km^2, distinguishing between existing functional wetlands and sites suitable for wetland restoration by considering recent land use options. The evaluation of existing wetlands relied on a cross-compilation of existing spatial datasets and extraction of spatial wetland information. The determination of potential wetland restoration sites was more complex, involving the integration and interpretation of a variety of GIS datasets by assuming that there is a relationship between environmental gradients (Franklin 1995). Knowledge rules for each biogeographical region were defined based on analysis and observed correlation of independent variables such as climate, hydrology, soil, elevation, and slope to analyse environment-wetland relationships. The information was extracted from spatial data, such as CORINE land cover (EEA 2000), the European Soil Database (Joint Research Centre 2004), BIOCLIM (Busby 1991), WorldClim (Hijmans *et al.* 2005), Gtopo30 (USGS [United States Geological Survey] 1996), and Potential Natural Vegetation (Bohn & Neuhäusel *et al.* 2003). Regression parameters that vary across space were estimated with the advantage that they allowed for regional differences in relationships (Miller *et al.* 2007). This was especially useful concerning the broad European scale of the model. Urban and other sealed off areas and their direct vicinity were assumed to be unsuitable for wetland restoration. Sites that contained already existing conservation areas like salt marshes or valuable sparsely vegetated areas were also excluded from potential wetland restoration sites. The GIS tool ArcGIS9.3 was used for analysis.

SWEDI distinguished three main wetland types (Fig. 1) that were further sub-divided into five wetland categories: wet forests (alluvial and swamp), wet grasslands (such as reeds and sedges; only one category), and peatlands (bogs and fens). However, most wetland species that were included in the Habitat model also needed open water habitat. Spatial data on the extent of water courses and water bodies were derived from CORINE land cover (EEA 2000) and the Global Lakes and Wetlands Database (GLWD) (Lehner & Döll 2004).

We integrated the fine-scale wetland data in terms of total areas of each wetland habitat type per planning unit. Both existing and wetland areas and sites suitable for restoration were included. The wetland sites were represented by the model parameter $a_{p,t}$ which contains the maximum available area for planning unit p and habitat type t (spatially explicit data on European wetlands are accessible via URL http://www.wetlandresearch.de).

Spatially explicit data on European land rents

Detailed data on land rents covering the entire European continent were estimated at HRU resolution (Fig. 1; Appendix 1, Table S2, see supplementary material at Journals.cambridge.org/ENC for the land rents for all European countries). An HRU is a discrete characterization of land quality with pre-defined ranges on relatively stable attributes at a precision of 5′. We used discrete classifications of altitude, slope and soil texture established through previous research (Skalsky *et al.* 2008, based on Schmid *et al.* 2006;

