8 Improving the rigor and usefulness of scenarios and models through ongoing evaluation and refinement

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Key findings

There are significant gaps in data availability for biodiversity and ecosystem services. The spatial, temporal and taxonomic coverage and resolution of monitoring of biodiversity change is heterogeneous. There are also gaps in information on social demand for ecosystem services and on high-resolution data of ecosystem properties relevant for ecosystem services. Much progress has been made in mobilizing data on biodiversity and ecosystem services, but significant barriers remain to data sharing. More efforts are required to provide easier access to well-documented data and models. (8.1.2 and 8.1.3)

There are already many models available to assess the impacts of drivers on biodiversity change and ecosystem services; however important gaps remain. These include gaps on (i) linkages between different aspects of biodiversity and ecosystem services; (ii) ecological processes at temporal and spatial scales relevant to IPBES assessments; (iii) early warning systems to anticipate ecological breakpoints and regime shifts; and (iv) coupling of, and feedbacks between, social and ecological components of ecosystems. (8.2.1)

Scenarios can bridge data and models to decision-making. Both short-term scenarios (10 years) examining alternative policy options and long-term scenarios examining plausible futures are useful in assessing the impacts of drivers on biodiversity and ecosystem services. Exploratory scenarios foster creative thinking and exchange of viewpoints between different stakeholders, but do not always provide clear actions that decision makers should implement to reach desirable outcomes. Normative scenarios are more likely to provide clear policy pathways but have been criticized for being value laden. (8.3)

Scenarios can be improved in an iterative cycle that includes engaging stakeholders, linking models to policy options, managing uncertainty, communicating the results and bringing scenarios outcomes to policy making. Assessments should identify stakeholders relevant at the scale of the problem, including scientists, decision-makers and people with local and indigenous knowledge, and engage them early in the modelling and scenario analysis process. (8.3.1) Models and scenarios can improve the transparency of policy-making, by rendering the assumptions explicit and facilitating the comparison of multiple options. (8.3.2.3)

Key recommendations

We recommend that IPBES engages with existing processes on increasing data collection and data sharing. A key task is to identify common metrics for monitoring, modelling and reporting of biodiversity and ecosystem services and develop cost-effective approaches that are geared towards the needs of users at multiple scales (8.1.1, 8.1.2). We recommend that the Task Force on Knowledge, Information and Data (Deliverable 1d) adopts existing data and model documentation standards and expand those as needed, makes use of existing central repositories, liaises with relevant organizations to develop new ones, and participates in on-going efforts to assure proper credit to data and model providers.

We recommend that the IPBES expert group on Scenarios (3c) develops guidelines and standards for verification and validation of models, and for assessing and managing uncertainty in scenario analysis and modelling. These standards need to be regularly updated based on scientific developments (8.2.2). We further recommend that the IPBES Regional and Global Assessments use verified and validated models and adopt appropriate methods for incorporating and communicating uncertainties. Depending on context and topical relevance, we suggest using multiple models, of differing complexities and types, to address the trade-off between model complexity, precision, and generality.

We recommend that the Thematic, Regional and Global Assessments use both short-term (10 years) and long-term scenarios (50 years) to assess the future of biodiversity change and ecosystem services and their implications for human well-being. For the regional assessments, existing long-term scenarios from other initiatives can be adopted and downscaled to the regions. We suggest that for global assessment a new set of long-term exploratory scenarios is developed around key issues specific to biodiversity and ecosystem services identified by the relevant stakeholder community. Short-term scenarios comparing policy options using models and qualitative information can be developed both in regional and global assessments.

We recommend that the Task Force on Capacity Building (Deliverable 1ab) supports the use of models and scenarios in assessments at different scales. This includes activities that give planners and policy makers a better understanding of models and scenarios, including limitations and uncertainties, and activities to assist modellers in engaging further with policy and planning processes. Further research is needed on developing robust methods to elicit local and indigenous knowledge for the development of models and scenarios (8.3.2, 8.3.3, 8.3.4). The Task Force on Indigenous and Local Knowledge (Deliverable 1c) may liaise with the Task Force on Capacity Building in order to foster this research.

We recommend that IPBES, through expert group on Scenarios and Modelling (3c) and Task Force on Policy Support (4d), ensure that the review of available policy support tools and methodologies for scenario analysis and modelling continues to reflect best available science. Because of on-going research and rapid progress on many aspects of scenario analysis and modelling of biodiversity and ecosystem services, there is a need to continually update the review of available policy support tools and methodologies for scenario analysis

and modelling of biodiversity and ecosystem services. We also recommend that IPBES, through Task Force on Knowledge, Information and Data (Deliverable 1d) engages in an ongoing prioritization of research needs, in order to encourage basic research that advances scenario analysis and modelling in contexts and scales that are relevant to IPBES with the ultimate objective of decision support. (8.2.1.3)

Previous chapters have demonstrated the variety of approaches to scenario analysis and modelling that can be used to inform decisions and evaluate policy options. Scenario analysis and modelling can address issues ranging from the local scale, such as assessing municipal land planning options consequences for ecosystem services and biodiversity, to the global scale, such as the impacts of alternative pathways of population economic growth on biodiversity and ecosystem services. Although IPBES assessments range only from regional to global scales, this chapter also provides relevant information for local scales. Previous chapters have identified the problems or challenges, and reviewed existing solutions on the use of models and scenarios in assessments of biodiversity and ecosystem services. The goal of this chapter is to chart the way forward for additional research and development that is required to take the use of models and scenarios to a whole new level of rigour and utility.

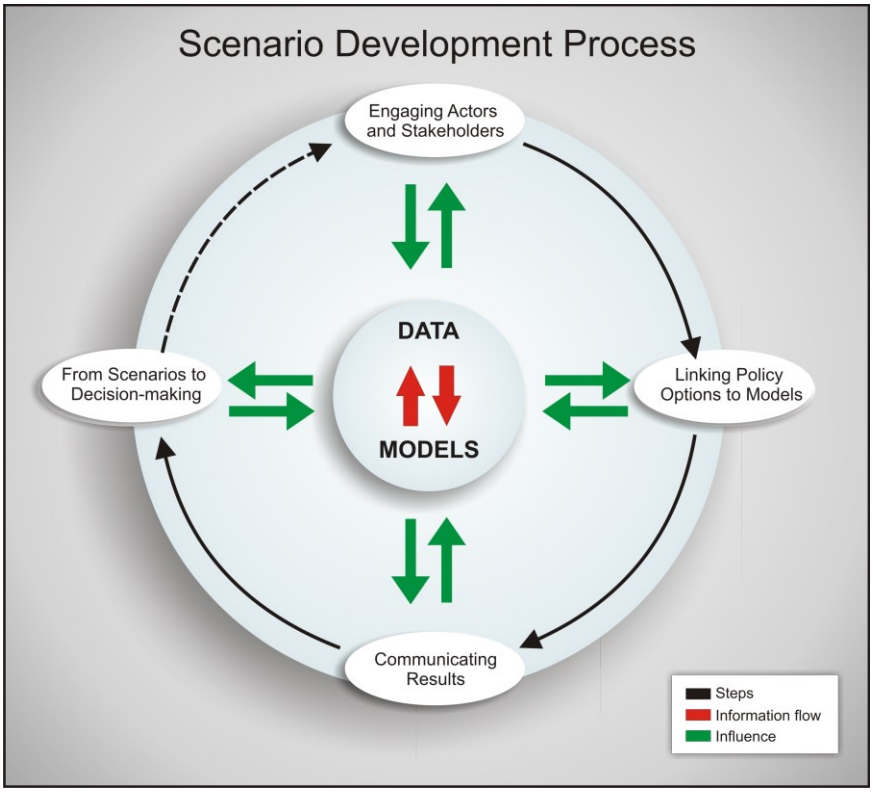


Figure 8.1.: Scenario development and analysis process involving steps (in white ovals) such as engaging actors and stakeholders, with each step interacting with the data and models (green arrows) and with information flow between models and data (red arrows).

The chapter is organised into three main sections. We first discuss approaches to improving the data used to calibrate and validate biodiversity and ecosystem services models, emphasizing linkages to various existing initiatives for biodiversity monitoring at national, regional and global

scales. We then discuss basic and applied science research needed to improve models of biodiversity and ecosystem services, both by promoting development of new models and by encouraging and facilitating functional linkages among existing models and modelling platforms. Finally we discuss directions for improving scenarios relevance for policy-making. We consider four key steps of the iterative cycle of scenario development which are supported in models and data (Figure 8.1): (1) engaging actors and stakeholders; (2) linking policy options to models and scenarios; (3) communicating results; (4) using the scenario results and analysis for decision-making.

