Project no. 006463

EuMon

EU-wide **mon**itoring methods and systems of surveillance for species and habitats of Community interest

Instrument: Specific Targeted Research Project

Thematic Priority: Biodiversity conservation

D26: Final version of a coherent integrated methodology and user manual

Due date of deliverable: Month 37, November 2007

Actual submission date: Month 42, April 2008

Start date of project: 1.11.2004 Duration: 42 month

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Project co-funded by the European Commission within the Sixth Framework Programme		
Dissemination Level		
PU	Public	XX
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

1 Final version of a coherent integrated methodology and user manualy

Deliverable 26 of Work package 5

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1.1 Contents

1.2 Summary/Introduction

EuMon developed recommendations for the design and analysis of monitoring programs that are implemented in the web-based support tool BioMAT. The following are the most important messages that often are ignored in monitoring programs: The selection of monitoring sites has to be based on random sampling, exhaustive sampling, systematic sampling, or stratified random sampling. Imperfect detection is a major source of uncertainty in monitoring. Therefore, replicated sampling is highly advisable to allow accounting for measurement error. If the impact of a given cause of biodiversity change is to be demonstrated, an experimental design is needed.

In this deliverable we give firstly a primer for biodiversity monitoring (EuMon policy brief 2) and secondly an overview about integrating ongoing biodiversity monitoring: potential benefits and methods a review and thirdly a framework for the integration of biodiversity monitoring at the species and habitat level. Contribution 3 and 4 are already published electronically in Biodiversity and Conservation (Henry et al. 2008 - DOI 10.1007/s10531-008-9417-1 and Lengyel et al. 2008 - DOI 10.1007/s10531-008-9395-3). The structure of the BioMat-Tool is presented in D28.

2 A primer for biodiversity monitoring (Policy brief)

(1) Why monitor biodiversity?

The very first step when launching, evaluating, or analysing a biodiversity monitoring scheme is to clearly define the questions that need to be answered. Usually, the questions will fall into one of the following three categories: which policy support, which management problem, or which scientific issue. These questions will constrain all the following characteristics of the monitoring: What to monitor? How to monitor? For the long-term, multi-purpose surveillance can be advantageous to address general questions, such as the status and trend of distribution and abundance of a set of species, and the causes for their changes. Narrowly targeted monitoring schemes may often die with a change in policy priorities and before they can yield the expected results.

Useful references: Elzinga et al. 2001; Yoccoz et al. 2001; Parr et al. 2002; Green et al. 2005; Teder et al. 2007 ; see also Nichols and Williams 2006.

(2) Choice of the biodiversity components to be monitored

The hierarchical decomposition by Noss (1990) of biodiversity into biodiversity components is useful for defining what measures of biodiversity may be monitored. For many management and policy issues distribution, abundance, demographic processes, and community processes are among the most important components. Appendix 1 provides guidance on which general data type is particularly appropriate for which of these components.

(3) Use of biodiversity indicators

Biodiversity usually cannot be measured in its full complexity. Therefore, a range of biodiversity indicators has been proposed. Besides species and habitats targeted by national and international legislations and agreements (e.g., Annexes of the Birds and Habitats Directives), birds and butterflies have emerged as the only taxonomic groups for which large-scale state and trend indicators can be assessed with available data. The EuMon database allows an evaluation of current monitoring practices for other candidate groups. EuMon has further advanced the concept of national responsibilities as a basis for setting priorities in monitoring (see Policy brief "Identification of national responsibilities and conservation priorities in Europe").

Useful references: Balmford et al. 2005b; Balmford et al. 2005a; European Environment Agency 2007 and references therein.

(4) Which field methods?

Textbooks and reviews provide practical introductions to standard field methods. These were not covered in EuMon.

Useful references: Cooperrider et al. 1986; Noss 1990; Bookhout et al. 1994; Elzinga et al. 2001)

(5) How to distribute samples in time and space?

This is the crucial step of sampling design and is essential if we want to make reliable inferences from the collected data. It is fundamental for any data collection, including monitoring, but is often neglected in many monitoring schemes (Nichols and Williams 2006; Henry et al. 2008). The most important components of sampling design choice are:

a. **Where to monitor?** Sites to be monitored must be representative at the spatial scales relevant for the monitoring targets. Site selection methods yielding unbiased data are random sampling, exhaustive sampling, or systematic sampling; stratification may help to reduce the number of samples needed. The absence of representative site selection impose that monitoring data be post-stratified to achieve unbiased conclusions. It is a serious weakness even in some widely recognised, long-term monitoring schemes (Buckland et al. 2005).

b. **When to monitor**? The designing of monitoring can be as refined in time as in space. Nonetheless, the common practice is to monitor every year (or every 2nd or 5th year for long-lived organisms or habitats, or several times a year for multivoltine organisms). For monitoring changes in phenology, in particular, repeated sampling within a year is required.

c. If the impact of a given **cause of biodiversity change** is to be demonstrated, an experimental design is needed (ideally, a control treatment, or at least before-after comparisons). Otherwise, only correlative tests will provide indications of potential causes of change.

d. **Accounting for error in the measures**. Replicated sampling (i.e., several samples at the same sites) is to be preferred so that measurement error can be accounted for in data analysis. A major source of measurement error in monitoring data is imperfect detection (detection probability < 1). In any monitoring, the recorded value is the product of the true value of the parameter of interest and the detection probability. The sampling design should allow for the estimation of detection probability. Otherwise changes in the recorded value may not reflect the true changes in the parameter but, instead, variations in detection probability. Although detection probability may require considerable field effort, it should be accounted for whenever its variations are expected to confound temporal or spatial changes in the parameter of interest.

Useful references: Appendix 2 of EuMon Deliverable 2 (eumon.ckff.si); BioMAT module 3; Caughley 1980; Olsen et al. 1999; Parr et al. 2002; Yoccoz et al. 2001; Margurran 2004;

Buckland et al. 2000; Buckland et al. 2005; Nichols and Williams 2006; Henry et al. 2008.

(6) How to analyse monitoring data?

Key messages are:

a. Use of **generalized linear models**. It allows testing and accounting for temporal trends with incomplete time series (missing data). Including the effect of site identity as a random effect partly compensates for among-site variations (e.g., observer effect, detection probability variations) without introducing biases, and only lowering the precision of the estimate. Appendix 3 in Deliverable 2 and BioMAT module 2 provide guidance on which statistical method may be used depending on data characteristics.

b. Use of **spatial interpolation**: it allows production of biodiversity estimates even for areas not monitored.

c. Use of statistical models that **account for measurement error** (i.e., detection probability).

d. **Considering spatial variation** in the temporal trend of the biodiversity indicator. An average value of the indicator can always be computed, but major spatial variations in the trend should not be neglected because of their major implications in terms of environmental policy.

Recommendations of suitable statistical methods for monitoring data are presented in EuMon Deliverables 2 and illustrated in Deliverable 12. They are integrated in BioMAT module 2. Further useful references: Olsen et al. 1999; Parr et al. 2002; Yoccoz et al. 2001; Margurran 2004; Buckland et al. 2000; Buckland et al. 2005; Nichols and Williams 2006).

Popular programs:

- for abundance trend analyses with count data: TRIM www.cbs.nl/nl-NL/menu/themas/natuur-milieu/methoden/trim/manual-trim.html
- for demographic and abundance trend analysis with capture-mark-recapture data: MARK http://www.cnr.colostate.edu/~gwhite/software.html

(7) Need for more integration of monitoring output across monitoring schemes.

Meta-analysis tools are particularly suitable for data integration, but they remain under-used in the context of biodiversity assessment. Avenues and methods for integration are presented in Henry et al. 2008 (compiled from EuMon Deliverables 16 & 18). BioMAT module 2 will further provide web-based guideline for integration of output across monitoring schemes (available at eumon.ckff.si end of 2008).

(8) How to evaluate a monitoring scheme?

To assess the reliability of monitoring results, the underlying monitoring scheme should be evaluated in terms of the criteria listed above under items (5) and (6). A framework for such an evaluation of monitoring schemes has been proposed in EuMon Deliverable 17. This framework additionally considers criteria for time- and cost-effectiveness. The Deliverable is available at eumon.ckff.si and the framework will be implemented in BioMAT module 3 (available end of 2008).

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Appendix to chapter 2: Primer of Monitoring

Appendix 1. Link between functional parameters to be monitored (rows) and measures to be taken (columns).

	Presence/absence	Counts of individuals	Age or size-structure	Individual follow-up (cf. Capture-Mark-Recapture)	Advantages	Disadvantages
Distribution	**Optimal**	Not used	Not used	Not used	Basic information required for status identification	Trends are detected late, after local extinction or colonisation only
Abundance	Appropriate but lower power to detect trends than counts of individuals	**Optimal**	Not used	Ideal but field intensive	Trends detected early, before local extinction or colonisation	No cues on demographic processes driving changes if only count data are available; if complementary information is available, inferences on demographic processes may be possible
Demographic processes	Appropriate for estimation of population growth rate inducing range extension / restriction only	Appropriate for population growth rate estimation only	Appropriate	**Optimal**	Detailed understanding of processes driving trends	Data consuming
Community dynamics	**Optimal**	Appropriate but theory to account for relative abundances in community parameters still need to be advanced further	To be developed	To be developed	Understanding of changes in biodiversity components across broad taxonomic groups	Community dynamics theory under development
Advantages	Large coverage because easy to implement	Large coverage because easy to implement	Intermediary level of detail	Highest level of detail		
Disadvantages	Poor precision	Limited information	Usually involves unrealistic simplifications for parameter estimation; Intermediary coverage	Restricted coverage due to intensity of field work		

3 Integrating ongoing biodiversity monitoring

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3.1 Introduction

To verify the state and trends for biodiversity and the effects of policies to maintain or improve the state of biodiversity, biodiversity monitoring is needed. Over the last 20 years or so, a number of biodiversity monitoring initiatives have been launched, making an increasing number of time series on species, communities, habitats and other aspects of biodiversity available. However, most of these time series tend to be separate, spatially-restricted, single trajectories that do not directly indicate general trends of biodiversity (Balmford et al. 2003; Mace 2005; Pereira and Cooper 2006). Hence, to get a broader and more representative picture of the state and trends of biodiversity, there is a need to integrate single trajectories into indicators of biodiversity components over large spatial and temporal scales. The integration of biodiversity monitoring is thus an essential step in the progress towards a unified, appropriately scaled, adaptive management of biodiversity (Parr et al. 2002; Nichols and Williams 2006).

Increased integration of biodiversity monitoring should benefit all interested parties: Researchers will be able to access broader data sets with an increased predictive power and an increased range of inference. Policy makers benefit from more general and more robust recommendations, that apply at more relevant, extended geographical and temporal scales. Environmental managers may assess the general impact of their management actions. Individuals and organizations engaged in monitoring benefit from increased awareness about, and legitimacy of, their activity with better recognition of their role as major data providers for biodiversity assessment.

To achieve integration, top-down and bottom-up approaches can be considered. Top-down approaches are based on highly standardised, international monitoring networks, and their benefits include coordinated monitoring variables and protocols for sampling, analysis and quality assurances, as well as common data access, analysis and reporting. However, top-down, global monitoring networks for biodiversity do not exist, and any plans for such networks face formidable logistic, administrative, financial and governance challenges. Hence, bottom-up approaches, such as combining available ongoing monitoring schemes, are the only realistic option to assess the global state and trend of biodiversity now and in the coming years. This is the strategy chosen by several research groups that are engaged in the production of biodiversity indicators and is the basis for the reporting by European Union Member States on their progress on implementation of the EU Habitats Directive. The scientific value and political usefulness of this integration process will greatly depend on the understanding of the potentials and limitations of integration of similar and dissimilar monitoring schemes.