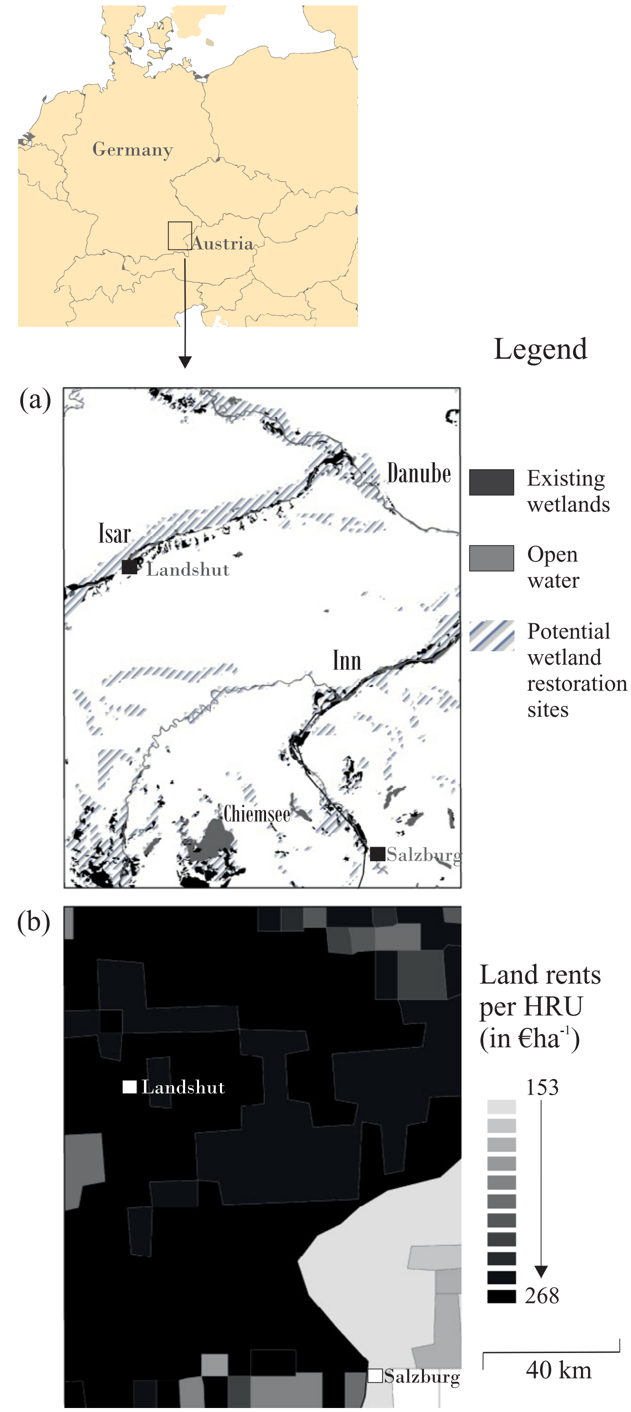

Figure 1 An example of fine-scale data for south-eastern Germany. (*a*) Wetland habitats at 1-km^2 resolution (source: Schleupner 2009, 2010). (*b*) Land rents at a 5′ resolution.

Balkovič *et al.* 2006; Stolbovoy *et al.* 2007). HRUs were delineated on the assumption that within defined ranges of attributes, biophysical processes (such as plant growth or nutrient movement) respond similarly to any set of exogenous impacts (such as rainfall or land management). Available data at HRU level included their spatial extent, biomass yields and environmental impacts on major food and non-food cropping systems. The last data resulted from simulations with the Environmental Policy Integrated Climate (EPIC) model (Izaurralde *et al.* 2006; Williams 1995). In addition, we used country specific land rents from the Global Trade Analysis Project (GTAP; Lee *et al.* 2009). Based on these data, we approximated detailed land rent data that were unique for each country and HRU.

We used the following notation: $u = \{1, \ldots, U\}$ is the set of HRU, $c = \{1, \ldots, C\}$ is the set of countries, $s_{u,c}$ represents the share of a given HRU u within country c, $mr_{u,c}$ denotes the marginal revenue of land for HRU u in country c, v_c is a value parameter representing the difference between the weighted commodity price and all production costs except for the costs of land in country c, $i_{u,c}$ depicts the weighted average yield per hectare for HRU u and country c, mc_c represents the marginal costs of land in country c, and $mc_{u,c}$ depicts the marginal costs of land per HRU u in country c.

$$\sum_u s_{u,c} \cdot mr_{u,c} = \sum_u s_{u,c} \cdot i_{u,c} \cdot v_c = mc_c \tag{8}$$

$$v_c = \frac{mc_c}{\sum_u s_{u,c} \cdot i_{u,c}} \tag{9}$$

$$mc_{u,c} = i_{u,c} \cdot v_c \tag{10}$$

Based on classic economic theory for competitive markets, Eq. (8) forced an identity between marginal revenues and marginal costs of land. While the marginal cost of land was given by its rental rate, the marginal revenue per hectare of land equalled yield multiplied by a value parameter, computed via Eq. (9), which depicts the difference between the weighted price of an agricultural or forestry commodity and its production costs. We assumed that this value did not differ within a country. Finally, we used Eq. (10) to compute HRU specific land rents by multiplying HRU specific yields by the value parameter.