8.1. Improving data

8.1.1. Identification of common metrics

Biodiversity has multiple dimensions, including genetic diversity, species diversity, functional diversity and ecosystem diversity, and can be measured in a multitude of ways (Noss, 1990; Pereira et al. 2012). Similarly, there are many ecosystem services and each ecosystem service can be quantified using different approaches, including biophysical, cultural and economic measurements (Daily et al. 2009), although important challenges remains in quantifying socio-cultural values of ecosystem services (Martín-López et al. 2012). Researchers often face the challenge of accessing adequate data for calibration and validation of models as different initiatives monitor different biodiversity metrics. There is a lack of harmonization and integration of monitoring methods and datasets across observation communities (e.g. different research communities, governmental agencies, non-governmental organizations) and across countries (Pereira et al. 2013).

A key challenge is the identification of common metrics that could be used by the modelling and observation communities. A common set of variables and parameters[1] for observation and modelling of biodiversity and ecosystem services would allow easier integration of data from different sources, and would facilitates calibration, validation of models and inter-model comparison. Currently two approaches, at different levels of data abstraction, show promise (Table 8.1): the Essential Biodiversity Variables being promoted by the Group on Earth Observations Biodiversity Observation Network (Pereira et al. 2013), and the biodiversity indicators adopted by the Convention on Biological Diversity to assess progress towards 2010 target and the 2020 Aichi targets (Butchart et al. 2010; CBD 2010; Tittensor et al. 2014; CBD 2014).

In recent years, scientific communities of different physical and biological phenomena have started to identify essential variables that are critical for monitoring and modelling. The first such effort was the identification of the Climate Essential Variables by the Global Climate Observing System. Similarly, the Group on Earth Observations Biodiversity Observation Network (GEO BON) has developed a process to identify Essential Biodiversity Variables (EBV). The idea behind this concept is to identify, using a systems approach, the key variables that we need to monitor in order to

[1]Parameters are input values for a model, whereas variables are calculated, predicted or projected by the model. Therefore a variable in a model can be a parameter in a different model.

understand biodiversity change. The Essential Biodiversity Variables are an intermediate layer of abstraction between the raw data, from in situ and remote sensing observations, and the derived high-level indicators used to communicate the state and trends of biodiversity. These variables can be used in models of the whole biosphere or parts of it as the main system variables. They can then be used to compare model simulations with data. For example, the population abundance variable is defined as a three dimensional matrix of population abundances per species, per location, per time. A gridded dataset of population abundances for a group of species requires the integration of population estimates from different methods and observers, and the interpolation of gap areas with models. Models for interpolation can use as inputs climate variables and other environmental variables, including variables that can be remotely sensed. A gridded dataset could be used to calibrate and validate species distribution models or models of the impacts of drivers on biodiversity such as GLOBIO (Alkemade et al. 2009).

Table 8.1: Examples of common metrics for observation, reporting, and modelling for each class of Essential Biodiversity Variables (EBV). For some EBV there are related indicators that are being used to assess progress towards the CBD 2020 targets. EBV development focuses on how to monitor, while indicator development focuses on how to report. Models have been developed that project the evolution of an EBV metric or an Aichi indicator under different scenarios. References: [1]Pereira et al. 2013; [2]Tittensor et al. 2014; [3]Brook et al. 2000; [4]Christensen and Walters 2004; [5]Harfoot et al. 2014; [6]Guisan and Thuiller 2005; [7]Newbold et al. 2015; [8]Alkemade et al. 2009; [9]Wise et al. 2008; [10]Daily et al. 2009.

EBV Classes[1]	**EBV Metrics[1]**	**Aichi Indicators[2]**	**Biodiversity and ES Models**
Genetic composition	Number of animals of each livestock breed and farmed area under each crop	Genetic diversity of domesticated animals	-
Species populations	Population abundance of selected species or functional groups	Living Planet Index	Population Viability Analysis[3]; Ecosim with Ecopath[4]; Madingley[5]
	Species occupancy of selected species	Red List Index	Species Distribution Models[6]
Species traits	Leaf senescence for selected species	-	-
Community composition	Species richness of a community	-	PREDICTS[7]; GLOBIO-IMAGE[8]
Ecosystem structure	Proportion of cover of each habitat type	Natural habitat extent	GLOBIO-IMAGE[8]; MiniCAM[9]
Ecosystem function	Nutrient Retention	-	InVEST[10];

A list of 23 EBV candidates has been identified, organized into six major classes (Pereira et al. 2013): genetic composition, species populations, species traits, community composition, ecosystem structure, and ecosystem function. An effort is on-going to identify appropriate monitoring schemes, propose data standards and develop global or regional datasets for each variable. A

similar process to identify essential variables for Ecosystem Services is under discussion in GEO BON. It is important for IPBES to engage in these processes in order to guarantee that the final set of variables and associated monitoring methods and data standards serves the user needs of the assessments. We envision a particular role for the Task Force on Data and Knowledge on this process.

An alternative approach is to develop biodiversity indicators and indices, focusing on aggregated metrics at higher levels of data abstraction (van Strien et al. 2012). Over the last decade several biodiversity indicators have been used to report on biodiversity change at the national and global level (Butchart et al. 2010; Tittensor et al. 2014). The Biodiversity Indicators Partnership (http://www.bipindicators.net) has played an important role in this process. Indicators condense a wealth of data into a few values. For instance the Living Planet Index condenses information on population counts of several thousands of vertebrate populations into a single global value per year, which inform on global vertebrate population reductions relative to a base year. The Red List Index condenses assessments of species status of >20 000 species into a single value for a time point which can be compared with values from previous time points to assess if there has been an acceleration or deceleration of biodiversity loss. Similarly, indicators have been developed to assess the supply, demand and benefits of ecosystem services. For instance for wood production, supply can be assessed by standing biomass, demand by wood production and benefit by the market value of good products (Tallis et al. 2012). The Mapping and Assessment of Ecosystem Services initiative has identified a wide range of indicators for provisioning, regulating and cultural services tailored to each major category of ecosystem in Europe: forests, agro-ecosystems, freshwater and marine (MAES 2014). A set of indicators has also been proposed for Experimental Ecosystem Accounting in the UN System of Environmental Economic Accounting (European Commission et al, 2013)

It is possible to model both the more disaggregated data of each EBV or the more aggregated data of biodiversity indicators and indices. For instance, many models are available to develop scenarios for population abundances or occupancy across ranges of individual species or groups of species (Table 8.1). But it is also possible to model the dynamics of aggregated indices such as mean species abundance or species richness at local to global scales (Nicholson et al. 2012; Visconti et al. in press). A particular challenge of using species richness or species abundance indices instead of the disaggregated data is the choice of the appropriate aggregated metric. There is a wide range of metrics being used to describe change in community composition, such as species richness, phylogenetic diversity, Simpson's diversity index, geometric mean abundance, arithmetic mean abundance, just to name a few (van Strien et al 2012; Buckland et al. 2005; Lyashevska and Farnsworth 2012). It is also possible to just focus on a subset of species such as rare or endemic species versus abundant species or threatened versus non-threatened species. The EBV framework is particularly flexibility in this regard, as calculating an index of an EBV can result in another EBV: e.g. using occupancy data for a set of species in a community to calculate species richness (Table 8.1). The appropriate level of aggregation for observations and modelling may depend on the spatial scale of the assessment but also on the questions being addressed.

The EBV framework focuses on variables describing the state of biodiversity. But, understanding the upstream drivers and pressures and the downstream impacts and management responses are crucial to assess biodiversity and ecosystem services. The Driver-Pressure-State-Impact-Responses

(DPSIR) indicator framework allows to consistently assess the dynamics of social-ecological systems (Sparks et al. 2011), and it is used to develop scenarios for biodiversity and ecosystem services (Pereira et al. 2010). The Aichi targets of the Convention on Biological Diversity for the year 2020 are organized into five strategic goals that closely follow the DPSIR framework and can be assessed by using indicators for each component (Tittensor et al. 2014). The DPSIR framework also makes clear that the variables used as outputs of some models can be the inputs of other models. A socio-economic model may project changes in the harvest pressure of fish stocks, leading to changes in the abundance different species. In turn this change in the ecosystem state may lead to changes in the fish provisioning from the ecosystem. Therefore the choice of metrics has to take into account the interoperability of different models. Finally, metrics or indicators should be chosen so that they are able to detect biodiversity trends reflecting changes in pressures or policy and management (Nicholson et al. 2012). Indicators at regional scales or for specific groups of taxa (e.g. taxa vulnerable to a specific driver) may be more likely to do so than generic global indicators.