Despite its importance, integration of information across existing biodiversity monitoring schemes is still poorly developed. According to the EuMon databases on monitoring practices in Europe, only 23 out of 547 monitoring schemes assemble data at an international or EU level. Lack of international funding for species monitoring, reluctance of institutions to share data, and diversity of approaches may discourage large-scale integration of monitoring output. In addition, biodiversity monitoring schemes were launched for very different objectives, and with restricted geographical scopes. Still, most biodiversity monitoring schemes contain a common core framework: they produce indicators of biodiversity components for defined units of space and time. This core framework can be the basis for integration, using meta-analysis tools designed for this purpose (Côté et al. 2005). Combining monitoring output across initiatives may compensate for the three main weaknesses of ongoing biodiversity monitoring (Mace 2005; Pereira and Cooper 2006): (1) fragmentary biological and spatial coverage, (2) no direct compatibility of data sets among initiatives, and (3) insufficient integration of biodiversity monitoring.

When integrating monitoring output from different schemes, both similarities and complementarities among schemes are of interest. If different taxa, countries, or habitats exhibit a similar response to the same environmental change, then similarity among schemes indicates that we can make strong inferences on biodiversity states and trends. If biodiversity responses differ in intensity or in direction across, schemes, taxa, or habitats, different schemes carry complementary information. Identifying these major differences, we may gain access to a higher level of understanding of the processes responsible for the changes. From a statistical perspective, similarities are additive effects that explain an important part of the total variation. These additive effects can be the effects of time or of habitats. Complementarities are to be considered when an important part of the total variation is explained by interaction terms between additive effects. For instance, if an important part of the variation is explained by the interaction between the effects of time and habitats, then biodiversity changed differently in different habitats. Last but not least, complementarity is also sought for when combining schemes that document different processes for the same biological components. Distribution changes can be extracted from information-poor but cheap data, such as presence-absence. But combination with information-rich and expensive data, such as demographic studies, is needed to identify the processes responsible for these distribution changes.

Here, we review and illustrate the information gained by biodiversity monitoring integration, and corresponding statistical tools. We also identify practical issues to be considered when combining existing monitoring schemes. We focus primarily on species monitoring and general methodological issues, whereas integration of habitat monitoring is developed by Lengyel et al. (2008b). We address three topics (1) the benefits of integrating information among monitoring schemes, (2) the integration of monitoring schemes with different sampling designs, and (3) commonly used statistical methods for integration of monitoring data. The latter section is presented to make clear what tools are at hand to implement the suggested integration pathways.

3.2 The benefits of integration: improving biodiversity coverage

The most obvious benefit of integrating existing information from separate monitoring schemes is an increase in the number of biodiversity components that are under survey. Increased coverage can progress along each of four dimensions: (1) the ability of monitoring to detect trends (statistical power), (2) the biological components and mechanisms determining the states and trends of biodiversity, (3) space, and (4) time.

3.2.1 Precision of estimates and statistical power

Precision of an estimate depends on the sample size (the number of sampling units available for estimation) and the natural variation of the measured parameter in time and space. The ability of monitoring to detect a change as significant (e.g., statistical power for the test of the effect of time) is a function of the precision of the estimate. Hence, to increase the chances of detecting significant sources of variation in biodiversity, we want to maximize sample size. Thus, combining information from different monitoring schemes is a straightforward way to increase sample size, precision of estimates, and, eventually, statistical power, without increasing sampling effort per scheme. For instance, Hochachka et al. (2000) compared count data collected opportunistically by several observers with precise estimates of population size. They concluded that variability in population size was correctly retrieved with opportunistic data, and that the increase in sample size due to the use of all available data outweighed the cost of high among-observer variation. We can expect that the same conclusions would hold when combining data among monitoring schemes.

3.2.2 Biological coverage

Here we consider integration at increasing levels of biological data heterogeneity, starting from combining similar data on similar species and ending with combining output of species and habitat monitoring schemes

A single biological process for a single (set of) species

The first, intuitive avenue for integration is to combine monitoring schemes that document the same biological process (e.g., survival rate, population size) for the same (set of) species. The benefits are increased precision but also increased generality of monitoring conclusions. Such an approach yielded, for instance, the first global evaluation of amphibian population trends, combining data from 936 populations of 157 species (Houlahan et al. 2001). At least within Europe, there is a large potential for such integration, with many schemes collecting the same data types on the same taxonomic groups (figure 3-1) or the same habitats (Lengyel et al. 2008b).

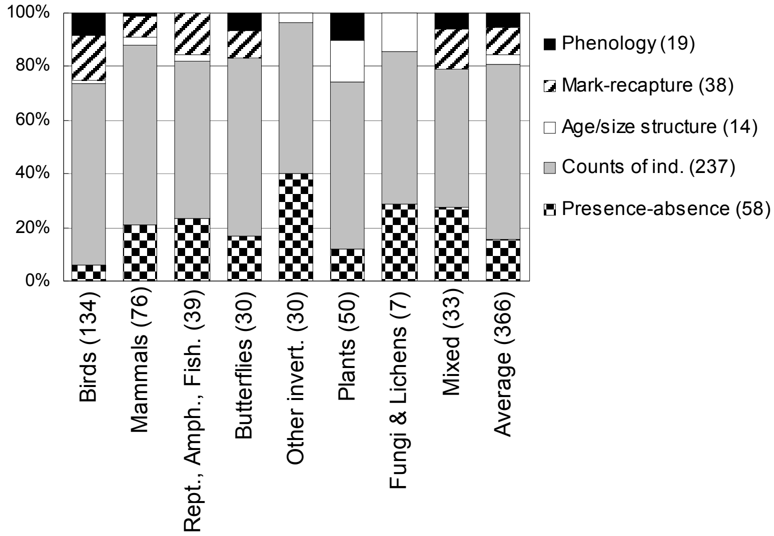


***Figure 3-1** Proportions of monitoring schemes collecting a given data type per taxonomic group in Europe (EuMon database). Scheme coordinators indicated only the main data type per scheme. 'Mixed' contains schemes that monitor more than one taxonomic group; 'Counts of individuals' includes plant densities. This figure gives a quantitative overview of the potential for integration of monitoring schemes collecting similar and complementary*

information within- and across-taxonomic groups.

The biological processes documented by monitoring schemes are largely determined by the type of the data collected. In species monitoring, four main data types are used (figure 3-1): presence/absence, counts (of individuals or species, including vegetation coverage), individual follow-up (capture-mark-recapture data), and measures of individual traits (e.g., age, size, state of individuals). Even if different monitoring schemes collect different data types, they still can be reduced to their smallest common denominator to document the same biological process, e.g. presence-absence data for geographic distribution or counts for population trend. Integration in this way extracts the information common to all monitoring schemes. Virtually all existing schemes could be combined in this way (figure 3-1). The EuMon database may identify schemes that could be combined per species, taxonomic group, or habitat in Europe.

Different biological processes for a single (set of) species

When different monitoring schemes collect different data types for the same (set of) species, they contain information on different biological processes. A goal of integration is to structure the complementarity among these biological processes to gain a more subtle and operational characterization of biodiversity change. Consider the case of changes in population size. Most data can be used to analyse and estimate trends in population size (Strayer 1999; Pollock 2006). However, only individual follow-up or age/size-structure dynamics contain the necessary information to explain the observed population trends in terms of demographic mechanisms. The identification of the driving process in turn is essential for the development of targeted management. Statistical methods were recently developed to combine capture-mark-recapture and count data to improve the analysis of population trends (e.g., Besbeas and Freeman 2006; Gauthier et al. 2007; Pradel and Henry 2007). In Europe, a large number of schemes collect time series of counts and capture-mark-recapture data for many bird species, as well as for several large mammals, reptiles, amphibians, and fishes (figure 3-1), underlining the great potential for more integration of monitoring data. Again, the EuMon database can be used to identify schemes that collect complementary information at the species level.

A single biological process for different (sets of) species and taxonomic groups

Multi-species trends are usually obtained by combining single-species trends across species. The resulting estimates have a broader biodiversity coverage than single-species approaches. The simplest method for combination is to consider that all species are equal, regardless of their characteristics (e.g., ecological function, life history traits), and to compute the mean.

When among-species heterogeneity is high, across-species integration can provided valuable information due to the complementarity among species traits: which set of species tells us what? Biodiversity indicators focussing on habitats, habitat specialization, functional traits, trophic levels, or any other species traits are designed to gain information from these differences among species. The main limitation when combining data from different species or taxonomic groups is the lack of scientific/theoretical knowledge to interpret the resulting composite biodiversity indices (Buckland et al. 2005; Green et al. 2005; Nichols and Williams 2006). For instance, the Living Planet Index (Loh et al. 2005) combines all available data into a single index, whatever realms, habitats and life-history traits of the groups are. The index is thus easy to define, but its biological meaning can be questioned. Another approach is to rely on a theoretical framework that formally links different taxonomic groups (e.g., Marine Trophic Index relying on explicit trophic networks; Pauly and Watson 2005). For terrestrial ecosystems, such a theory-based integration framework is still largely lacking (but see Pettorelli et al. 2005).

Integrating monitoring according to causes of change

An intuitive goal when combining monitoring datasets is to search for a common response across species or taxonomic groups to a given cause of environmental change (e.g., pollution, land-use, climate change, invasive species, table 3-1) (Elzinga et al. 2001; Henle et al. 2004, 2008; Balmford et al. 2005a; Gregory et al. 2005; but see limits of the approach in Nichols and Williams 2006). There is great potential for integration per cause of change since 85% of species (table 3-1) and habitat (Lengyel et al. 2008a) monitoring schemes in Europe claim to document at least one possible cause.

Table 3-1 *Proportions of species monitoring schemes documenting a given cause of change per taxonomic group in Europe (EuMon database, species). These figures give a quantitative overview of the potential for within- and among-taxonomic group integration per cause of change. Scheme coordinators could declare more than one cause of change per scheme.*

Taxonomic group	Land use	Fragmen-tation	Climate change	Pollution	Invasive species	No. of schemes
Birds	0.79	0.28	0.48	0.31	0.19	95
Mammals	0.83	0.58	0.15	0.13	0.10	48
Reptiles, Amphibians, & Fishes	0.88	0.67	0.33	0.55	0.55	33
Butterflies	0.82	0.57	0.57	0.14	0.14	28
Other invertebrates	0.78	0.41	0.41	0.52	0.33	27
Plants	0.82	0.48	0.27	0.34	0.39	44
Fungi & Lichens	0.57	0.29	0.57	0.86	0.14	7
Several taxonomic groups	0.89	0.70	0.33	0.26	0.33	27
Nb. schemes	228	146	107	92	72	309

The first benefit of integration per cause of change is to increase the robustness of conclusions on the causes of biodiversity change, and their respective intensity. Meta-analysis tools are specifically developed to derive such conclusions about the average effect of, e.g., climate change or habitat fragmentation, from independent, small-scale correlative tests with monitoring data (Côté et al. 2005).