In the Habitat model, HRU specific land rents in euro per hectare (Appendix 1, Table S2, see supplementary material at Journals.cambridge.org/ENC) were projected to all planning units. Since the Habitat model did not distinguish different HRU within a planning unit, the land rents in each planning unit were area weighted averages over all contained HRU. The data fed into the model as parameter $r_{c,p}$, which denotes the annual land rent per hectare in country c and planning unit p (the spatially explicit data on European land rents are accessible via URL http://www.wetlandresearch.de).

Costs of the fine-scale datasets

The fine-scale datasets were generated from the integration of existing and freely available geographical, biophysical and economic data. The rather complex methodology for acquiring the wetland habitat data was originally developed by Schleupner (2009) and adjusted to the specific needs of this study. In contrast, the methodology for the estimation of spatially explicit land rent data was exclusively developed for this study. Altogether, the costs of obtaining the new data mainly involved personnel. In particular, the generation of each dataset took approximately one person month. The monthly personnel costs for employing a researcher were *c.* € 3500 (according to German tariffs for civil service employees TV level 13; see http://oeffentlicher-dienst.info/tv-l/). Thus, the total costs of obtaining the two datasets were estimated at € 7000. We used this information to compare costs and benefits of using EO data for conservation planning.

RESULTS

Costs of habitat protection and area requirements

Annual costs for renting the land needed for habitat protection differed substantially between scenarios (Fig. 2*a*). The implementation of detailed wetland habitat data in the habitat-data scenario incurred a mean increase of 29.8 % in costs of habitat protection compared to the baseline non-GEOSS scenario. Conversely, integrating detailed land rent data in the cost-data scenario led to an average cost reduction of 5.9 %, because heterogeneous land rents within countries provided opportunities to select regions with below-average rents and avoid regions with above-average rents. Considering both factors simultaneously in the GEOSS scenario, total land costs for habitat protection were on average 38.1 % higher than those of the non-GEOSS scenario.

Fine-scale land rent data in the cost-data scenario did not notably influence the extent of conservation areas compared to the baseline non-GEOSS scenario (Fig. 2*b*). However, the implementation of fine-scale wetland data shown in the habitat-data scenario implied higher overall area requirements. The reserve areas of the habitat-data and the GEOSS scenarios were on average approximately one-third higher than the baseline scenario, due to the habitat type specifications that restricted reserve allocation to given endowments. With detailed wetland habitat area data, the model could not exploit habitat synergies (one habitat simultaneously protecting multiple species) as successfully as the coarse datasets.

Initially, it may seem as if better resolved land cover and land rent data (for example in the GEOSS scenario) led to higher costs of habitat protection and higher overall area requirements for achieving the same conservation target (Fig. 2). Thus, an investment in EO data may seem counterproductive. However, closer examination revealed that the displayed costs and area shares could not be compared directly. In all scenarios with coarse-scale datasets, the Habitat model only had limited information on habitat locations and/or land rents due to the coarse input data. These shortcomings led to severe underestimations in conservation costs and area requirements.