We suggest that regional and global IPBES assessments should report results of models and scenarios using a set of common metrics. For example, models assessing the impacts on species populations could report geometric or arithmetic mean abundance changes or aggregated changes in extinction risk, although particular examples of individual species changes in population or occupancy may also be relevant in some instances. Models assessing the impacts on ecosystem services should use a group of indicators for a standard classification of ecosystem services such as the Common International Classification of Ecosystem Services or CICES (MAES 2014). The set of indicators to adopt should be further explored by a Task Force on Modelling and Scenarios, which would also update regularly the guidelines presented in the current report. Engaging the scientific community in discussing common metrics is very important. But the choice of indicators should consider not only modelling requirements but also the needs of end users. Therefore the participation of both scientists and users is important to ensure a balanced choice of indicators.

8.1.2. Increasing data availability for model calibration and validation

Despite recent increases in the variety and amount of biodiversity-related data, there are significant gaps with respect to quantity and quality (Brooks and Kennedy 2004), and significant biases in the availability of biodiversity and ecosystem services data (Box 8.1). IPBES will need to use a range of approaches to fill these gaps including: improving monitoring programs, mobilizing data, and modelling.

In many cases, existing databases can be improved with concerted and coordinated efforts to increase spatial (regional) coverage, spatial resolution (e.g., smaller grid size or denser sampling points), temporal resolution (regular and frequent observations), and temporal coverage (long-term, sustainable monitoring for the future; historical reconstruction for the past). For example, the PREDICTS database collected data from existing literature of 78 countries representing over 28,000 species (Hudson et al 2014), including invertebrates, vertebrates, and plants in terrestrial ecoregions around the world. However, the areas covered by the database are not balanced, but representative of the data availability (see also Figure 8.2), which reflects a necessity for improvement on the existing data. Monitoring programs should have a data strategy that leads to making optimal choices about what and how to measure (Section 8.1.1); and be cost-efficient,

sustainable through space and time, and effective, avoiding duplication (Box 8.2). For instance, in terms of taxonomic coverage, adding large numbers of species in poorly studied taxonomic groups may not be cost effective. However, a taxonomically sampled approach, as used in the *Sampled Red List Index* (Baillie et al. 2008), can provide taxonomic coverage in a cost-effective way. It would also be beneficial if monitoring programs would expand their efforts in observations of ecosystem services of most importance to human well-being, and if the data were more accessible (see section 8.1.3).

New and promising approaches to obtaining data, and building and curating datasets include citizen science and crowd-sourcing (Silvertown 2009, Wiggins and Crowston 2011), and new technological tools such as automated data collectors and sensor networks that are embedded in the environment (Collins, et al. 2006; Porter et al. 2009; Rundel et al. 2009; Benson et al. 2010). The new field of ecoinformatics envisions building ecological data sets in the context of a "data life cycle" that encompasses all facets of data generation to knowledge creation, including planning, collection and organization of data, quality assurance and quality control, metadata creation, preservation, discovery, integration, and analysis and visualization (Michener and Jones 2012). Ecoinformatics tools that support and assist various steps of the data life cycle include data management planning tools (e.g., http://dmp.cdlib.org/); metadata standards and tools; relational data bases which allow specification of constraints on the types of data that can be entered (i.e., data typing) assuring data integrity; scientific workflow systems, such as Kepler, Taverna, VisTrails and Pegasus (see section 8.2.1.2); and cloud-computing resources.

In some cases, gaps in datasets can be filled using quantitative approaches such as statistical and modelling methods. One approach is imputation, which is a particularly useful approach when analysing large data sets of demographic traits (e.g., Di Marco et al. 2012). Imputation is a valuable alternative to removing missing observations in databases, because it produces low errors while retaining statistical relationships among the variables (Penone et al. 2014). Another option for filling data gaps is making inferences based on allometric relationships between biological variables such as body size, metabolic rates, population density, generation time and maximum population growth rate (e.g., Damuth 1987). Although allometric relationships have been used, e.g., in size-structured food web models (Blanchard et al. 2009) and in models of energy budgets (Simoy et al. 2013), large uncertainties in the predicted values limits their usefulness in estimating parameters of predictive dynamic models at the species level. However, they may be useful if limited to groups of functionally related species (such as herbivorous mammals). A third approach involves sampling demographic parameters of population models using a "generic life history modelling" approach. Although linking ecological niche and population models gives more realistic predictions of the effects of changing environmental conditions on species (Keith et al. 2008), widespread application of such coupled niche-population models is hampered by the availability of species-specific demographic data. The generic life history modelling (Pearson et al. 2014; Stanton et al. 2014) gets around this problem by using ensembles of population models designed to encompass the full set of life history parameters characteristic of a particular group of species. This approach avoids the need to obtain species-specific demographic parameters, which are rarely known, and enables generalising results beyond the well-studied species, at the cost of not being able to make species-specific predictions of population dynamic s (Pearson et al. 2014).

Remote sensing and in situ data are vital for modelling and monitoring environmental parameters relevant for biodiversity conservation (Buchanan et al. 2009, Koghan et al. 2010). Satellite remote sensing is useful to collect data across different spatial and temporal scales. However, there is a lack of capabilities of users to deal with these data; access to training and education in using satellite-based observations are essential in the future (Turner et al. 2015). Some initiatives for increasing access to remote sensing data globally are the international Group on Earth Observations (GEO) and ESA Climate Change Initiative (Bontemps et al.,2011). There is a need to improve the existing statistical and modelling approaches discussed above, as well as developing new quantitative approaches for filling data gaps (Figure 8.2).

Box 8.1. Biases and gaps on data availability of biodiversity and ecosystem services

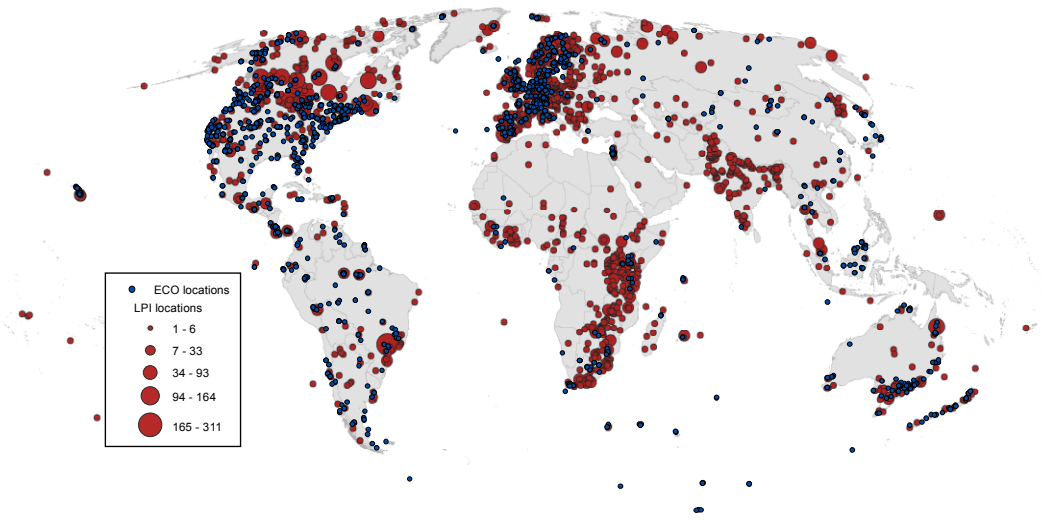
- **Regional biases in coverage:** Historically, ecologists studied non-urban but relatively human-accessible areas, in wealthy countries, resulting in a very uneven global distribution of study areas (Figure 8.2). The **disparity among terrestrial, freshwater and marine realms is also noteworthy (Loh et al 2005).**
- **Taxonomic biases in coverage:** Ecological studies have focused disproportionately on conspicuous species. Vertebrates, particularly birds and mammals, are much more often the focus of ecological studies than invertebrates and plants (Pereira et al 2012). One of the most popular indices to measure global biodiversity change, the Living Planet Index (LPI), is based on vertebrate populations only (Loh et al. 2005).
- **Spatial and temporal resolution:** Most ecological studies either have high spatial resolution and small spatial extent, focusing in detail on small areas, or have low spatial resolution and focus on larger regions. For some scenario analysis and modelling approaches, high resolution data with global coverage are needed (Pereira et al. 2010). Such data exist for some biodiversity-related variables (such as forest cover data available at http://earthenginepartners.appspot.com/), but this is rare.
- **Thematic gaps:** There is a lack of regional and global consensus on what to monitor. Some EBV classes such as species traits and genetic composition have received less attention from monitoring programs than others such as species populations. Regulating and cultural ecosystem services and particularly their benefits for populations are not monitored or only partially monitored in most places (Tallis et al. 2012).