The second benefit of integration per cause of change comes from testing for differences among species, and among taxonomic groups, in their response to one same cause of change. Understanding these differences should increase the robustness of biodiversity assessment conclusions, and the adequacy of corresponding management policies. Monitoring and among-species differences have been successfully used to develop predictors of birds sensitivity to habitat loss and fragmentation (Henle et al., 2004). Another example is the combination of monitoring time series on butterflies and birds. Butterflies are shorter-lived and more specialized than birds. They are therefore expected to react more rapidly and at smaller spatial scales, whereas the longer-lived and less specialized birds would react more smoothly and at a broader spatial scale (Thomas 1995, 2005). Hence, butterflies would document finer-grained changes, whereas birds would integrate changes over larger spatial and temporal scales. An integrated monitoring of birds and butterflies would thus provide a complementary understanding of biodiversity changes (e.g., Thomas et al. 2004; see Kati et al. 2004 for a similar recommendation for conservation purposes). In an extreme case, species from different taxonomic groups could even behave more similarly than species from the same taxa. For instance, generalist birds and butterflies may respond similarly to some environmental changes, whereas specialists could exhibit different responses (e.g. review by Henle et al. 2004 for fragmentation response of generalists and specialists).

The third benefit of integration is to challenge observational, correlative results about causes of change from surveillance monitoring (sensu Nichols and Williams 2006) with results from monitoring schemes using an appropriate experimental design. Theoretically, only monitoring schemes with well-planned, experimental designs can demonstrate that a given cause of change actually explains the temporal or spatial trends observed (Nichols and Williams 2006). However, surveillance monitoring data is the only source of material available for evaluating large-scale changes in biodiversity, identifying putative causes of change, and measuring the intensity of these changes at the relevant spatial scale through post-hoc correlative evidence. In Europe, a large part of schemes lack any experimental design (72% of species schemes, 48% of habitat schemes; the EuMon database). When different areas are monitored, with some areas affected and others unaffected by the change, correlative comparisons can come close to an experimental design (e.g., different forms of land use; Henle 2005). Combining monitoring schemes with and without experimental designs would benefit each type of monitoring: experiment-based monitoring would gain in spatial and temporal range of inference (external validity), whereas correlative-based monitoring would gain in inferential power about the role of underlying causes of change.

Integrating species and habitat monitoring

Monitoring of biodiversity is needed both at the level of species and habitats. Habitat monitoring is the monitoring of habitat characteristics, with habitats defined as distinguishable and repeatable assemblages of species (see Lengyel et al. 2008a). Thus, an integration of species monitoring and habitat monitoring has a high potential to provide a better insight in biodiversity changes. On the one hand, the states and trends of habitats provide information on the potential states and trends of their constitutive species. For example, if the coverage of a habitat is reduced by 10% per year, species depending on this habitat may be expected to also decrease by at least 10% per year. On the other hand, since habitats are most often defined as assemblages of plant species, species monitoring will be informative on the states and trends of habitats. Evaluations of the number of species lost through deforestation are based on this rationale (Hughes et al. 1997). Obviously, these approaches are rather crude, and they can be refined with ecological data if available (e.g., adjustment for density-area relationship, transitory increase of density in remaining habitat fragments, habitat specialization per species). Since several environmental policies rely on the assumed tight relationship between species and habitats, and use them for assessing their conservation status (e.g., Habitats Directive), integration of species and habitat monitoring schemes are essential for the evaluation of these policies. Actually, this integration effort has been requested by the European Commission to the Member States for the production of national reports on states and trends of Habitats Directive species (Habitats Directive Article 17, Council of the European Communities 1992). As an additional example of the benefits of integrating habitat and species monitoring, Devictor et al. (2008) combined a standardized, European-scale geo-referenced database of habitats (CORINE Landcover) and breeding bird survey data, providing the first large-scale empirical evidence of the positive relationship between landscape disturbance and homogenization of bird communities.

3.2.3 Spatial coverage

Integration of existing monitoring schemes through space has three main benefits: (1) it increases spatial coverage without increasing sampling effort, (2) it secures that spatial variation in biodiversity components can be accounted for, and (3) it facilitates directing new monitoring schemes to areas not yet covered.

Monitoring schemes often have a moderate spatial coverage. In Europe, 52% of species schemes and 55% of habitat schemes (EuMon database) are restricted to a small area or a region within a country. The integration of local, regional and national monitoring schemes is an efficient way of increasing spatial coverage without increasing monitoring effort. The EU Bird Indicators are based on such an integration of national monitoring schemes (Gregory et al. 2005; European Environment Agency 2007). The EU Butterfly Indicators are being developed with the same integrated structure, also including regional schemes when national monitoring is lacking (van Swaay et al. submitted; European Environment Agency 2007).

State and trends of biodiversity vary through space. Thus, extrapolation of measures from one localised monitoring scheme to a wider area may often not be warranted. A better practice is to rely on integration of monitoring output through interpolation across different monitored regions. This rationale is included in the construction of most Red Lists of species. A great advantage of spatial interpolation from existing monitoring schemes is to allow biodiversity estimation even for areas not monitored (e.g., Jiguet et al. 2006). The predicted values for these areas come with estimates of their precision, i.e. of their reliability. Local environmental authorities then benefit of robust estimates of states and trends of biodiversity for all the areas under their responsibility, even those not monitored. However, beyond a certain distance, data from one site are useless to predict biodiversity at another site. This distance, i.e. the limit between interpolation and extrapolation, is the maximum distance at which the measured biodiversity component is spatially autocorrelated. In this situation, new monitoring sites (or schemes) are needed to fill monitoring gaps.

Even in the presence of spatial variation of biodiversity, policy makers may need a single indicator value for large regions that may contain several monitoring schemes. If sampling design and weighting issues are appropriately handled, the estimate of the global indicator should provide an unbiased assessment of biodiversity. In addition to the global picture, decision makers may need a finer-grained indicator to adjust local management recommendations to local conditions. In this case, the average indicator should be spatially disaggregated to identify areas of homogenous trend within the area of interest. From a statistical perspective, areas with contrasted temporal trends will be identified by significant interactions between the effects of time and of space (e.g., time*sites, or time*regions, or time*schemes). This concept can be illustrated with climate warming in temperate regions. Spring arousal occurred earlier in recent warmer years, but this effect was stronger at northern than at southern latitudes (Menzel et al. 2006). Spatial disaggregation may also be considered at the habitat level. The European Bird Indicator can be computed over all species, but distinguishing trends per major habitat types revealed that the major concern was for farmland and grassland species (Gregory et al. 2005).

Spatial integration also stimulates the launching of new monitoring schemes in regions or countries that are not covered so far. Such new monitoring schemes have the possibility of benefiting from the experience of network partners. The integration of existing butterfly monitoring schemes had such a positive effect on the launching of new schemes (van Swaay et al. submitted). From a logistical perspective, this is particularly helpful for identifying the monitoring design that makes the best compromise between local constraints and biodiversity monitoring goals (Yoccoz et al. 2003; Green et al. 2005).

3.2.4 Temporal coverage

Integrating different existing initiatives allows increasing temporal coverage. Similar field monitoring techniques have been used for decades. In Europe, at least 17 schemes have been running for more than 40 years, and two schemes even for more than one century (EuMon database). Thus, by using similar monitoring data, monitoring assessment could go back far into the past by integrating data from old, abandoned monitoring schemes with ongoing and starting schemes (e.g., Loh et al. 2005).

Surveys are often not implemented with the same inter-annual frequency. Although this rises technical problems (see 'Temporal design and missing data' below), a benefit of having different time frequencies is to obtain complementary insights on the temporal patterns of the biological component of interest. Long-term monitoring with low survey frequency (i.e., wide temporal gaps) allows picking up long-term trends, while short-term monitoring with high temporal frequency (e.g., annual) allows picking up faster changes in population size. This is particularly critical when monitoring species with cyclic population dynamics (e.g., Krebs and Berteaux 2006).

3.3 Integration of monitoring schemes with different sampling designs

Setting clear goals for monitoring defines the biodiversity components to be monitored at specific spatial and temporal scales (Elzinga et al. 2001; Yoccoz et al. 2001; Parr et al. 2002; Green et al. 2005; Teder et al. 2007). The choice of the sampling design then defines how samples are to be distributed in space and time to fulfil the monitoring goals. If the sampling design is not well planned, it can strongly impair the strength of the conclusions derived from monitoring data. Combining information from schemes with different sampling designs is a way to partly compensate for potential defects in the design of some schemes. We consider here solutions to overcome or to take advantage of differences among schemes in three major components of sampling designs: (1) accurately accounting for spatial variation (cf the methods to choose sites to be monitored), (2) handling of missing data in time series, and (3) measurement error. The interest of combining schemes with and without control samples (i.e., experimental designs) has already been addressed in the section 'Integrating monitoring according to causes of change'.

3.3.1 Spatial variation and choice of sampling sites

All monitoring schemes using site selection methods that secure an objective representation of spatial variation can be combined without any correction. This concerns the schemes where all sites are monitored (exhaustive monitoring), or where the subset of sites to be monitored is chosen randomly or systematically. However, the prevailing practice is to choose sites freely or according to expert knowledge (58% of schemes in Europe; EuMon database). Since criteria underlying these choices are subjective and undefined, these monitored sites may provide a biased documentation of the monitored area. In this situation, data have to be transformed a posteriori (or weighted, named post-stratification) so that the estimates and conclusions derived from the data provide a representation as unbiased as possible of the biodiversity change at the spatial and temporal scales of interest (see part on weights for 'Different ranges of inference').

Stratification of sample collection is another method to optimize sampling effort according to specific monitoring goals while maintaining unbiased site selection. Stratification is similar to giving different weights at the design step. Stratification is used, for instance, when some habitats, regions, or species need to be sampled with a higher, but known and quantified, effort (e.g. in Green et al. 2005; Henle et al. 2006). This is particularly the case for rare or localised species that are usually badly covered by fully systematic or random sampling designs. It is often preferred to stratify a priori the field effort among habitat types, and to monitor only sites where the species is likely to occur. Integration of monitoring schemes with different stratification designs needs then to apply the inverse stratification when analysing combined data. For instance, when computing the average estimate, if one habitat type was sampled twice as much as others, data from this habitat type should be given a weight of 0.5, whereas others should be given a weight of 1.

3.3.2 Temporal design and missing data

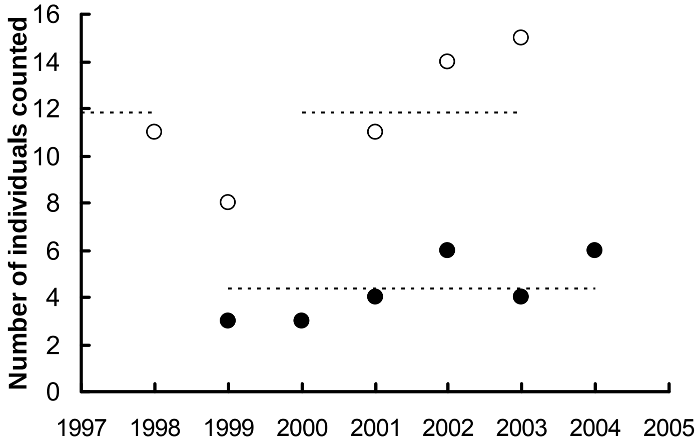
When integrating different existing initiatives, the temporal design usually differs among monitoring schemes: their activities did not start or will not end in the same years, and surveys are not implemented with the same inter-annual frequency. A similar problem arises in 'adaptive monitoring', i.e., when new monitoring needs are identified while the monitoring is ongoing, or when defaults of the monitoring design need to be corrected. The dilemma is then whether to change the protocol, which will introduce heterogeneity in the monitoring design within the time series, or to keep using a suboptimal design but consistently through time. In Europe, 14% of species and habitat monitoring schemes declare to have implemented major modifications of their monitoring protocol after the monitoring had started (EUMon database). The need to account for discontinuity in the time series is one of the important difficulties when integrating monitoring data (Balmford et al. 2003).