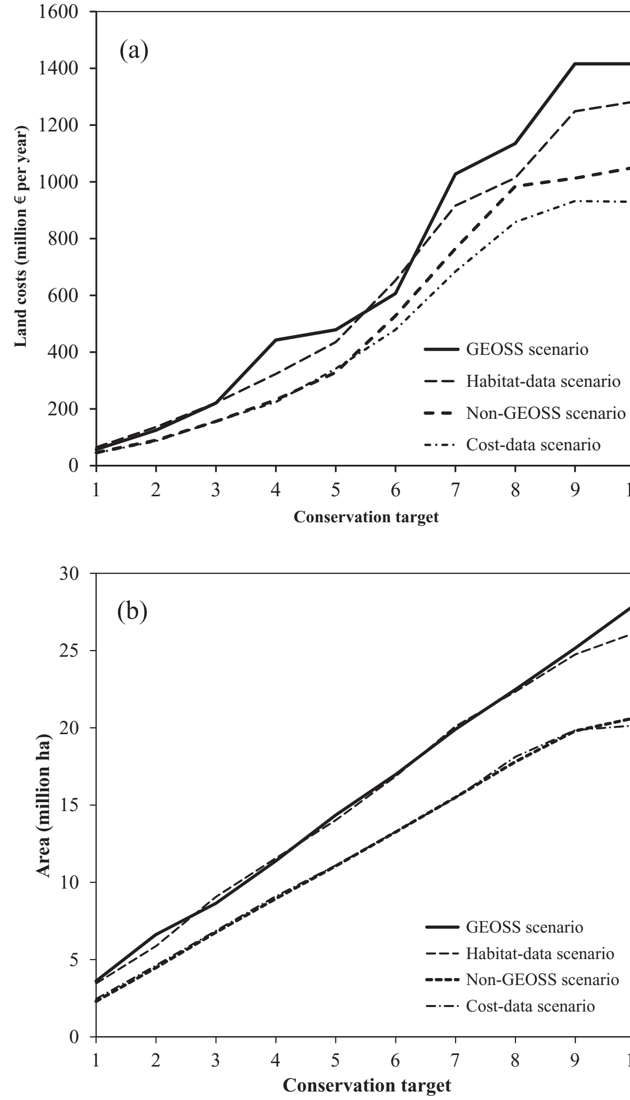

Figure 2 Costs of habitat protection and reserve area requirements for conserving 72 European wetland species. A conservation target stands for the protection of the corresponding number of viable populations of all species. (*a*) Annual land costs for acquiring reserve areas. (*b*) Required reserve areas.

Shortcomings of coarse-scale data

The cost estimates (Fig. 2*a*) for scenarios with coarse-scale data were biased and did not represent the true total costs of habitat protection because incorrect data on habitat endowments and/or incorrect land rents were used. In addition, coarse-data solutions resulted in inefficient land allocations because the conservation planning model could place habitats in unsuitable or expensive locations. The analytical bias in coarse-scale data was obvious when we corrected the results estimated under the non-GEOSS scenario to account for the two different types of fine-scale data (Figs 3 and 4). Technically, we used the sizes and locations of the conservation areas determined under the setup with coarse-scale data. We then recalculated conservation costs and

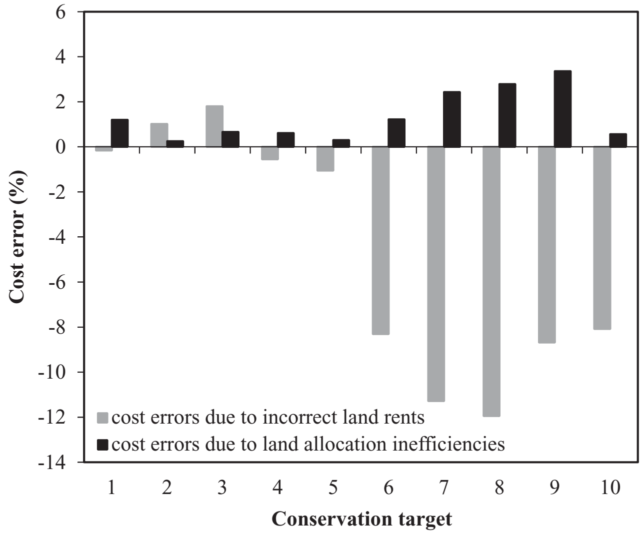

Figure 3 Shortcomings of coarse-scale land rent data: errors in estimating conservation budgets. Shown are cost errors of the non-GEOSS scenario in relation to the cost-data scenario.