BOX 8.2: Data strategy (modified from Scholes et al. 2012 and other sources)

1. Relevant to the goals and data needs of scenario analysis and modelling at global, regional and local scales.
2. Global in coverage, but with sufficient resolution and accuracy at subnational scales to be useful to the main decision-makers at this scale.
3. Statistically sound basis for repeated measurements of biodiversity.
4. Following best practices for metadata specification.
5. Provisions for coordinating and managing data that are collected by disparate institutions and individuals for different purposes.
6. Sufficiently comprehensive in terms of taxonomic coverage.

7. Quality controlled, with well-defined standards for formats, codes, measurement units and metadata; traceability of the observation (incl. place and time of origin, the techniques used to make the observation, and methods used to modify the data); enforced data-typing
8. Cost efficient. Avoiding duplicative work in recording or analyzing the same observations for the same time period.
9. Sustained. Ensuring data continuity and comparability over time, including provisions for long-term storage and data management.
10. Adaptive. Responsive to new technical possibilities, emerging societal needs and changing system state.
11. Interoperable. Data available to (and discoverable by) other parts of the system, with tools to enable analyze data from different parts together. Requires metadata (see above) and harmonization of observations, analysis and data exchange standards and protocols.

Metrics and indicators of the quantity and quality of ecosystem services are essential to knowing if these services are being sustained or lost or how they need to be managed in order to sustain human welbeing and biodiversity (Layke 2012). While some ecosystem services (e.g., providing goods) can be directly quantified, most regulating, supporting and cultural services are less straightforward to quantify, so indicators or proxy data are required (Egoh et al., 2012). Development of robust indicators is an important step towards mapping ecosystem services and meeting biodiversity targets (Egoh et al., 2012). In recent years, ecosystem services modelling has improved with governmental demand for standardized practices to measure, value and map ecosystem services (Waage & Kester 2014). For instance, InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) combines data on the economy, human well-being, and the environment, in an integrated way for 16 services and models the impacts of alternative resource management choices (Daily et. al 2009). However, there is a need for demonstrating the role of biodiversity and ecosystem health in underpinning ecosystem services and for reinforcing the understanding of the relationships between ecological mechanisms and ecosystem services to create the realistic end products for managers (Wong et al. 2015). Approaches to include institutional and governance realities (e.g. regulations, policies) into ecosystem service values should be improved to satisfy the needs of scenario analysis and modelling at global, regional and local scales.



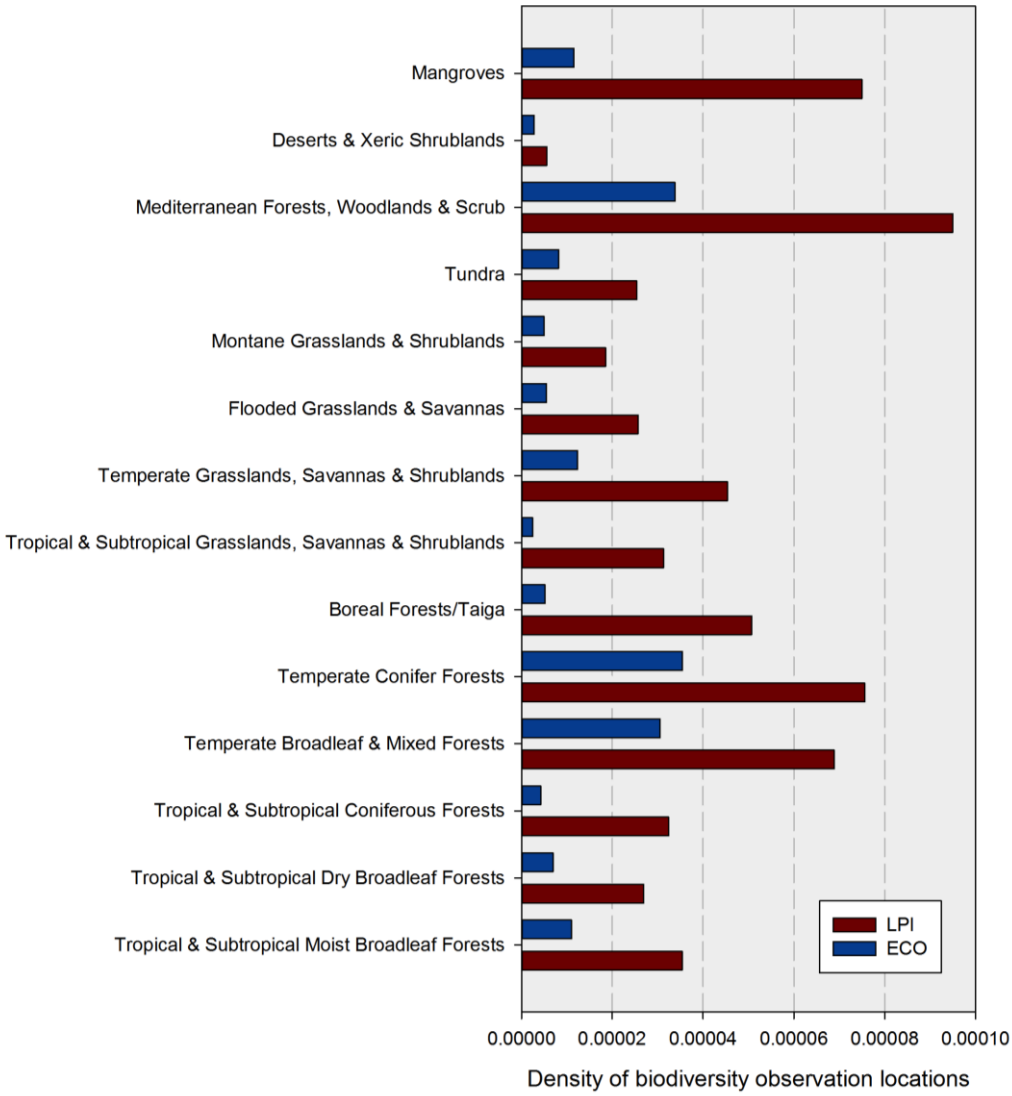


Figure 8.2: Regional biases in coverage of biodiversity studies and monitoring. (a) Map of the global distribution of ecological field sites (Martin et al. 2012) and populations in the Living Planet Index (Collen et al 2009). (B). Density per biome of ecological field sites and populations in the Living Planet Index.

8.1.3. Facilitating data access for model calibration and validation

Data availability is drastically increasing, especially for biodiversity information (Pimm *et al.* 2014); however major barriers remain associated with the limited usability of and accessibility to data.

8.1.3.1. Improving data sharing

There is currently a major movement to "open data", reflecting an increasing interest and demand for data being made publicly available (Molloy 2011; Reichman *et al.* 2011). The CBD Aichi Target 19 emphasizes that biodiversity information needs to be "widely shared and transferred, and applied." In coming years, data release is expected to be more often required by funding sources and by research journals, and it will become a common norm of conduct of scientific societies. Note that this is not just a response to increasing calls for transparency from stakeholders; archiving data in public domains can potentially yield multiple benefits to the scientific community and the data providers. The opening-up of data does not only help reduce the duplication of work needed for data collection but also facilitates scientific exploration (Ruegg *et al.* 2014) and helps to address conservation problems. Considering that combining past inventory data with present data can serve as a surrogate of long-term monitoring (e.g., estimating a temporal change in species distribution in response to climate change; Moritz et al. 2008), digital mobilization of existing data is crucial. Similarly, local and indigenous communities are sometimes the only repositories of historical data, and it is important to promote the uptake and publication of traditional knowledge.

Creating large datasets spanning several temporal, geographical and biological scales, which are essential for global assessments, require numerous inputs from a large number of contributors. Field data, which are the crucial part for the majority of models, need enormous effort to be collected. Therefore, data are undoubtedly precious and some people may feel reluctant to provide their data to public domains. Local communities may fear sharing their traditional knowledge because of concerns with knowledge misusage and the loss of their intellectual property.