A solution to compensate for incomplete time series is to use statistical models that account for missing data (Olsen et al. 1999; Buckland et al. 2005; Gregory et al. 2005; but see Houlahan et al. 2001). Generalized linear models, with appropriate selection of data distribution, link-function and parameterization of the effects of schemes and year, intrinsically account for heterogeneity among schemes and through time (figure 3-2). For instance, for the EU Bird Indicators, counts of birds are analysed with a log-linear model, which allows estimation of trends despite missing data (Gregory et al. 2005; van Swaay et al. submitted – this volume). Note that interpolating values for missing data does not change estimates of the indicator or of the temporal trend.

When only a few different protocols are to be combined, another solution is to calibrate data among protocols from portions of the time series when two or more protocols were applied simultaneously within the same geographical area (e.g., Buckland et al. 2005).

3.3.3 Accounting for measurement error

The measurement error quantifies the range of statistical validity of the measure. The sampling design should take this uncertainty of the measure into account when inferences are made from the data. When measurement error cannot be estimated in some of the datasets to be combined, a solution is to include independent estimates of this error in the statistical model for the joint analysis. Such methods are still under development (e.g., Hooten et al. 2007).



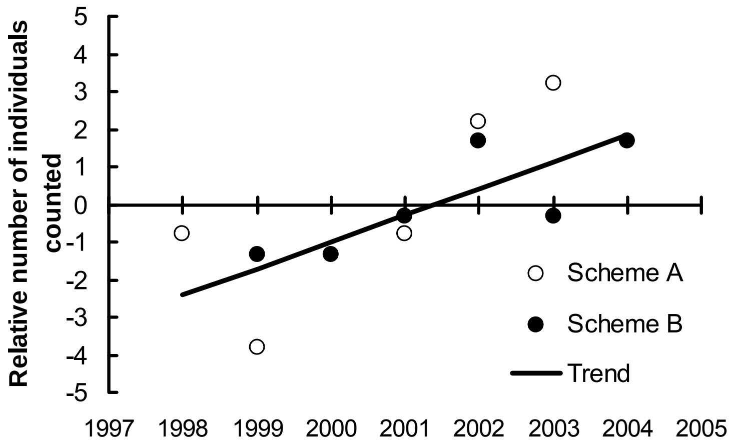


Figure 3-2 *Temporal trend analysis in the presence of missing data and differences of average value among schemes.*

Top*: Two schemes, A (open dots) and B (filled dots), counted individuals from 1997 to 2005. To avoid the problems of missing counts in some years, as well as the problem of systematic differences in relative abundance among schemes, the combined dataset can be analysed with a log-linear regression model, with the number of individuals counted as dependent variable and the effects of year and scheme identity as additive explanatory variables.*

Bottom*: Including a scheme effect accounts for systematic differences among schemes in relative abundance. The inclusion of the year effect is similar to averaging counts standardised for the effect of schemes per year (i.e., year-specific deviations from the scheme average). The average temporal trend in relative abundance can be estimated by including a linear effect of years in the model. For the sake of clarity, the Y axes (counts) are on an arithmetic scale, whereas their natural scale should be logarithmic.*

A common source of measurement error in monitoring schemes based on counting individuals (or species) is the fact that the observer cannot detect all individuals (or species) present during monitoring visits. In other words, the detection probability is usually lower than one. A specific sampling design based on repeated sampling needs to be implemented so that monitoring data can be adjusted for fluctuations in detection probability. When integrating monitoring schemes with and without detection probability design, two approaches can be followed. First, it is common practice to ignore detection probability. This practice may be reasonable if a pre-analysis showed that detection probability can be considered constant through space and time, or that variation is random and cannot generate spurious trends. However, this may rarely be the case and the many possible sources of variation in detection probability can critically confound the conclusions of monitoring. Second, uncertainty in the measure can be systematically quantified by additional information (e.g., extra field-work). If such post-hoc measures are not feasible (too technical or time consuming), a solution is to incorporate independent estimates of the error in the joint analytical model. Estimates of detection probability can be extracted from monitoring schemes with appropriate sampling designs and incorporated in analyses of data from monitoring schemes with inappropriate sampling designs (e.g., MacKenzie et al. 2005; Hooten et al. 2007; Schaub et al. 2007). More generally, Bayesian models provide a promising analytical framework for such combinations of heterogeneous data, or the integration of extra-biological knowledge in the statistical analysis. Applications of these methods to monitoring data are under development.

3.4 Statistical methods for integration

There are two main ways to integrate information from different monitoring schemes: combining data or combining estimates. Combining raw data into a single dataset is possible when data are compatible, i.e. when they are measured in the same unit (or can be reduced to the same unit) and they quantify the same biological process; table 3-2). When data types differ but still document the same biodiversity indicator, a solution is to combine estimates of the indicator across datasets. Two supplementary methodological issues are also considered hereafter. Whatever the data to be integrated, if contributions to the global indicator should not be equal among monitoring schemes, species, or regions (etc.), data or estimates need to be weighted. Finally, when different monitoring datasets document a similar biodiversity component, cross-validation could be used to assess the robustness of the conclusions.

Table 3-2 *Three levels of combining information from different monitoring schemes so that combined data can be analyzed with a single statistical model. Corresponding conditions of application and examples are given.*

Data to be combined across datasets	Conditions of application				Example
	Measurement unit in original datasets	Biological parameter to be analysed (i.e., Y) in original datasets	Biological effect to be tested (i.e., X) in original datasets	Statistical method	
Y: raw data for dependent variable in the statistical model	Same	Same	Can differ	Classical	Population growth rate documented with counts of individuals
$\hat{Y}$: estimates of Y	Can differ	Same	Can differ	Classical + weights for precisions of estimates, or Meta-analysis methods	Population growth rate documented with counts of individuals and presence-absence data
$\hat{z}$: estimate of effect size, the standardized estimate of the intensity of an effect of X (independent variable) on Y	Can differ	Can differ	At least one X needs to be the same	Meta-analysis methods, or Classical + weights for precisions of estimates	Linear effect of time (temporal trend) on population growth rate documented with counts of individuals and presence-absence data

3.4.1 Combining data

When the measurement unit is the same among different monitoring schemes, raw datasets can be combined easily (table 3-2). For simultaneous analysis with the same parametric statistical model, data need to follow the same theoretical distribution. Then, combined data can be jointly analysed to produce an estimate averaged across all monitoring data in regard to the parameter of interest. Summary statistics are straightforward to compute from the integrated dataset. For instance, Julliard et al. (2004a) estimated national population growth rates for bird species with a single model combining data from two separate monitoring schemes, one counting individuals detected acoustically and the other counting captured individuals. Although the numbers of individuals per sampling effort could not be compared because counting techniques were different, data still followed a similar theoretical distribution (Poisson distribution) and documented the same biological parameter, population growth rate (estimated by the slope for the linear effect of year; figure 3-2). Such approaches provide access to parameter estimates across all datasets with a single analysis, despite differences in sampling units and scales among monitoring schemes. When combining heterogeneous data, the general model may not fit satisfactorily all data (cf overdispersion). In this case, it would not be warranted to combine all data into a single analysis. Estimates of the population growth rate should be extracted separately from each dataset and then combined with meta-analysis methods.

When the nature of the data collected differs among monitoring schemes, the simplest method for data combination is to reduce the complexity of information to the lowest common level (common denominator). For instance, if a set of individual follow-up, counts of individuals, and presence-absence data is available (figure 3-1), the lowest complexity level would be presence-absence (e.g., Roberts et al. 2007). Combining data in this way is rather straightforward. However, much of the original information and precision contained in the data is lost (Strayer 1999). In this case, combining estimates instead of the raw data would make a more optimal use of the information to be integrated (see following section).

If data heterogeneity is so high that no common quantitative currency can be defined, better than nothing is to synthesize the sparse, available information on states and trends into standardized ratings. This is how the IUCN evaluates extinction risk status with the help of standardized criteria assessed by independent experts (Miller et al. 2007). These criteria are then used as raw data for biodiversity assessment (e.g., Butchart et al. 2005).

3.4.2 Combining estimates and meta-analyses

When different data types are collected, parameter estimates rather than original data can be integrated. Estimates become the dependent variable in the joint analysis. The difference between analysing raw data or estimates is that error of the measurement is usually ignored for raw data. Raw data are analysed as if they were known without error (i.e., perfect measurement). To the contrary, measurement error for estimates is known; it is measured by the standard error. Then, a proper analysis using estimates as dependent variables should simultaneously account for estimates of the mean and of the standard error. Estimates to be integrated can characterize state or trend of a biodiversity component ($\hat{Y}$ in table 3-2), or the response of this state or trend to an external factor ($\hat{z}$ in table 3-2).

Combining estimates of dependent variables

When measurement units differ, information from each monitoring scheme can be summarized as the estimate of a single biological parameter for each separate data set. Then, integration is achieved by analysing these estimates with a single statistical model. For instance, trends in population size can be estimated both from counts of individuals per unit of time or with presence-absence data (e.g., Strayer 1999; Pollock 2006). Both estimates can be combined to obtain an integrated, average estimate of the population growth rate. For example Julliard et al. (2004a) estimated population growth rates from different data types (point counts versus numbers of individuals captured) for a large set of species. Then, they tested with a single ANOVA model whether among-species variation in population growth rate could be explained by species traits, while accounting for differences of estimate precision among species.

When producing summary statistics from combined estimates, the recommended method is the geometric mean (instead of the arithmetic mean), i.e., averaging on a log-scale and exponentiation of the average (Buckland et al. 2005). The formula for computing standard errors for geometric means is provided in Appendix A of Gregory et al. (2005). An interesting property of the geometric mean is that its temporal trend is invariant with respect to the weights attributed to each monitoring scheme (or species; Buckland et al. 2005).

An illustrative study is the estimation of the average trend of breeding bird populations per major habitat in Europe (Gregory et al. 2005). In 2000, up to 18 EU countries maintained a national breeding bird survey and counted individuals per species but with different methods. Thus, data could not be combined into a single dataset from which trends could be estimated. The integration procedure comprised three steps. First, each country produced national estimates of population growth rate per year for each species. Second, these estimates were combined with independent estimates of national population sizes to produce yearly estimates of the European population size, allowing the computation of population growth rates at the European level for each species, with missing data accounted for by interpolation. Finally, species were attributed to broad habitat categories based on expert knowledge, and estimates of population size changes were averaged across species by the geometric mean to produce estimates of trend per habitat in Europe. For several other groups, e.g. butterflies, but also raptors, large mammals, bats, beetles, a number of schemes suitable for similar integrative analyses exist (EuMon database), the integration of which would considerably improve our understanding of biodiversity conservation needs.