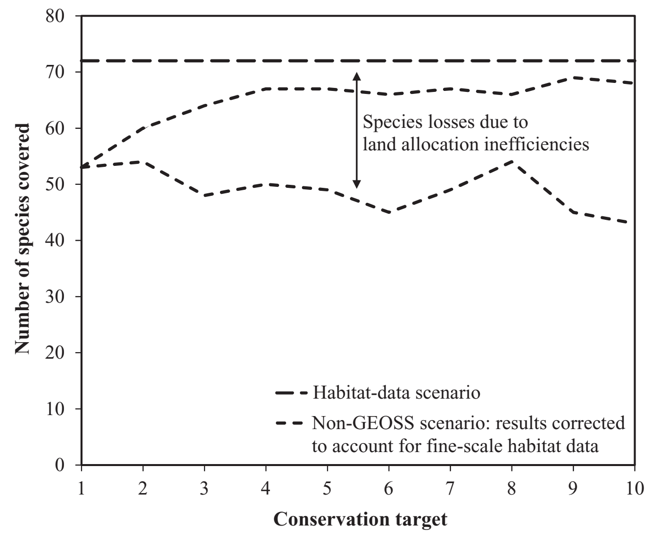

Figure 4 Shortcomings of coarse-scale habitat data: losses of species coverage. The upper line shows the number of species ($n = 72$) that should be covered under all scenarios. The middle dashed line shows species actually covered under the non-GEOSS scenario when analysed with the fine-scale habitat data. The lower dashed line shows species that are covered for each conservation target in the non-GEOSS scenario.

target achievement using the fine-scale data models (cost-data and habitat-data scenarios) to quantify the shortcomings of the coarse datasets.

In the case of land rent data, shortcomings of coarse-scale data implied errors in the estimation of conservation budgets (Fig. 3). There were two types of errors in the estimations based on coarse data and the cost errors were partly opposed (Fig. 3). First, misspecification of conservation costs in the non-GEOSS scenario due to incorrect land rents ranged from –11.9 to +1.8 % (Fig. 3), depicting the relative differences between the habitat costs of the non-GEOSS and the cost-data scenarios (Fig. 2*a*). For eight out of 10 conservation targets, the cost error was negative. Thus, the costs of habitat protection in the non-GEOSS scenario were overestimated by up to 11.9 % because the coarse land rent data masked the heterogeneity of land costs within countries. Second, cost errors due to land allocation inefficiencies ranged from +0.3 to +3.4 % (Fig. 3). Thus, the costs of habitat protection were continuously underestimated in the non-GEOSS scenario due to land allocation inefficiencies. With the coarse data on land rents, the model could place reserves in expensive regions of a country.

For habitat data, shortcomings of coarse-scale data in the non-GEOSS scenario implied losses in species coverage (Fig. 4). Analysing sizes and locations of reserves from the non-GEOSS scenario with the help of the fine-scale wetland data revealed that several species were not able to meet the respective conservation targets. The species losses due to incorrect habitat data were substantial. In the non-GEOSS scenario, only 43–53 species out of 72 were covered according to the respective conservation target. Several species (3–19) were not covered at all throughout the targets, the reason being that with coarse-scale habitat data, the model exploited more habitat synergies (one habitat simultaneously protecting multiple species) than were actually possible.

Regional allocation of conservation areas

Application of fine-scale data also affected regional reserve allocation between European countries. For example, for conservation target 5, five viable populations of each of the 72 wetland species were protected (Fig. 5). The required wetland area was largely distributed between 4–8 countries out of 37 in all four scenarios. In the non-GEOSS scenario, with coarse data on both wetland habitats and land rents, reserves were allocated mainly to Serbia and the Baltic states of Estonia, Latvia and Lithuania. These countries are rich in wetland-dependent species and provide comparably low land rents. The more realistic fine-scale wetland data in the habitat-data scenario implied a spreading of the total required area across more countries. Three countries, namely Norway, Sweden and Romania, were allocated more species reserves than in the non-GEOSS scenario. The application of spatially explicit data on land rents in the cost-data scenario did not have such a notable impact on the country scope but led to changes in reserve shares between regions. For instance, in Poland, more wetland reserves were established than before.