For scientists, incentives for data sharing, including career rewards, are of importance to ensure further development of data archives (Borgman 2012; Costello *et al.* 2013). While potential benefits of open data have been extensively discussed in the literature, not enough emphasis has been placed on crediting and rewarding aspects of providing data. Advocates for opening up data tend to stand on the side of the "data user", and do not necessarily view the issue from the side of the "data collector". According to a survey, the most dominant answer from data collectors as a condition for the use of data is formal citation (Michener *et al.* 2012). However, given a strict, short page limit with a limited number of citations allowed in many journals, it is often difficult to "formally" cite all data sources, especially for papers that rely on spatially and temporally large multiple datasets. Data collectors may instead to prefer to openly publish only the metadata. However, conflicts exist as raw data are often required by other users. Archiving data as a metadata require users to resort to multiple, sometimes lengthy procedures to access raw data.

Given the "top-down pressure"(Molloy 2011) for open data, development of additional incentives and initiatives will be necessary for shortening the time for data to become available for models and scenarios. In this regard, inviting data collectors to be involved in data analysis may potentially help as data collectors have first-hand knowledge about the strengths and weaknesses of the data.

This co-development and collaboration between data collectors and users may benefit both, leading to "win-win solutions". This is one possible way to overcome the issue and would not provide an ultimate solution, because it may not be feasible to include all data collectors as co-authors or to be able to coordinate an analysis with potentially large numbers of people. In synthesis, data collectors should be more encouraged to publish their data on open repositories and acknowledged for their critical work.

8.1.3.2. Accessing and using data

Both biodiversity and ecosystem services data, which are increasingly available to public (e.g., Boxes 8.3 and 8.4), have been evaluated with different spatial/temporal coverage and resolution, and metrics themselves are very diverse. In using such data, there are several issues to be considered. An important issue is data standardization. Models and scenarios often require multiple data types, sourced from different databases. Combining data from multiple sources may be difficult; for example, biodiversity information such as taxonomic names are often stored in different ways or following different published taxonomies. Although a number of tools are available to unify data from different sources, such as uBio (http://www.ubio.org/), which can help match and integrate names of species from different sources, the lack of a common language in data management could be a large barrier that prevents information of biodiversity and ecosystem services from being widely usable by different users. Also, the licensing form of data also needs to be considered. For instance, many institutions make data available in open access for non-commercial use; however, data licensing policies for commercial use may have some restrictions or require a fee for usage (see for instance the Creative Commons multiple licensing modes). Some new frameworks that help retain currency and attribution back to the original data sources will be also important to strengthen the direct linkage between data collectors and users. Another issue that needs to be discussed is the operability of data is different between databases and between data types, largely limiting the direct application of existing data for model calibration and validation. Considering the increasing visibility of data, platforms that facilitate user access will play a crucial part in the coming years (Box 8.3). While biodiversity information such as those archived in the Global Biodiversity Information Facility (GBIF; http://www.gbif.org/), in the IUCN Red List of Threatened Species (http://www.iucnredlist.org), and in the Ocean Biogeographic Information System (http://www.iobis.org/) are widely recognized and relatively-well organized, data for ecosystem services tend to be collected individually and more diversely. This difficulty to coordinate development of repositories for large database for ecosystem services results from the lack of common and agreed language, definitions and framework on ecosystem services.

Generally, ecosystem services data are often produced by combining datasets sourced from multiple databases into a focal type of data (Tallis et al. 2012; MAES 2014). These datasets are diverse and can be physical, biological and social, such as satellite images, digital elevation models, LIDAR (Light Detection and Ranging) data, land/ocean use information, crowd-sourced data (e.g., for taxa distribution and phenology), meteorological data, human health statistics, cultural/religious information, and economic/financial statistics. Another reason why these diverse datasets are required is that, in the real-world decision-making, it is important to identify trade-offs and synergies between multiple services (e.g., Bateman *et al.* 2013; Brandt *et al.* 2014). Handling such different datasets needs multidisciplinary and interdisciplinary skills and knowledge, a task generally not easy for the majority of users. At the local scale, the shortage of human resources can

be as serious as data incompleteness. Another issue that needs to be addressed is cultural values, which are heterogeneously distributed across the globe. Localized information such as traditional knowledge, which would be tightly associated with cultural ecosystem services, have not been well archived.

Currently, some synthesized information, which potentially facilitate non-experts to use ecosystem services information, are available online. For example, the Ecosystem Service Valuation Database of the Economics of Ecosystems and Biodiversity (TEEB) (http://www.fsd.nl/esp/80763/5/0/50), gives the global overview of the estimates of monetary values of ecosystem services, potentially benefiting local stakeholders who are unfamiliar with environmental economics. Another example is the Global Forest Change (http://earthenginepartners.appspot.com/), which makes it possible for groups without a remote-sensing expertise to visualize and assess the changing status of forest coverage in a specific region of interest (Hansen *et al.* 2013). Although such different frameworks to increase availability of ecosystem services data are currently emerging, comprehensive ecosystem services database would ultimately require a global consortium to develop and manage.

In addition to open data, open tools are drastically increasing; however, it is crucial to assist different users to use diverse datasets. In this regard, it is desirable to expand opportunities for learning how to handle different types of data, including online-learning modules and webinars that can be accessible worldwide. Many organizations, universities and research institutes now provide various databases; in addition to the information regarding to what types of available data they have, they must also be encouraged to provide the knowledge on how to use these data. Online learning, web database and crowd-sourcing can certainly bridge people working at different regions/nations, having different backgrounds, and lacking expertise for using scenarios and models for policy-formation and decision-making. Because developing and managing interfaces that are user-friendly would require enormous efforts and costs, this issue will remain as a challenge that needs to be addressed.

BOX 8.3: Examples of existing biodiversity databases at the species level

A. Databases of occurrences, trends, and threats

- GBIF -- http://www.gbif.org
- IUCN Red List -- http://www.iucnredlist.org/
- Living Planet Index -- http://livingplanetindex.org/
- Global Population Dynamics Database -- http://www3.imperial.ac.uk/cpb/databases/gpdd
- North American Breeding Bird Survey -- https://www.pwrc.usgs.gov/bbs/
- PREDICTS -- http://www.predicts.org.uk/
- Global Invasive Species Database -- http://www.issg.org/database/welcome/
- WORMS World register of marine species (http://www.marinespecies.org)
- EOL Encyclopedia of Life Global access to knowledge about life on Earth (http://eol.org)
- AlgaeBASE: a list of the world's algae. (http://www.algaebase.org)

B. Databases of demography and life history characteristics

- TRY: Plant Trait Databases (https://www.try-db.org/)
- COMPADRE Plant Matrix Database & COMADRE Animal Matrix Database (http://www.compadre-db.org/)

- MAPS: Monitoring Avian Productivity and Survivorship (http://www.birdpop.org/nbii2006/NBIIHome.asp)
- BROT: plant trait database for Mediterranean Basin species (http://www.uv.es/jgpausas/brot.htm)
- AnAge: Database of Animal Ageing and Longevity (http://genomics.senescence.info/species/)
- PanTHERIA: life history, ecology, and geography of extant and recently extinct mammals (Jones et al. 2009 http://esapubs.org/archive/ecol/E090/184/)
- FishBase: a global information system on fishes (http://www.fishbase.org/home.htm)
- SeaLifeBase (http://www.sealifebase.org)
- EltonTraits (Wilman et al., 2014; http://www.esapubs.org/archive/ecol/E095/178/)
- The Primate Life History Database (Strier et al. 2010 Methods in Ecol. Evol. https://plhdb.org/)
- OBIS Ocean biogeographic information system (http://www.iobis.org)

BOX 8.4: **Examples of existing ecosystem services databases and biodiversity databases at the ecosystem level**

- BEDIC numerical information on biodiversity and ecosystems. (https://www.naturalsciences.be)
- Biodiversity information system for European biodiversity and habitat types (http://biodiversity.europa.eu)
- Ecosystem service indicators database (http://www.esindicators.org)
- ESP The Ecosystem services partnership (http://www.fsd.nl)
- EcoDB Ecosystem database (http://ecomdb.niaes.affrc.go.jp)
- NOAA Geophysical Data Center (http://www.ngdc.noaa.gov)
- MESP Marine Ecosystem Services Partnership: ecosystem service database (http://www.marineecosystemservices.org)
- United Nations Framework Convention on Climate Change Database on ecosystem-based approaches to adaptation (http://unfccc.int)
- EBM The Ecosystem-Based Management information about coastal and marine planning and management tools (http://www.ebmtools.org)
- FAO Fishstats, Sea Around Us project catch data (http://www.seaaroundus.org/faq.htm)
- Emissions Database for Global Atmospheric Research (EDGAR) (http://edgar.jrc.ec.europa.eu/
- FAOSTAT (http://www.faostat.fao.org)
- TREES Database (http://bioval.jrc.ec.europa.eu/)
- EFDAC Forest resources

Lastly, those who are involved in constructing and maintaining web interfaces and large-scale repositories have not been necessarily well acknowledged. While maintaining such interfaces and databases generally need people who are devoted to user support, appropriate accreditation is not necessarily given to them by other stakeholders. They are a critical part in scientific communities to support data accessibility and facilitate data users.