Combining estimates of the effect of explanatory variables

The idea behind meta-analysis is that results of independent studies are treated as input units for the analysis of a general pattern (Gurevitch et al. 2001). Such an approach allows combining information coming from various monitoring schemes regardless of the differences in their sampling designs, objects monitored, data characteristics, and to some extent even statistical methods applied. If statistical analyses applied on each separate dataset included the same effect (the same independent variable), then the average effect can be computed to infer the average pattern across all datasets (table 3-2). Meta-analysis methods use the effect-size concept to integrate estimates of effects across analyses (e.g., Hedges and Olkin 1985; Cooper and Hedges 1994; Osenberg et al. 1999; Gurevitch et al. 2001). The effect size is a standardized estimate of the magnitude of the effect of an explanatory variable. A common metric of effect size z is the estimate of the slope for the explanatory variable, divided by the standard error of the slope estimate (see Osenberg et al. 1999 for other metrics). Effect size is computed independently for each monitoring. The mean effect size is then computed by summing effect size estimates from all monitoring schemes and dividing this sum by the square-root of the number of degrees of freedom (i.e., number of monitoring schemes – 1). If the supposed cause of change has an effect, the mean effect size will depart from 0. Whatever the magnitude of the true effect in each monitoring scheme, the expectation of the test statistic will be negative if there is a general negative effect or positive if there is a general positive effect. The statistical power of the resulting meta-analysis will depend on the magnitude and precision of the effects in the various monitoring, but power should be reasonable in the case of small to moderate effects in all monitoring schemes. A meta-analysis has a good probability of detecting the effect of the cause of change over all observations, which is not the case for separate tests on each single dataset. Another important advantage of meta-analysis is the possibility to identify different patterns of response across monitoring schemes with tests of homogeneity of effect size. This statistical framework allows estimation of average trends across monitoring schemes, as well as discriminating sets of regions with contrasted trends.

When only qualitative information is available for the tested effect or cause of change (cf significant positive, non-significant, significant negative; e.g., Parmesan and Yohe 2003), non-parametric tests can be used to identify whether the proposed cause of change has, on average, a significant effect over all monitoring schemes (Cooper and Hedges 1994). As for any analytical method, meta-analysis cannot compensate for all defaults of the data. For instance, they will not compensate for biases in data availability (cf sampling or publication biases, non-independence of data-points; e.g., Møller and Jennions 2001; Côté et al. 2005). As for the design of monitoring schemes, the design of meta-analyses has to be planned carefully to secure accurate contributions to biodiversity assessment.

Given all these methodological possibilities, and their suitability for monitoring integration, it is surprising that meta-analysis methods remained so rarely used for biodiversity assessment from monitoring data (Sutherland et al. 2004; Balmford et al. 2005a). Two explanatory variables would be particularly good candidates for meta-analysis: the effects of time, and of given causes of change. Nearly all monitoring schemes aim at testing for temporal trends in the measured biodiversity component. The effect size for time would be the very first candidate for the application of meta-analyses in the context of biodiversity assessment. Two temporal effects can be analysed: the unconstrained effect of years, or the linear effect of years, i.e. the linear trend throughout the time series (figure 3-2). Estimates of the slopes for the linear effect of time can be combined among analyses to obtain the averaged, global population growth rate, and to test for a global temporal trend. A good example of meta-analysis of the effect of time is the assessment of the world-wide trend in coral reef coverage (see Côté et al. 2005). Note that in the case of the analysis of linear effect of time, an analysis of time effect estimates, weighted for estimate precisions, would be similar to a meta-analysis of effect size estimates (table 3-2).

The second important application of meta-analysis is the analysis of causes of environmental change across monitoring datasets (Côté et al. 2005). Classical components of global change (table 3-1) are documented by several tens of monitoring schemes in the same and/or complementary taxonomic groups. For instance, coordinators of 27 bird monitoring schemes, 28 mammal schemes and 16 butterfly schemes considered that they could assess the effect of fragmentation with their monitoring data. Hence, there is a large potential for coordinated analysis of independent datasets and meta-analysis of size effects for widespread causes of change. Another good candidate for meta-analysis of monitoring data is the study of climate change. The effect of climate warming is often tested for with the effect of yearly temperatures. Since many different monitoring schemes use this same explanatory variable in their analysis of time series, estimates of the effect size for the yearly temperature can be combined across monitoring schemes. Combining all these estimates into a single meta-analysis provides a robust, general test for the response to yearly temperature, as an indicator of climate warming, across all datasets (Menzel et al. 2006). Other examples of explanatory variables used in meta-analysis of monitoring data are human-induced or natural disturbances (e.g., Pons et al. 2003; Côté et al. 2005).

3.4.3 Compensating for differences in biodiversity coverage and monitoring designs: the use of weights

When combining information from different monitoring schemes, the issue of differences in biodiversity coverage and monitoring designs among schemes arises (Balmford et al. 2005a; Buckland et al. 2005). Are all species, countries or estimates equally indicative of biodiversity state or change? Should some have higher contributions to the global biodiversity index than others? The monitoring goals (should) answer these questions. Once priorities are set, a common practice to implement these choices is to apply weights to the data or estimates prior to statistical testing or averaging. Hereafter, we present some standard weights used when combining biodiversity monitoring data. Weights have two functions: weights that formally adjust for differences in precision, and weights that are used to compensate for biased measures of the parameter of interest (e.g., over-/under-sampling) or to intentionally bias the contribution of different data to an indicator (e.g., differences in contribution among species, taxa, habitats). This second type of weights is a pragmatic response to an important need, but they have no methodological background. Standard methods to simultaneously use these two types of weights (precision and bias) in a single analysis remain to be proposed.

Different precisions of estimates

If estimates have different precisions (i.e., standard errors, SE), the weight to be used should be the inverse of the squared standard error for each estimate (i.e., $1/(SE)^2$; e.g., Julliard et al. 2004b). In this way, when testing for a temporal trend with estimates from different monitoring schemes, differences in precision of trend estimates per scheme are accounted for. A moderate but precisely estimated decline will contribute more to the global estimate and to the test of a temporal trend than a very steep but largely imprecise decline. If standard error estimates are not available, surrogates of precision, such as the squared number of monitored sites, or the monitored area per scheme (Côté et al. 2005), may be used as weights. Note that the size effect statistic *z* used in meta-analysis already accounts for estimate precision.

Different geographical contributions

If population sizes differ across monitored geographical regions to be combined, a suitable weight would be the proportion of the total population size held per region. For instance, for the European Bird Indicators (Gregory et al. 2005), weights are the percentage of the total European population size held per country per species.

Different ranges of inference

For assessing states and trends for a species or a taxonomic group, it is important that all inhabited habitats and/or biogeographic regions are accounted for. This is typically achieved during the planning phase by selecting monitoring sites that provide an unbiased coverage of habitat composition. However, if no sampling design is used, it is likely that habitats will not be equally represented. To obtain an unbiased, average trend across all regions, weights need to be applied to the data so that each habitat is represented according to its actual surface area. For example, when producing national trends for butterfly population sizes in the Netherlands (van Swaay et al. 2002), indices of population size per monitored site were post-stratified according to habitat availability at the national scale. Such a procedure was necessary because butterflies and transects were not equally distributed over the country and habitats.

Post-stratification should also be used when a biodiversity component is known to vary through space (which is likely to be true in most cases). Data from regions with contrasted trends need to be appropriately weighted so that the overall estimate is an unbiased combination of spatial variations in the trend (e.g. in Olsen et al. 1999; Houlahan et al. 2001).

Different species/taxonomic groups

If different species or different taxonomic groups are to be combined, several weighting rationales can be considered. First, *no* weighting is used when biological knowledge of the relationship among species and taxa is insufficient (Buckland et al. 2005). In practice, the same weight is given to all species and taxonomic groups (e.g., Living Planet Index, Loh et al. 2005). Second, weights can be used to give priority to a given biological property, e.g., degree of specialization, rarity, originality, ecosystem function, or trophic level (e.g., Butchart et al. 2005; Pavoine et al. 2005), or to policy goals or conservation priorities (Yoccoz et al. 2001; Nichols and Williams 2006; Miller et al. 2007; Schmeller et al. submitted b; Schmeller et al. submitted a). These ad hoc weights are to be defined according to monitoring goals. The analysis may also need to account for phylogenetic non-independence across monitored species. The same response to a given environmental change from phylogenetically distant species is more convincing about the general impact of the change than the same response exhibited by closely related species (Helmus et al. 2007). Thus, comparisons among distant species should be given a higher weight than comparisons between closely related species. Several data transformations exist so that among-species comparisons are independent of phylogenetic relationships (Harvey and Pagel 1991; Faith et al. 2004; Pavoine et al. 2005).

3.4.4 Cross-validation and robustness of conclusions

For a given dataset, at the end of the model selection (or effect selection in a stepwise regression), there will always be one final model, i.e. the model that supposedly makes the best compromise between good description of the data and parsimony (low number of parameters). The final statistical model, or the dataset, however, may be of poor generality. To evaluate the robustness of the conclusions, i.e., the external validity of the statistical analysis, a method is to use cross-validation. Part of the data is used for identifying the best statistical model, and the remaining part of the data is used to challenge this best model. This process is repeated several times. Cross-correlation coefficients quantify the departure between model predictions and observed data (Hastie et al. 2001).

When integrating data from different monitoring schemes, several datasets are at hand. The external validity of the model could be evaluated by computing cross-correlations across the different datasets. For instance, Breeding Bird Survey data from one set of countries could be used to parameterize the statistical model. Then, data from the remaining countries could be used for challenging the final statistical model by cross-correlation. This approach is particularly useful for assessing the robustness of spatial interpolations of biodiversity measures. If cross-correlation coefficients are high, the selected statistical model has a high predictive power, and it can also be concluded that the same major effects apply in the different sub-datasets. In other words, biodiversity states or trends are similar across schemes. At the opposite end, if cross-correlation coefficients are low, it means that important causes of biodiversity variation (i.e., effects) are still missing in the final statistical model.

3.5 Recommendations for future monitoring integration

From our overview and understanding of the monitoring practices, we suggest four priorities for future integration of ongoing biodiversity monitoring.

The experience of bird and butterfly monitoring (Gregory et al. 2005; European Environment Agency, 2007; van Swaay et al. submitted – this volume) should be used to develop similar bottom-up, international, federative monitoring programmes that produce indicators for other taxonomic groups. The number of existing schemes (EuMon database) suggests that most vertebrates groups would be suitable, as well as several macro-invertebrates (e.g., beetles, Odonata, and Orthoptera), and plants as a whole (with a possible group focussing on orchids).

The next integration step would be the production of indicators combining information from different taxonomic groups, e.g. for trophic chains per ecosystems. Several monitoring schemes already monitor different taxonomic groups simultaneously (figure 3-1). Land-use and fragmentation are the first causes of biodiversity change that could be assessed with such multi-taxa indicators (table 3-1). Much research is still needed in this area for the definition of scientifically sound and user-friendly indicators for terrestrial ecosystems.

Intellectual property and differences in sampling designs should no longer be a barrier to data exchange. Better than nothing is to exchange meta-data, i.e. estimates derived per scheme with standard statistical procedures.

Statistical tools (cf. meta-analysis methods, interpolation models, models mixing different data sources, cross-validation) should be further developed and fully enjoyed by biostatisticians implementing the integration of data from monitoring. Policy makers would benefit from more robust conclusions, at more appropriate spatial and temporal scales.

3.6 Conclusion

Monitoring data in Europe are scattered and heterogeneous (EuMon database), but contain a massive amount of information on biodiversity changes and drivers of these changes. This information would be much more valuable for biodiversity assessment if it were more easily accessible, e.g., if assembled in meta-databases. Such meta-information should encourage researchers to develop biodiversity monitoring integration across schemes, and policy makers to support and rely more on output from integrated monitoring.