DISCUSSION

This study corroborates that the value of conservation planning tools (Margules & Pressey 2000; Possingham *et al.* 2000) depends on the availability and spatial resolution of

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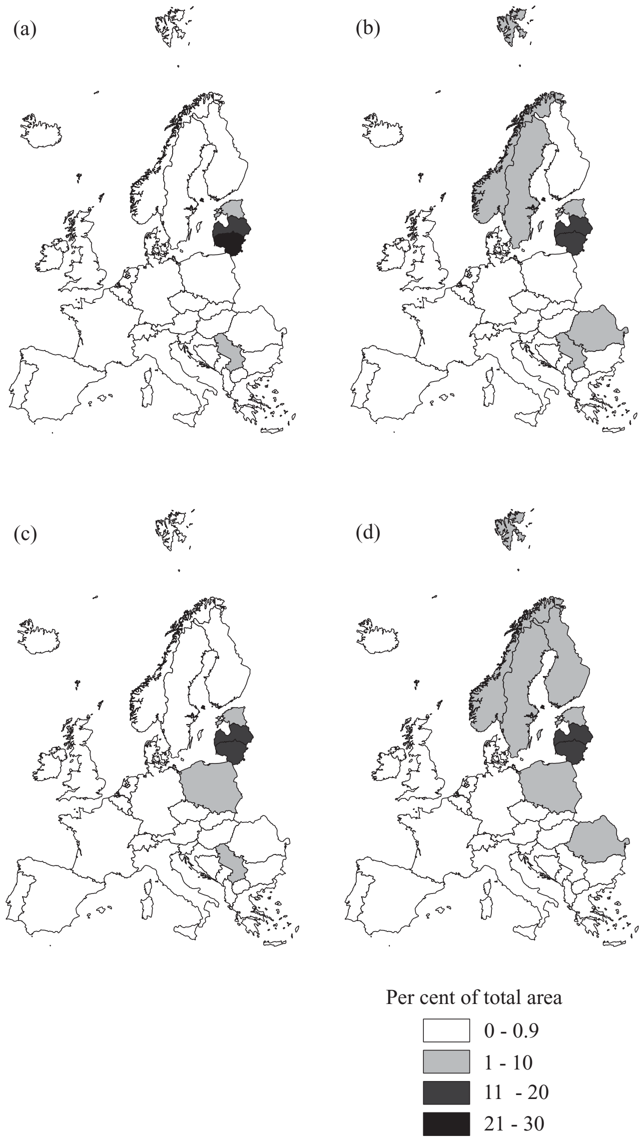

Figure 5 Allocation of habitat area to European countries using conservation target 5 as an example. (*a*) Non-GEOSS scenario. (*b*) Habitat-data scenario. (*c*) Cost-data scenario. (*d*) GEOSS scenario.

required data. Coarse or incomplete data on biodiversity and socioeconomic aspects may hinder the effective allocation of conservation resources (Grand *et al*. 2007; Bode *et al.* 2008; Reside *et al.* 2011).

However, the benefits of improved data come at the costs of acquiring them. The real question of importance is whether the benefits from improved conservation plans outweigh the expenditure on better data. For instance, the costs of habitat protection for conserving only one viable population of each of the 72 included wetland species is estimated at € 45 million per year for the non-GEOSS scenario with coarse-scale datasets (Fig. 2*a*). The analysis of this solution with the fine-scale data reveals that 19 species were erroneously omitted from the proposed reserve system (Fig. 4) and that costs and habitat area requirement were inaccurately estimated (Fig. 3). Conversely, the cost of acquiring the fine-scale data on land rent and wetland habitats was € 7000. While the land rent has to be paid yearly, the investment on better data is made only once. Taking into consideration the magnitude of errors related to the coarse-scale data (Fig. 3) and the shortcomings of target achievement (Fig. 4), the benefits to conservation do essentially exceed the costs of acquiring better data. Trapp *et al.* (2012) showed that the financial benefits achieved by using EO data from a range of studies were on average four times larger than the costs.