8.2. Improving models

8.2.1. Basic research to fill thematic gaps and build functional linkages

As previous chapters have demonstrated, there is a wide variety of approaches to scenario analysis and modelling that can now be used to inform assessment of status and trends, to assess future

risks, and to evaluate policy options. Despite recent advances in these approaches, there are significant gaps, both in types of models for analyzing and forecasting different ecological processes, and in linkages between different types of models. This section focuses on basic science needs, i.e., research directed towards further development of theoretical and conceptual underpinnings of ecological and social-ecological systems. Most research of this type is included in the basic science research carried out by academic scientists in various disciplines. This section gives examples of research that would advance scenario analysis and modelling, in contexts and scales that are of interest to IPBES.

8.2.1.1. Thematic gaps

There is a need for research that leads to development of new types of models to analyse and forecast ecological processes and ecosystem services that have so far not been the focus of much research. In this section, we give a few examples of these "thematic gaps".

Species interactions and community dynamics

Models for performing scenario analyses and projecting regional biodiversity dynamics under IPBES will need to incorporate species interactions and community dynamics (including, for example, trophic interactions and disease dynamics). There is already much progress in this area in marine systems, especially at the community and ecosystem levels (Fulton 2010). For example, the Ecopath with Ecosim model combines trophic relationships, environmental indicators, and biomass dynamics in the marine environment at a range from local to global scales. The model also incorporates the spatial and temporal dynamics primarily designed for exploring impact and placement of protected areas. It can be used to evaluate past and future impact of fishing and environmental disturbances as well as management policy options (Christensen and Walters, 2004). The mechanistic General Ecosystem Model is a process-based model that allows predicting ecological implications of human activities and decisions on both marine and terrestrial ecosystems. The model uses biological and ecological data of functional groups to explore the interactions between them and with the environment, and to make predictions about the ecosystem structure and function ranging from the local to the global scales (Harfoot et. al, 2014).

Although there is also much theoretical and empirical research on trophic interactions and disease dynamics in terrestrial systems and at the species level, these developments have not been translated into predictive tools at large temporal and spatial scales (Thuiller et al. 2013). For instance, while it is generally acknowledged that much of the impact of climate change will be through disruption of existing species interactions and emergence of new ones (Van der Putten et al. 2010), most large-scale models that project impacts of climate change on biodiversity either exclude such interactions or incorporate them only implicitly or under strong, simplifying assumptions (Albouy et al. 2014). When species interactions are explicitly included in predictive models of biodiversity, they are often limited to only two or few species, such as one-predator-one-prey (Fordham et al. 2013) and predator-prey-pathogen (Shoemaker et al. 2013); or they are limited to specific types of well-studied interactions such as pollination (Bascompte et al. 2006). Part of the reason for this thematic gap is that, in the context of projecting the effects of particular policy or management actions on specific systems, the challenges in community ecology are even greater than in population ecology of single species. In other words, our understanding about dynamics of communities is less than that of populations of single species, thus making it difficult to develop models that have sufficient skills to directly inform policies and management. Therefore,

basic science investments that lead to incorporation of species interactions and community dynamics into scenario analysis and modelling at large spatial and temporal scales would benefit global and regional IPBES assessments. Research needs include large scale experiments (e.g., experimental translocations), long-term and large spatial scale monitoring of the effects of conservation or policy actions (e.g., monitoring following the establishment of protected areas and invasive species control measures), and studies designed to translate measurable properties (such as comparison of ecological niche models of potentially interacting species) to parameters commonly used in theoretical models of species interactions (such as interaction coefficients or partial derivatives of population growth equations; Tang et al. 2014).

Recent studies have attempted to improve the mechanistic understanding of the relationship between species diversity and ecosystem functioning by using a functional group (trait) approach instead of species richness. In terrestrial environments, a comparison between a trait-based approach and a taxonomic approach indicated that ecosystem functioning was predicted better by the trait composition rather than the number or abundance of species (Gagic et al., 2015). However, a review of over 110 experimental studies has shown that richness is positively associated to ecosystem function (Cardinale et al. 2006). An increase on species richness increases the ability of that functional group to exploit and deplete resources, such as primary space, food, or nutrients, which has usually been considered an indication of "ecological performance" (Wieters et al., 2012).

Early warning of regime shifts

Another research need is developing practical early warning systems to anticipate ecological breakpoints, tipping points, and regime shifts (Leadley et al 2014). At the species level, warning systems based on current status and recent trends of populations have been in use for decades (Mace et al. 2008), and have been recently tested under scenarios of climate change (Stanton et al. 2014). At community or ecosystem levels, warning systems based on statistical properties of time series—such as increasing temporal variance and autocorrelation, and slowdown of system recovery from small perturbations—have been proposed (Scheffer et al. 2009) and empirically tested (Carpenter et al. 2011). For example, Mumby et al. (2013) used ecological models and field data to show that coral reef systems likely have multiple attractors and they can shift to and get stuck in an undesirable (degraded) alternative stable state. Although much research has been done on regime shifts in ecosystems, there are significant gaps, with the result that no practical early warning system for regime shifts (i.e., a set of generally agreed-upon measurable indicators), is currently available for adoption by IPBES. Practical limitations include dependence on long-term time series data (which are not as practical as static measures such as spatial patterns often used at the species level), difficulty of determining critical thresholds for a specific ecosystem, difficulty of predicting the timing of the transition and the nature of the altered state. A promising research direction is linking theoretical research on network robustness and empirical research on indicators of resilience, which have been largely unconnected so far (Scheffer et al. 2012). A related, and also promising, research direction is using time series data of ecological variables to infer causal drivers of ecological change. Regime shifts may be more predictable if we understand what drives the underlying ecological processes. Methods such as maximum likelihood (Wolf & Mangel 2008), convergent cross-mapping (Sugihara et al. 2012), and Bayesian model selection (Shoemaker and Akçakaya 2014) have been used to infer causes of species decline and to separate causality from

correlation. Further development and refinement of these approaches will help advance the use of mechanistic models for building early warning systems as well as for evaluating the effect of policy options on biodiversity and ecosystem services.

Response to variability and extreme events

One critical research need related to regime shifts, at both species and ecosystem levels, involves the effects of changes in environmental variability and environmental regimes, and biodiversity responses to extreme events (Zimmermann et al. 2009). In particular, global climate change is expected to result in increased frequency and intensity of extreme weather events. Predicting the effects of this on the properties of biological systems (including their persistence and variability) requires multidisciplinary collaboration among climatologists and ecologists, as well as integration information from demographic models, physiological models, and predictions of climatic variability.

Linking indicators to models

There is need for research that links indicators and modelling (Nicholson et al. 2012), directed towards developing indicators that can be used to not only measure the current status but also to forecast the future state of biodiversity and ecosystem services, based on scenario analysis and modelling. Many of the currently used or proposed indicators (see section 8.1.1) are useful for assessing current status and recent trends of components of biodiversity and ecosystem services, but few can be projected into the future. Research that links indicators and modelling can fill this gap. One key research direction is to develop indicators that are firmly based on scenario analysis and modelling so that future values of the index can be calculated for alternative policy options. For instance, in marine systems, size-based indicators allow predicting size distributions, abundance, and productivity of multiple species (Blanchard et al. 2014). Another research direction is for modellers to develop methods to forecast existing indicators reliably.

IPBES-relevant scales

Most basic ecological research involves short time periods and small spatial scales, which may not be relevant to the global and regional assessments to be undertaken by IPBES. There is a need for investments in research on ecological processes at the spatial and temporal scales relevant to IPBES assessments. This is especially important for regional assessments, both because IPBES will undertake them first, and because global assessments will need data and model support from sub-global assessments to fill knowledge gaps. In addition, there is bias in taxonomic and regional coverage of basic research, with a disproportionate amount of research involving populations of few groups (such as birds and mammals), and focusing certain regions (such as northern temperate regions). There is also a need for academic modellers and ecologists to become more familiar with applied fields such as forestry, fisheries, and agriculture, where policy relevant models have been used at scales relevant to IPBES (e.g., Platts et al. 2008; Blanchard et al. 2012).