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4 A review and a framework for the integration of biodiversity monitoring at the habitat level

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Summery

The monitoring of biodiversity at the level of habitats is becoming widespread in Europe and elsewhere as countries establish national habitat monitoring systems and various organisations initiate regional and local schemes. Parallel to this growth, it is increasingly important to address biodiversity changes on large spatial (e.g. continental) and temporal (e.g. decade-long) scales, which requires the integration of currently ongoing monitoring schemes. Here we review habitat monitoring and develop a framework for integrating data or activities across habitat monitoring schemes. We first identify three basic properties of monitoring activities: spatial aspect (explicitly spatial vs. non-spatial), documentation of spatial variation (field mapping vs. remote sensing) and coverage of habitats (all habitats or specific habitats in an area), and six classes of monitoring schemes based on these properties. Then we explore tasks essential for integrating schemes both within and across the major classes. Finally, we evaluate the need and potential for integration of currently existing schemes by drawing on data collected on European habitat monitoring in the EuMon project. Our results suggest a dire need for integration if we are to measure biodiversity changes across large spatial and temporal scales regarding the 2010 target and beyond. We also make recommendations for an integrated pan-European habitat monitoring scheme. Such a scheme should be based on remote sensing to record changes in land cover and habitat types over large scales, with complementary field mapping using unified methodology to provide ground truthing and to monitor small-scale changes, at least in habitat types of conservation importance.

4.1 Introduction

Many countries have pledged to reduce the accelerated rate of the loss of biodiversity by 2010 (Convention on Biological Diversity, http://www.biodiv.org). European countries went further by committing themselves to halt the loss of biodiversity in Europe by 2010. In order to judge whether these ambitious goals are met, detailed information on different components of biodiversity are necessary. Such information needs to be collected by properly designed monitoring systems (Pereira & Cooper 2006). Recently, much work has been focused on describing the desirable properties of monitoring systems or the indicators proposed to measure large-scale trends in biodiversity (Gregory et al. 2003; Weber et al. 2004; Balmford et al. 2005; Gregory et al. 2005; Mace et al. 2005; Heer et al. 2005).

To measure the biodiversity changes in light of the ambitious targets, the integration of monitoring systems over large, supra-national spatial scales and possibly over long time scales is essential (Balmford et al. 2003). Integrated monitoring systems can come about in two ways. First, a monitoring system can be designed 'from scratch' based on general recommendations of current 'best practices' (top-down approach). Alternatively, currently existing monitoring systems can be integrated to form a large-scale system to monitor changes in biodiversity (bottom-up approach, Henry et al., 2008).

An example for a newly designed, large-scale monitoring system for species is the Pan-European Common Bird Monitoring scheme (PECBM, Gregory et al. 2005). The PECBM scheme attempts to quantify trends in populations of European breeding birds, and to develop an index of biodiversity to measure progress to the 2010 goals. Currently, no such explicit monitoring of habitats exists at the European level. The CORINE Biotopes project (Devillers et al. 1991) was the first effort at describing habitat types according to a unified typology. The CORINE Land Cover project (http://reports.eea.europa.eu/COR0-landcover/en) contained some components of habitat monitoring as it collected data on land cover types using remote sensing and its own typology. The CORINE Land Cover project conducted the first pan-European mapping of land cover in 1990, and the revised survey was repeated in 2000, providing information on the changes in major land cover types over a decade (European Environmental Agency 2006). Finally, the BioHab project developed and tested field-based methods for Europe-wide monitoring of habitats using a typology based on plant life forms and an emphasis on landscape-scale data collection (Bunce et al. 2005). Despite these promising developments, most monitoring programmes in Europe remain small in scope both spatially and temporally (Balmford et al. 2003; Lengyel et al., 2008).

The aim of this article is to develop a common framework for the integration of monitoring systems focusing on habitats. Integration can progress in two ways. The first approach combines information obtained by separate monitoring schemes in the form of raw, processed, interpreted, or analysed data, whereas the second approach combines and integrates monitoring methodologies to unify resources, from smaller spatial units into a large-scale monitoring system. Here, our primary question is how to integrate different monitoring schemes but we will also briefly address data integration. We first identify which properties of monitoring schemes are important from the perspectives of integration and then develop different avenues for the integration of different types of habitat monitoring schemes. Next we demonstrate the most important integration avenues by highlighting their advantages and potential problems. Finally, we evaluate the chances of such integration by drawing conclusions from data collected on existing habitat monitoring schemes in Europe by the EuMon project and make recommendations for pan-European habitat monitoring. We do not attempt to provide a worked-out example of integrating habitat monitoring, which is likely to differ case by case and, therefore, would be beyond the scope of this paper. Rather, we present general guidelines and draw on examples pointing towards integration. In this paper, we focus specifically on habitat monitoring. Integration and benefits related to species monitoring as well as options to combine different measures and estimates obtained from monitoring are discussed in Henry et al. (2008).

4.2 Definitions and types of habitat monitoring

4.2.1 Habitat, habitat type and habitat monitoring: definitions

We use the term 'habitat' in a wide sense when generally referring to the physical, chemical and biological components of a defined geographical area (cf. Blondel 1995). We use the term 'habitat type' for specific kinds of habitats that have been described as separate from other such entities in habitat classification systems (e.g. Annex I of the 'Habitats' Directive: Council of the European Communities 1992; CORINE: Devillers et al. 1991, EUNIS: http://eunis.eea.europa.eu).

Habitats are characterised by a typology relating the various habitats to a specific classification and a given habitat patch to a specific type, where each type has a set of defining characteristics. Using an analogy borrowed from vegetation science (Barkman 1979), the texture of habitats concerns the number of patches for each habitat type and the size distribution of habitat patches. The structure of habitats is given by the spatial structure or layout of the patches and the geographical relationships between the patches. Most often, the typology, texture and structure of habitats is described on habitat maps, showing the patches of different types. The spatial structure may also be described by a variety of spatial statistics or indices (e.g. fragmentation indices, landscape metrics). Finally, each habitat patch can be characterised by their internal properties, i.e., various aspects of habitat quality (Firbank et al. 2003).

The overall objective of habitat monitoring is to describe and to understand the state and changes in habitat-relevant aspects of biodiversity. Typology is obtained by identifying different habitat types based on similarities in physiognomy, abiotic conditions, plant community composition, plant dominance, succession stage and, occasionally, animal community composition (Dierschke 1994). Texture is assessed when the number of patches and the relative or absolute surface area covered by each habitat type are quantified. Finally, spatial aspects can be described by mapping that identifies the location and spatial relationships of each habitat patch. Monitoring data are either collected in the field (field mapping) or derived from remotely sensed imagery (satellite sensors and/or aerial photography) with the appropriate ground-truthing. The state of habitats is typically evaluated using data on physico-chemical properties, species composition and/or relative abundances and on the distribution of habitat types (absolute and relative surface area, fragmentation etc.). Habitat monitoring often involves collecting additional information on internal properties of habitat patches such as habitat quality (e.g. naturalness, degradation, pollution etc.), environmental parameters (soil type, weather) and potential drivers and pressures (land use, human influence).

4.2.2 Main types of habitat monitoring

The EuMon survey of habitat monitoring schemes in Europe (Lengyel et al., 2008) suggests that there are several properties of habitat monitoring that deserve special attention from the perspectives of integration. Three properties are of central importance: use of a spatial aspect, approach for documenting spatial variation and extent of habitat coverage. These basic differences need to be considered in developing and applying a common framework for the integration of monitoring schemes.

Spatial aspect

The objectives of habitat monitoring fundamentally vary by whether schemes collect qualitative or quantitative information on the habitats of interest. In this article, schemes that collect qualitative information (defined here as typology and texture) on the habitats will be referred to as 'non-spatial schemes'. For example, many schemes operate by collecting data on community composition and structure at stationary sampling units (quadrats/transects etc.), but without explicitly addressing spatial variation. In contrast, schemes that also collect quantitative information (structure), termed as 'spatial schemes' monitor changes in the range/area/shape of the habitat types of interest. Spatial schemes often use georeferenced databases (Geographical Information System, GIS), consisting of either points, lines, raster cells or polygons as features and various attribute information associated with each feature, to create and analyse electronic habitat maps (Longley et al. 1995).

Documenting spatial variation: field mapping and remote sensing

Another basic difference among habitat monitoring schemes is whether they use field mapping or remote sensing as their primary source to document spatial variation in the monitored habitats. Field mapping is based on field surveys and measurements, such as phytocoenological/phytosociological surveys or vegetation mapping. In a phytosociological approach, a detailed description of the plant community is compiled in replicated relevés (Braun-Blanquet 1964). Relevés are often arranged in permanent plots or transects, thought necessary to detect fine-scale changes in habitats (Bakker et al. 1996) e.g. in species composition or relative abundances of species. Field mapping, however, rarely provides complete spatial coverage of the focal area and sampling needs to be invoked in most schemes. Sampling is conducted by restricting actual surveys to certain locations and by making inferences from these locations to non-surveyed areas, either by a priori randomisation or a posteriori spatial modelling or extrapolation.

Remote sensing-based monitoring is based on imagery of the area of interest obtained through aerial or satellite sensors and interpreted by various methods (Turner et al. 2003). A broad range of remote sensing data sources are used for habitat monitoring, e.g. panchromatic or colour photography, multispectral imaging, laser scanning, radar imaging (Lillesand et al. 2003). Satellite-based remote sensing usually covers areas ranging from regional to supra-national, although with the advent of high-resolution scanners (e.g. Quickbird), it has been also applied locally (e.g. Rocchini et al. 2005). A multitude of remote sensing-based habitat mapping and monitoring approaches have been developed, ranging from photo-interpretation by humans to automated quantitative algorithms by computers, often with several methods in combination (e.g. Nagendra et al. 2004; Asner et al. 2005).

Field mapping and remote sensing provide higher accuracy and precision at opposite ends of the continuum of geographical scales. Field mapping is effective at documenting spatial variation at local and regional scales, whereas remote sensing can provide accurate and precise quantitative information at regional, national and supra-national spatial scales. The large-scale mapping of habitats based on remote sensing is faster and cheaper per unit area and requires less ecological expertise than based on field mapping (Lillesand et al. 2003).

Extent of habitat coverage of monitoring

The third distinction in habitat monitoring is whether schemes monitor one or a few specific habitat types or monitor all habitat types within the area of interest. Schemes monitoring all habitat types within an area hereafter will be termed as holistic schemes, whereas those monitoring one habitat type will be referred to as targeted schemes. These categories are analogous to the 'full-coverage' and 'partial coverage' approaches of landscape monitoring (Dramstad et al. 2002, Groom 2004). Although the differences between holistic vs. targeted approaches affect the scope and the multivariate nature of monitoring, the basic issues of sampling design and statistical analysis are essentially similar.

4.3 INTEGRATION OF DATA AND MONITORING SCHEMES

4.3.1 Integration of data or processed information

The basic question regarding data integration is: How can the different properties of habitats be characterised for separate data sets and still allow integration of the data sets or of the inferences made from them? When data are integrated, it is first important to clarify whether raw data or some processed information are integrated. Raw data for integration may involve non-processed scenes from remote sensing, whereas processed information can range from data already classified to habitat types in the form of a map to estimates of changes in certain properties of the habitats. We further explore the approaches to integrating estimates derived from monitoring in another paper (Henry et al., 2008).

If the basis for integration is raw data, then the origin of those data (targeted/holistic scheme) and their spatial extent and scale or resolution will be important. A special problem with integrating raw data from different spatial scales is the different degree of representativity because data from small geographical scales (e.g. regions within countries) may not be representative at larger scales (e.g. Europe) (Bunce et al. 2006). With maps or estimates as input, commonalities in habitat typology, spatial extent and scale/resolution will be relevant. How the integration should be handled on the basis of this input will depend on the more direct objective of integration, as certain types of input/data will be well suitable for some objectives but not for others. One example for ongoing data integration is the compilation of information provided by member states as part of the first EU-wide baseline assessment of Natura 2000 habitats and species, conducted by the European Topic Centre on Biological Diversity (http://biodiversity.eionet.europa.eu). Specific issues for data integration involve:

- relating habitat information to the same typology (habitat classification), either by having the same basic typology and habitat types, or by transforming the habitat units into a common typology, possibly at a more aggregated level of classification,
- evaluating whether comparable spatial scales are used to identify and measure habitat types or whether they can be converted to comparable scales,
- ensuring that characterisations of spatial structure address the same spatial phenomena and that quantifications of these phenomena can be made comparable, and
- ensuring that aspects of habitat quality address the same quality phenomena and that quantifications of these phenomena can be made comparable.