A specific aspect of the Habitat model in this context is the endogenous representation of reserve sizes (see also Jantke *et al.* 2011). Common reserve selection tools apply the basic formulation of the set-covering problem from operations research, where planning units are only selectable in their entirety as priority areas for conservation (see Early & Thomas 2007; Tognelli *et al.* 2008; Nhancale & Smith 2011). However, there is a considerable gap between the resolution of European-wide species occurrence data and the land area available for conservation purposes in Europe. Therefore, the Habitat model selects only those fractions of a planning unit which are necessary to fulfil the respective conservation target and are theoretically available for reservation under the given land-use pattern. If species' area requirements cannot be fulfilled within a single planning unit, further habitat is selected in adjacent planning units. Marianov *et al.* (2008) proposed a method to select reserves for species with differential habitat size needs exceeding planning units' areas. Our approach goes beyond that by also considering the fact that species' area requirements may be smaller than a planning unit's area. The total area selected as priority area for conservation in a planning unit considers MVP sizes of all species protected in it. This procedure allows easy implementation of planning units with varying sizes. Thus, the Habitat model does not only address persistence criterions directly, but also does this regardless of the planning unit's size. When better resolved species distribution data are available for Europe, the analyses could easily be refined.

There were both advances and limitations in the data generated. The empirical distribution model of wetland ecosystems at the European scale (SWEDI) distinguishes several wetland types. For the determination of existing wetland locations, several spatial datasets were jointly analysed. Potential wetland restoration sites were evaluated through geographic data analysis using rule-based statements (Schleupner 2010). The orientation towards physical parameters and the allowance of overlapping wetland types within the suitable restoration areas characterizes the SWEDI model. However, the accuracy of SWEDI model results is strongly restricted by the availability and quality of geographical data. Soil information is generally poor and often misleading with regard to wetland functionality. Another uncertainty involves the current state of existing wetland ecosystems. SWEDI is unable to assess the naturalness of the site. Nevertheless, validation with independent datasets of wetland biotopes, such as RAMSAR sites, corroborated the high accuracy of the existing wetland sites in SWEDI (see Schleupner 2009).

The second dataset generated for this study included land rents at a 5′ resolution based on HRUs, which arranged heterogeneous land attributes into discrete classes. Each combination of altitude, soil and slope class was considered to be unique. However, within a certain class element, the response was considered to be homogenous. Thus, depending on the number of classes for each attribute, HRUs involved more or less approximation error. For example, the first altitude class of our classification scheme ranged from the lowest level to 300 m above sea level. All locations within this range were represented through the same weighted average altitude value. Furthermore, we used weighted, productivity-based, marginal value differences as proxies for differences in land rental values between HRUs. In reality, other factors related to markets and local policies may influence local land rental values. Thus, our approach must be interpreted as a first approximation until comprehensive land rent data for Europe are available. To foster the further development of such data by the scientific community, we publish the applied fine-scale datasets together with this study.

Another limitation in our analysis was that species occurrence data were used with only one resolution in our model, the reason being that comprehensive data with a resolution higher than UTM 50 were not available for Europe. An option to overcome this constraint in future studies would be to predict species distributions at finer spatial scales (see Araujo *et al.* 2005; McPherson *et al.* 2006; Barbosa *et al.* 2010).

Several simplifications of the Habitat model should also be noted (see also Jantke & Schneider 2010 for a detailed description). First, we included only land opportunity costs from acquiring land for conservation, whereas there are important additional costs, such as costs of reserve establishment and maintenance (Naidoo *et al.* 2006). As we included sites suitable for wetland restoration in our analysis, further costs are related to the rehabilitation of wetland habitats. Second, we did not account for spatial reserve design criterions like connectivity or compactness and did not consider spatio-temporal aspects of persistence.

CONCLUSIONS

The costs of habitat protection may be severely underestimated when conservation planning relies on coarse-scale data. Benefits of EO data for conservation planning encompass more accurate estimations of area requirements for conservation and of habitat protection costs. Fine-scale habitat data ensure better coverage of the species of conservation concern in the conservation plan. Heterogeneous land rents within countries provide opportunities to select regions with below average rents and avoid regions with above average rents. In our study, we found that the conservation benefits achieved far outweighed the costs of acquiring fine-scale data.

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