8.2.1.2. Functional linkage gaps

A second type of research need concerns the development of linkages between existing approaches to modelling different aspects of biodiversity and ecosystem services.

One type of linkage that is needed is between human socio-economic systems and natural systems. Improving the coupling of the social and ecological components of models and scenarios requires

well developed, specific feedbacks from the ecological to the social systems and vice versa (Carpenter et al. 2009). Research on these matters requires not only an understanding how people make decisions to enhance their wellbeing, but also an understanding under what context they make those choices. Moreover, it is important to consider if information about their effects or consequences is available, and if available, if it is used by them to take decisions. These decision processes are poorly understood but remain essential. Linkages between human and natural systems may have complex structures, and may form cascades. For example, the effect of human activities on the world's climate is fairly well studied. There are also studies on the second link, the effects climate change on human activities, such as shifts in agriculture and urbanization. And the third link is the effect of these changes in human activities on biodiversity and ecosystem services, compounding the direct effects of climate change on natural systems. Other examples include the linkages among human population growth, land-cover change, and ecosystem services (Pereira et al. 2010; Brock et al. 2009). Such cascades of causal connections are often difficult to predict (Chapman et al. 2014; Watson et al. 2014). Understanding the linkages between the ecological and the social components and identifying the underlying feedbacks and cascades are vital to understanding the dynamics of the coupled system. Understanding how people perceive that their wellbeing is affected by environmental conditions, how policies are designed and accepted, and how people may change their behaviour as their environment changes are essential components of scenario modelling (Perrings 2014). It is thus critical to encourage research on the coupling of human and ecological systems that focuses on these causal chains and feedbacks, and on the scale at which these linkages operate to help modellers make more realistic projections of future changes in biodiversity and ecosystem services. In addition, approaches to use time series data to infer causality mentioned above (under *Early warning of regime shifts*) will help untangle these causal chains.

A critical research need involves the functional linkages between biodiversity and ecosystem services (Mace, 2012; Díaz et. al. 2007). As the previous chapters have emphasized (e.g., see Chapters 4, 6), there is only a limited number of models that attempt to predict the impact of ecological changes on human well-being (for some examples see Pattanayak et al. 2009; Bauch et al. 2015). One of the few well-developed connections is between pollinators and human well-being (see IPBES Thematic assessment of pollinators, pollination and food production). A particular challenge is modelling not only the supply or potential supply of ecosystem services, but also the service actually used or enjoyed by the people, which often requires assessing the demand for the service and the social preferences of the communities (Tallis et al. 2012). Another significant challenge is that existing models are usually one-way linked, which may not capture the non-linear dynamic linkages between different components of biodiversity and ecosystem services. (e.g., see Chapter 6). Developing such integrated models, tools, and methods will require basic research involving multi-disciplinary teams of scientists (including economists and social scientists, in addition to natural scientists) as well as policy makers and other stakeholders (see section 8.3).

Development of the types functional linkages between different types of models of biodiversity and ecosystem services discussed above can be facilitated by research into mechanistic as well as statistical (e.g., correlative) relationships. For example, analysis of statistical relationships between environmental drivers (climate, land-cover) and biodiversity components (e.g., species occurrence) allows some predictive ability. Such an approach has been successfully implemented as ecological

niche models and used to project the future potential distribution of species in response to environmental change (e.g. Guisan and Thuiller 2005). However, in order to predict beyond the current conditions, and to evaluate the impact of management and conservation options, a deeper understanding of ecological processes is needed. This need has led to the development of more mechanistic models that incorporate ecological processes such as dispersal and demography (e.g., Keith et al. 2008), and coupling of correlative and mechanistic approaches (Boulangeat et al. 2014). Similarly, the development of linkages discussed in this section will likely benefit from coupling of correlative or statistical methods with mechanistic models of ecological and socio-economic processes, such as some of the models incorporated in the InVest package (Daily et al. 2009).

On the technological side of developing these linkages, there is a need to encourage development of models that can communicate with (or embedded in) software platforms that are designed for linking different models. Two main types of such platforms are "scientific workflow managers" and "integrated environmental modelling frameworks". Both of these approaches allow users to assemble and run a system composed of existing simulation models that can exchange data at run time. Examples of scientific workflow managers include Kepler (kepler-project.org), with applications in areas such as ecological niche modelling (Pennington et al. 2007) and environmental sensor data analysis (Barseghian et al. 2010); VisTrails (vistrails.org), recently applied to habitat modelling (Morisette et al. 2013); and Taverna (http://www.taverna.org.uk), recently applied to mapping potential distribution patterns (Leidenberger et al. 2014). The integrated modelling frameworks include OpenMI (openmi.org), Object Modeling System (www.javaforge.com/project/oms), and Metamodel Manager (www.vortex10.org/MeMoMa.aspx), which have been applied to models of hydrology (Butts et al. 2014), sediment transport (Shrestha et al. 2013), trophic interactions (Prowse et al. 2013), and solar radiation (Formetta et al. 2013). An important difference between these systems is that the workflow managers are mainly designed for infrequent, unidirectional transfer of data among component models whereas the integrated modelling frameworks are designed for among-component interactions (i.e., feedbacks) and for frequent exchange of data among modules (e.g., passing key information at every time step), thereby allowing two-way interactions between two linked models.

Other technological improvements include compatible spatial and temporal scales (coverage and resolution; see Chapter 6); data-based and region- or system-specific functional relationships; and interacting drivers (see Chapter 2).

8.2.1.3. Evolving guidelines, evaluations, prioritization

Research on many aspects of scenario analysis and modelling of biodiversity and ecosystem services is progressing at a rapid rate. Many of the approaches reviewed in this report will be further developed in the near future; others may become obsolete. Therefore, there is a need to ensure, through ongoing updates and new evaluations, that the review of available policy support tools and methodologies for scenario analysis and modelling of biodiversity and ecosystem services continues to reflect best available science. Similarly, there is a need for ongoing prioritization of research needs. Some of the research and development directions and needs identified in this chapter will have already matured in the next few years, and others will not be pursued, or will be proven to be not beneficial. Therefore, it is critical that IPBES develops mechanisms for research prioritization, in order to encourage basic research that advances scenario analysis and modelling in

contexts and scales that are relevant to IPBES. This could be through Task Force on Scenarios and Modeling (3c), Task Force on Knowledge and Data (1d), and Task Force on Policy Support (4d), which could make recommendations to research funding agencies about the significant gaps that remain in our understanding of the fundamental processes that are the subject of scenario analysis and modelling used in IPBES assessments. Such recommendations would benefit from input from policy makers, both applied and academic natural resource modellers and researchers, and ecological, economic, and social scientists.

8.2.2. Verifying and validating models

To be of any use for IPBES and other applications such as conservation planning or for decision-making, models and ultimately scenarios need to have a full treatment and report of uncertainty together with a proper and sound validation. In biodiversity and ecosystem modelling, the heterogeneity of data and the range of factors influencing the results mean that the tasks of analysis and validation can be complex. Model validation covers different approaches and goals, but the overall idea is to use a set of criteria to classify and select an acceptable model. Agreement between model output and observed/experimental data of any sort can be analysed qualitatively using appropriate graphical design, to visualise model performance. In addition, and complementary to visual validation, statistical analyses and accuracy tests are pivotal to make model validation and model comparisons robust, general and quantitative. However, there is a lack of standardized terminology and approaches to validate biodiversity and ecosystem service models and their application for scenario building. IPBES could be the driving force to prepare such guidelines as they are critical for users to trust models and scenarios and for building standards for developing global or regional syntheses.

A model may be general (can be useful in many different situations), realistic (parameters and variables are based on true cause-effect relationships), and precise (accurate quantitative output), but it is impossible to have a perfect model that can maximize all three of these attributes simultaneously (Levins 1966). Models are often built for gaining a deeper understanding of the interactions between systems' components and for responding to questions about the systems' functioning (thus increasing "reality"). Hence, the limitations of a model need to be assessed from the start and adequately informed to the stakeholders that will be using the outputs.

There are several issues modellers and users should consider when validating a biodiversity or an ecosystem service model and associated scenarios.