These criteria are not equally relevant in integration. Experience from previous attempts at integration suggest that common habitat typology is probably the most challenging of the above-mentioned criteria and will also be among the most important criteria in other types of integration explored below. Two ways to resolve this problem are to use broader habitat categories (see e.g. Firbank et al. 2003 describing the integration of the Countryside Surveys of Great Britain and Northern Ireland) or to apply interpretation algorithms (see e.g. Jansen 2004 for thematic harmonisation for landscape-monitoring in Nordic countries) to achieve compatibility.

4.3.2 Avenues for integration of monitoring schemes

Habitat monitoring schemes can be grouped into six classes based on the three aspects detailed above (table 4-1). Integration of two or more schemes can be envisioned both between schemes belonging to the same class (within-class integration, e.g. holistic remote sensing-based with holistic remote sensing-based) and belonging to different classes (between-class integration, e.g. holistic remote sensing-based with targeted field mapping-based) (table 4-2). Based on this conceptualisation, ten logical avenues for integration exist for spatial schemes (four within-class and six between-class integration avenues, table 4-2).

Table 4-1 Six classes of habitat monitoring based on three main properties of schemes and the number of schemes in each class according to the EuMon database of European habitat monitoring schemes (as of August 31, 2007).

Spatial aspect	Documenting of spatial variation	Extent of habitat coverage	Number of schemes
Spatial (n = 63)	Field mapping	Holistic	16
		Targeted	26
	Remote sensing	Holistic	16
		Targeted	5
Non-spatial (n = 83)	-	Holistic	66
	-	Targeted	17
		Total:	146

Table 4-2 Illustration of possible integration combinations for the four classes of schemes with spatial aspect. Arrows indicate between-class integration (n = 6 combinations); within-class integration, i.e., integration of schemes of similar class, is not shown (n = 4).

Class	**Holistic**	**Targeted**
Remote-sensing		
Field mapping		

4.3.3 Integration of monitoring schemes within class

Integration of remote sensing-based holistic schemes

Remote sensing-based monitoring schemes belonging to the holistic approach are highly appropriate for integration (Nagendra 2001). These schemes have a common ‘currency’ in the form of georeferenced, remotely sensed spatial information from entire spatial entities. Thus, holistic remote sensing-based schemes have the best chances to provide a foundation for a pan-European integrated monitoring scheme. The compatibility of such information systems depends on their technical properties, including:

- comparable sampling intensity in space (all parts equally measured in the focal area) and time (seasonally and/or according to phenological changes of the habitat types),
- comparable sensors and spectral resolution, comparable conditions for input imagery (acquisition date/frequency, cloud cover etc.),
- comparable mapping scale or spatial precision: the minimum mapping unit (for vector maps) or the spatial resolution (for raster maps) should be similar,
- comparable mapping accuracy, consisting of thematic accuracy (percent of correctly classified habitats) and spatial accuracy (habitat delineation errors),
- compatible map projections and geo-referencing,
- comparable sensitivity to changes,
- compatibility of habitat nomenclatures (habitat classification systems), compatible level of habitat nomenclature hierarchy.

If all of these criteria are fulfilled, the input data sources can be combined for analysis. A review of methods for integrating data from remote sensing projects is beyond the scope of this review. For concrete methods and technical advice, the readers are encouraged to consult reviews (e.g. Hinton 1997; Nagendra 2001; Duro et al. 2007) or textbooks

(Lillesand et al. 2003) on the subject. The result of integration can be an increase in the extent and/or the resolution of the area where all habitats are monitored. By combining data, a common map can be prepared and common parameter estimates can be calculated. If these criteria are not fulfilled, calibration and interpretation of differences is essential prior to a direct combination of remotely sensed data. If such calibration is not possible, separate maps and separate parameter estimates can be used. For example, easily interpretable or comparable indices can be estimated for not comparable data sources (e.g. normalized difference vegetation index, NDVI, Pettorelli et al. 2005).

Integration of remote sensing-based, targeted schemes

In this type of integration, schemes covering disjunct areas are combined in order to increase the monitored area of focal habitat types. In addition to the criteria presented in the previous section, all schemes should cover the same or at least comparable sets of habitats. Issues related to temporal non-compatibility (e.g. different spectral properties due to weather) are likely to be higher in this type of integration than for holistic RS-based schemes. If the types of habitats monitored differ between schemes, the next higher level of the common habitat classification system can be used to accommodate information from both schemes. Such integration can be relevant for monitoring of disjunct but similar habitat types, for example, the alpine habitats in Europe.

Data integration here can also be of two kinds: (1) integration of remotely sensed input data (when all the above criteria apply), and (2) using the input data and/or map results of the scheme with higher spatial and thematic resolution to support and validate results in the less detailed scheme, which potentially covers a larger area. A special case is when several monitoring schemes each monitoring a different target habitat type within some common area are integrated. In such cases, the aim of integration can be to broaden the spectrum of habitats monitored. A reasonable set of such schemes may be collated to form a holistic scheme for the common area.

Integration of field mapping-based, holistic schemes

Field mapping-based, holistic schemes are frequent, but usually cover widely different geographical areas. The scale of habitat or vegetation mapping often varies depending on the scope of the schemes. Even national-level habitat or vegetation mapping schemes vary a lot e.g. by the size of the country involved. Even if spatial coverage is close to 100%, there can be several issues deserving attention, such as:

- the proportion of the focal area actually sampled and refinement of the sampling strategy (e.g. site selection randomly or systematically),
- the use of permanent plots/quadrates/transects in subsequent sampling occasions,
- constancy of sampling intensity in space and time, across habitats and habitat types,
- method of obtaining information for non-sampled areas (extrapolation, other sources etc.),

- comparability of precision (ability to detect trends or changes in the habitats) and error rates (e.g. measurement of observer biases),
- quantification of errors in mapping and data processing e.g. by inherent variability of the attribute vs. accuracy/precision of measurement,
- habitat classification system used.

If these differences can be resolved, the result of integration will be that the area monitored will increase. Such integration has a high potential of becoming a key component of a pan-European habitat monitoring scheme (Bunce et al. 2006). The disadvantage may be that the results may not be generalizable or applicable over non-sampled areas or large spatial scales (a problem inherent in field mapping).

Integration of field mapping-based, targeted schemes

Schemes in this class are concerned with one or a few habitat types, monitored in several distinct sites with similar or different mapping methods. One example for such schemes is the monitoring of bogs or fens. Integration of such schemes is rather straightforward if the schemes to be integrated monitor the same (group of) habitat types. In such cases, only the differences in field mapping methodology is important from the perspectives of integration. If different habitat types are monitored within some common area, integration can be used to broaden the spectrum of the habitats monitored. Theoretically, a reasonable set of such schemes might sum up to form a holistic scheme for the common area.

4.3.4 Integration across classes

Across-class integration is more challenging than within-class integration, but can provide valuable insight that within-class integrations cannot provide. The end product in such integrations will be a more valuable source of knowledge than the sum of the component parts (Groom 2004). For example, a holistic-targeted integrated scheme will have added values that the constituents do not have individually, such as the ability to monitor large areas with the concomitant ability to monitor small changes of some selected target habitat types. After such integration, the result is increased quality and/or quantity of information in at least some parts of the monitored area. Integration of information from several different sources is also likely to be the most important input in policy support (Wyatt et al 2003).

Integration of remote sensing-based and field mapping-based schemes of the holistic approach

This type of integration may be advantageous when both are complementary in habitat attributes covered or when the combination is more cost and time-efficient. It makes particular sense to use the high precision field survey data to support interpretation of remotely sensed data or to validate the remote sensing-based mapping and monitoring results (ground-truthing). Field mapping also can provide additional information on environmental variables (e.g. soil quality) not accessible to remote sensing. Alternatively, remote sensing may be used to complement or even adjust spatial information obtained by field mapping, by providing information on spatial patterns of the habitats (e.g. fragmentation, connectivity) that are difficult to detect in field mapping. Criteria for such integration are as follow:

- comparable areas and spatial scales used in each scheme,
- compatibility of habitat nomenclatures (habitat classification schemes), compatible depth of habitat nomenclature hierarchy, exhaustiveness of field mapping,
- comparable thematic precision,
- comparable monitoring/mapping accuracy,
- comparable sensitivity to changes (ability to detect trends),
- common data formats, compatible data management systems (the latter is not necessary if a scheme is only used to validate the results of the other scheme).

Integration of holistic and targeted schemes within remote sensing-based and within field mapping-based methods

The main advantage of this type of integration is that a targeted scheme can complement the holistic scheme in the common area, where the latter does not adequately cover or entirely leaves out certain habitats. A set of targeted schemes that is complete enough over a common area can be combined into a holistic scheme. If the set of targeted schemes is incomplete for a common area, it can still be used to provide additional spatial and thematic detail in some important parts of the common area. For example, monitoring of the NATURA 2000 network, which, by definition, is a targeted scheme, can contribute relevant and detailed focus to a generalized holistic scheme in a region/country or even at the pan-European level. Furthermore, the data from the high-precision field survey can be used in ground-truthing the remote sensing-based mapping results (see above).

4.4 Chances for integration in light of current practices

We evaluated the integration potential of currently existing habitat monitoring schemes in Europe by drawing data from the EuMon project, which attempted to collect descriptive data on such projects between 2005 and 2006 (more on the project: Henle et al., in press; Lengyel et al., 2008; http://eumon.ckff.si). The EuMon project database contains information in the form of an online questionnaire filled out by monitoring coordinators (n = 150 schemes at the time of writing, 31 August, 2007). Here we present the most important results that bear on the potential for integration from the analysis of the database.

To evaluate the proportion of spatial vs. non-spatial schemes, we used information given by coordinators regarding the method used in their schemes to document the spatial variation in habitats. Choices offered were 'field mapping' and 'remote sensing'. Schemes for which none of these choices were marked were, therefore, likely to be non-spatial schemes. Interestingly, no method was given for 83 of 149 schemes, which were thus were considered as non-spatial schemes. In all, the proportion of spatial and non-spatial schemes (44.3% vs. 55.7%, respectively), was not significantly different from an equal distribution (χ^2_1 = 1.940, p = 0.164).

Among schemes that had one of the choices marked (spatial schemes, n = 66), field mapping was more frequent as it was used in 44 schemes, whereas remote sensing was used in only 22 schemes (χ^2_1 = 7.333, p = 0.007). Almost a third (29.5%) of all schemes (n = 149) used field mapping and only 14.8% of the schemes used remote sensing.

We evaluated the frequency of the holistic vs. the targeted approach using information given by coordinators whether they monitor all habitats or not in their focal areas. Two-thirds (67.1%) of the habitat monitoring schemes (n = 146 schemes with any data) monitored all habitats within their specified area (holistic approach or 'wall-to-wall' monitoring), whereas the rest (32.9%) monitored specific habitat types within a region (targeted approach). This difference in proportions was significantly different from random (χ^2_1 = 17.123, p < 0.001).

Interestingly, field mapping-based schemes tended to be targeted in approach, whereas schemes using remote sensing or not documenting spatial variation at all were more often holistic in approach (table 4-1) (χ^2_2 = 22.598, p < 0.001). It is especially noteworthy that 79.5% of non-spatial schemes (n = 83) were marked as holistic in approach, i.e., monitored all habitat types within a focal area.

The average number of habitat types monitored by the schemes was 5.0 and varied considerably (SD = 11.85). The reason for the high variation was that a large proportion (43.7%) of the schemes (n = 119) monitored only one habitat type, whereas some schemes monitored up to 37-38 habitat types. One national-level scheme monitored 116 habitat types.

To study the frequency of habitat types monitored, we grouped the habitat types marked by the coordinators as focal habitat types in their monitoring schemes in the 10 major habitat groups (level 1) used in the EUNIS system. The most frequent targets of habitat monitoring were forests (27.5% of major habitat types marked by coordinators, total n = 156), followed by marine habitats (16.0%), grasslands (13.5%) and coastal habitat types (12.8%). Other habitat types were subjects of monitoring in less than 9% of the cases (figure 4-1).

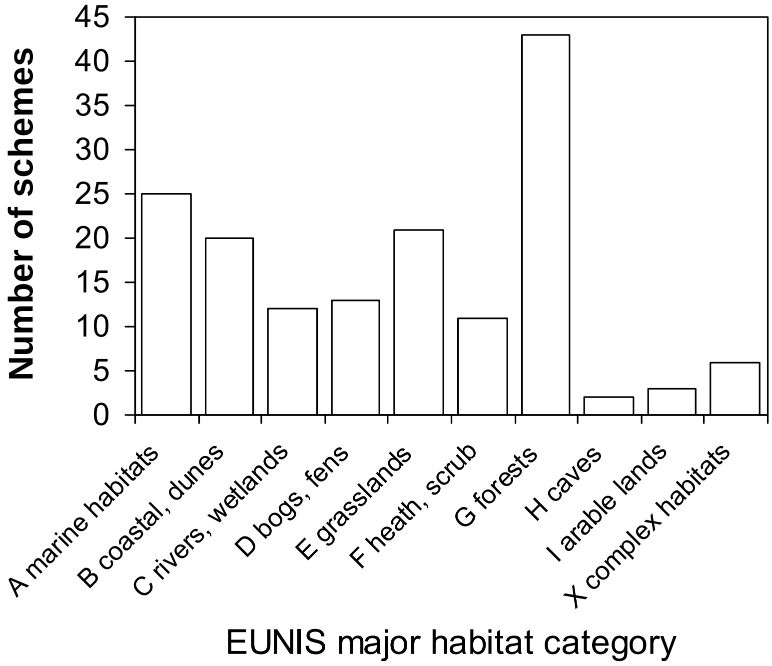

Figure 4-1. Number of monitoring schemes targeting major EUNIS habitat categories according to the EuMon database (based on total n = 156 habitat types marked in n = 142 schemes; more than one habitat type could be marked for each scheme).

There were two other methodological details important from the perspective of integration. First, many schemes are conducted at very small spatial scales. Almost half (49%) of the schemes (n = 41 schemes with information on scale) were operating at scales of 1:300 or lower, another 20 operated within the range 1:2000 and 1:50000 and only one marked 1:100000 as operating scale. Second, only five (or 3.4%) of the schemes (n = 148) use the more recent EUNIS system for the classification of habitats and most use the CORINE system (39.2%) or other, presumably national systems (31.1%). In more than one-quarter (26.4%) of the schemes, no habitat classification system was given by coordinators.

4.5 Discussion

Our survey shows that there are a large number of habitat monitoring schemes in Europe (a full account of current practices is given in Lengyel et al., 2008). However, the survey also suggests that habitat monitoring activities are fragmented. Monitoring projects are scattered, data collection methods are not standardised and, thus, processed information is not easily accessible for decision-makers and stakeholders. Most reported schemes have been started only recently (Lengyel et al., 2008) and many monitoring schemes are small in geographical scope, operate on small spatial scales, and cover typically only one or a few habitat types. Many of the reported schemes lack an explicit spatial aspect and appear to monitor only qualitative habitat properties. Remote sensing is rare, and the more traditional field mapping is only slightly more frequent. In our data, forests were the most frequent habitat type monitored, followed by marine, grassland and coastal habitats, whereas bogs and fens, heaths and scrubs and especially agricultural areas are monitored less often. Furthermore, the monitoring of inland surface waters is probably under-reported in our data.

These patterns clearly suggest that there is a real need for integration of monitoring efforts if we are to quantify pan-European trends in habitat-level biodiversity by 2010. Our findings thus provide substantial support for previous calls based on less extensive data to substantially expand the geographical and temporal coverage of monitoring activities (Balmford et al. 2003; Vieno & Toivonen 2005) if we are to measure changes in biodiversity across large scales.

The recognition of the need for integration is far from new; this paper is first only in that it presents data on existing practices to underline this need. A discussion of integrating remote-sensing and field-mapping was presented previously by Barr et al. (1993) and various other aspects of integration were addressed by Parr et al. (2002). Calls from the scientific community have struck a chord in policy-making as well: several strategic papers (Anonymous 2004a) and action plan proposals (Anonymous 2004b) by European bodies refer to this need. For instance, the specific objective of key target 8 of the Kyiv resolution on biodiversity (http://www.unep.ch/roe/programme_biodiv_kiev.htm), a reinforcement of the Gothenburg declaration is that: "by 2008, a coherent European programme on biodiversity monitoring and reporting, facilitated by the European Biodiversity Monitoring and Indicator Framework, will be operational in the pan-European region". To achieve this target, a joint activity entitled "Streamlining European Biodiversity Indicators" (SEBI 2010) has been launched by the European Environment Agency, the European Centre for Nature Conservation and the UNEP World Conservation Monitoring Centre with the aim to review and test specific indicators in line with the EU list of 16 headline biodiversity indicators. With recognizing the need for a coordinated effort of harmonising national and international monitoring systems, SEBI currently works (among others) on developing indicators for large-scale changes in biodiversity from currently existing data sources and ongoing activities (http://biodiversity-chm.eea.europa.eu/information/indicator/F1090245995).

Similar lines of thought are currently being explored in the integration of landscape monitoring programmes. Monitoring of land cover changes has a long tradition in Europe, starting with the SISPARES programme in Spain in 1956 and the Countryside Survey of the UK in 1973 (Brandt et al. 2002, Firbank et al. 2003, Bunce et al. 2006). In several of these programmes, the integration of different approaches of surveillance and monitoring has already been achieved. For example, the SISPARES programme, the most comprehensive of the national landscape-monitoring schemes, is based on a combination of aerial photography-based interpretation of land cover and field mapping surveys in 206 samples of 4x4 km squares (Bunce et al. 2006). The Danish Small Biotope programme, originally started in 1981 as a targeted, field-based programme, has been supplemented with satellite-based, remotely-sensed information on land cover since 1990 (Brandt et al. 2002). The monitoring of agricultural landscapes in Norway is based on aerial photography and interpreted spatial information serves as a foundation both for field mapping (beyond ground-truthing) and for applying various landscape metrics to monitor changes (Dramstad et al. 2002). Despite these examples, we know of only one fully worked example when two previously different habitat monitoring schemes were integrated. The only worked example is the integration of the British Countryside Survey with the Northern Ireland Countryside Survey in 2000. This integration was made feasible to a large part because Broad Habitat categories were set up to accommodate the different habitat typologies used previously in the two schemes (Firbank et al. 2003).

The framework proposed here identifies most of the difficulties associated with integration of data or activities of habitat monitoring. The integration of small, scattered monitoring schemes requires some generalisations or finding the common denominator of schemes. Such uniformisation often results in loss of valuable information (Groom 2004, Bloch-Petersen et al. 2006). Alternatively, advance measures can be taken to increase the potential for integration in each of the schemes planned for integration. Our survey shows that the introduction or enhancement of addressing the spatial aspect in monitoring can be one such major improvement. Furthermore, field mapping and recording methods developed and recommended for uniform use over Europe, such as the BioHab methodology (Bunce et al. 2005; Bloch-Petersen et al. 2006), can be recommended for use.

Although recommendations for best practices in monitoring have been given before (e.g. MacDonald & Smart 1993; Yoccoz et al. 2001; Balmford et al. 2005; Mace et al. 2005; Tucker et al. 2005), this study provides new insights into areas for improvements. Obviously, an ideal solution for a pan-European habitat monitoring system would incorporate the best of both the remote sensing approaches (large spatial scales, relatively straightforward integration etc.) and the field mapping-based approaches (small scales, high sensitivity, detailed etc.). An integrated pan-European monitoring system should be based on remote sensing as the main data collection method due to its applicability over large spatial scales. Ideally, such a system would be holistic and cover the whole of Europe. The CORINE Land Cover project can be a good starting point or common reference for such a remote sensing basis, as shown by calculations of changes in habitat types between 1990 and 2000 (European Environmental Agency 2006). The original spatial resolution of the CORINE system (100 by 100 m raster cells), however, may not be appropriate to record small-scale changes, therefore, higher-resolution data from other sources (e.g. LANDSAT data, 25 m2 pixel size; IKONOS, Quickbird: 0.7 m2) could be used. As an intermediate level that helps both in the interpretation of satellite imagery and in the designation of sites for field mapping, aerial photography has proved useful in several landscape monitoring schemes (Bunce et al. 2006). For classification of habitat types, the use of the more recent and more detailed EUNIS system can be recommended. The EUNIS habitat classification is comprehensive and hierarchical, i.e., the levels can be adjusted to accommodate different resolutions. For example, Bock et al. (2005) provide an example for using object-oriented classification of data from remotely-sensed images across different spatial scales. Although the EUNIS system was not primarily designed for integrated monitoring purposes (e.g. "dry" means largely different habitat types in northern and southern Europe), many national habitat classification systems use categories transferable to the EUNIS system.

Beyond remote sensing of habitat cover over large areas, field mapping should also be a component part either as the primary tool for ground-truthing and/or as a means of obtaining more detailed information on habitat types. A scientifically sound system of field mapping as well as taxon-specific studies on the link between habitat-level changes and species diversity (reviews in Nagendra 2001; Duro et al. 2007) is necessary to enable the monitoring of smaller-scale processes. The landscape-scale approach recommended and field mapping methodology developed by the BioHab project could provide information detailed enough to detect changes in habitat types in a uniform manner over larger spatial scales (e.g. Bloch-Petersen et al. 2005). Such in-depth field mapping should focus on habitat types of conservation importance, e.g. priority habitat types of the Habitats Directive or habitats for which a country has high national responsibility (e.g. Dimopoulos et al. 2006). Currently, insufficient attention is paid to such priority habitats (Lengyel et al., 2008). Ideally, field mapping or measurements use an appropriate, internationally agreed sampling design and record important background information (environmental parameters, socioeconomic factors, drivers, pressures, threats).

Time until 2010 is probably too short to devise and implement a fully functional integrated European monitoring scheme. Therefore, integration of data from currently existing schemes is fast becoming a high priority (Henry et al., 2008). On a longer time scale, however, integration of monitoring schemes appears inevitable. There is no doubt that such integration will bring about a major advance in biodiversity monitoring (Brandt et al. 2002). Independently from pan-European efforts, integrated monitoring schemes can be formed at regional, national and supranational levels. We believe that the common logic and framework developed in this article, together with the EuMon database (available at http://eumon.ckff.si) can contribute to the success of such future efforts.

4.6 References

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