<u>The goal of the validation</u>: There are several ways of validating a model and the appropriate approach depends on the overall purpose of the validation. The purpose of validation should thus always be clearly defined and reported since the subsequent tests, whether they are qualitative or quantitative, will be linked to that specific validation purpose. The output of the validation procedure gives important feedbacks to the modeller on how the models could be improved, but also to the end users on whether the model can be used or with what confidence it can be used for a specific purpose. In biodiversity modelling, one may want a model that correctly predicts the equilibrium range of a species. In that case, visual inspection of observed and predicted maps and associated statistics would be sufficient. However, such a validation procedure will not give any

information to the end-user or stakeholder on the ability of the model to simulate the transient dynamics of species in response to a given environmental change. For such purposes modellers require dynamic models and time series of data for validation.

Model and scenario comparison: Model and scenario comparisons should also be part of the validation procedure. For any given phenomena, several alternative models and scenarios can be developed, for instance at different levels of complexity. Comparing several models or scenarios built or calibrated for the same system and purpose allow us to: (i) understand their respective behaviour, (ii) chose the best one if needed, (iii) average them or (iv) build an ensemble forecast to visualize and apprehend the overall variation of the models and scenarios given the data and system (Araujo and New 2007). Species range modelling is one of the areas where statistical models and process-based models of increasing complexity can be benchmarked against observed data. Cheaib et al. (2012) compared eight different species distribution models from purely statistical models to highly complex individual-based models under current and future conditions. While varying the effects of environmental drivers, they singled out the assumptions made, the drawbacks therein, and the ability of these models to project the potential distribution of species (Cheaib et al. 2012). Although such evaluations and comparisons have been done in number of studies for modelling the distribution of species (Kearney et al. 2010; Morin & Thuiller 2009), of dynamic vegetation processes (Cramer et al. 2001), or of resulting ecosystem services (Bagstad et al. 2013), we argue that systematic comparison of different models and scenarios and the building of model ensembles to project both trends and uncertainties should be a gold standard, as is currently done in climate change research. Such comparisons, together with analysis of uncertainties are critically important if the outputs of such models are to be used for decision-making or conservation planning. Ensemble modelling or ensemble forecasting is the appropriate method in this regard if paired with appropriate validations and formulation of uncertainty.

Model predictions and scenarios: Most biodiversity and ecosystem services models are built to provide predictions based on scenarios, for instance under changing climate and land use. As such, these predictions can be compared with expert knowledge, experimental data, observed, and virtual data. A plethora of approaches and statistical techniques exist (e.g. residual mean square errors) and they have already been thoroughly compared and discussed. Validation of model predictions requires making clear predictions, using robust statistical methods, and generating enough data (either experimental or observational) so as to reach the level of quality needed for validation. Biodiversity and ecosystem services models are often subject to data limitations because of the difference between the scale of the prediction and the scale of measurement. For instance, most dynamic vegetation models use growth curves that are calibrated over dozen of individuals (of e.g. trees) measured in situ with precise climate measurements. These curves are then extrapolated over large spatial scales and with resolutions such as 20x20 km for which climate is highly smoothed. The outcome can then no longer be directly compared to the growth of single individual trees. To overcome this limitation, cross-scale validation has been proposed (using data generated at a finer scale to validate models built for a larger scale). But even here, the question of interchangeability of processes between scales has not been truly addressed (Morozov & Poggiale 2012).

Predictions involving future conditions pose special problems for validation, since the temporal scales are such that we often cannot test the validity of models in the future. In this regard, biodiversity and ecosystem service models can be considered validated if they successfully predict past events (retrospective testing; e.g., Brook et al. 2000). However, the probability of making meaningful projections decreases with the length of the time period into the future. A continuous exchange of validation data among developers and test teams should either ensure a progressive validation of the models by time, or highlight the need for updated interpretations of the analysed system (population, ecosystem, community, or landscape). To this end, spatially and temporally dynamic models of biodiversity or ecosystem services must be validated against monitoring data. Although fruitful initiatives were launched in the past decades (e.g., the ILTER network: http://www.ilternet.edu, GEO-BON: http://geobon.org, the IUCN Red List of Threatened Species: http://www.iucnredlist.org), monitoring datasets maintained over longer periods are still the exception rather than the rule. Promising new directions include sediment archives (Willerslev et al. 2014) and remote sensing/air-borne data that now provide systematic information about change in diverse communities through time or about spatial and temporal change in biophysical variables such as NDVI (Petorelli et al 2014). Overcoming data limitations require significant additional effort towards the building of long-term data collections, and towards the coordination and sharing of such data (see section 8.1.3). However, more than their quantity, a particular effort will be necessary to improve the quality of the data used and their spatial and/or temporal independence, which affects the quality of both the calibration and the validation process (section 8.1.2).

8.2.3. Managing uncertainty in models

With the rise of statistical and mechanistic predictive models of biodiversity and ecosystem services, quantifying, incorporating, and propagating uncertainty have become key issues. Regan (2002) recognized two main types of uncertainty in environmental science: epistemic and linguistic (Table 8.2). Epistemic uncertainty relates to the knowledge of the system and includes data bias and limitations (e.g. participatory science), structural uncertainty, parameter uncertainty, extrapolation and interpolation. Linguistic uncertainty comes from the vague, ambiguous, imprecise and context-dependent vocabulary. The definition of a species as a unit and its general use is one simple example, and the word biodiversity is another. Although integrating linguistic uncertainty is not new in conservation biology where policy and decision-making are part of the process, it is generally ignored in most cases and only epistemic uncertainty is considered.

A model is as good as the assumptions behind its construction, that is, what is accepted as true or as certain to occur as model output. Structural uncertainty is key here when sub-models or assumptions are likely to be wrong or uncertain. When stakeholders and policymakers are involved in the model building process, these assumptions can be discussed and analyzed in the light of the data and generated output that will be used. Stakeholders should then provide additional information to enrich the conceptual model since such discussions generate feedbacks that can improve the conceptual model in an iterative process. Also, the knowledge of “local experts” (people who may not be scientist or have any particular training but know the ecosystem functioning well and/or understand its response to diverse types of pressure) should be integrated into such processes. It is very beneficial if stakeholders are involved from the outset of defining the scope of a model, so that the envisioned goals, the model parameters, the modeled processes, the

targeted results and accepted uncertainties are identified clearly; and the possible weaknesses and limitations of the model are discussed and known to everyone. In such a process, modelers have to be ready to listen to what the other actors have to say, without presuppositions or prejudice, and they have to be honest with regard to the limitations that their models have in answering questions raised. It is crucial that this process is organized well so that all stakeholders are satisfied with the discussions and that they are aware of the gaps that may remain in the conceptual model. Understanding the degree of structural uncertainty is particularly important when the results are supposed to affect important policy decisions such as land planning. For instance, a comparison of three types of modeling approaches for mapping ecosystem services found significant disagreements between models (Schulp et al. 2014).

Table 8.2. Sources of uncertainty and potential treatment. Adapted from Regan 2002 and Elith et al. 2002.

	Source of uncertainty	**General treatments**
Epistemic uncertainty	Measurement error	statistical techniques; intervals
	Systematic error	Recognize and remove bias
	Natural variation	Probability distributions, intervals
	Inherent randomness	Probability distributions
	Model uncertainty	Validation, revision of theory based on observation, discussion with end-user, prediction
	Subjective judgment	Degree of belief, imprecise probabilities
Linguistic uncertainty	Numerical vagueness	Sharp delineation, fuzzy sets, rough sets, superevaluations
	Non-numerical vagueness	Use multidimensional measures than treat them as numerical
	Context dependence	Specify context
	Ambiguity	Clarify meaning
	Indeterminacy in theoretical terms	Make decision about future usage of term when need arises
	Underspecificity	Provide narrowest bounds

Data are essential for developing conceptual models that will later translate into quantitative or qualitative models. Yet, they are also indispensable for calibrating and evaluating those models. When the information is incomplete, unreliable, imprecise, fragmented, contradictory, or in any way deficient, it is fundamental that stakeholders can understand that even a simple model based on very general data can still be useful at providing insight into the possible effects of different alternatives. For instance, there are diverse mathematical or statistical techniques that allow dealing with information deficiencies, among which fuzzy inference systems and uncertainty-based information theory (Klir & Yuan, 1995; Cao 2010). One advantage of fuzzy inference systems is that these allow incorporating qualitative information that “local experts” and stakeholders may volunteer to provide. This information may then be integrated into a more rigorous framework of model construction. Qualitative reasoning helps in the construction of *knowledge models* that capture insights from domain experts about the structure and functioning of the system (Recknagel, 2006). Artificial Neural Network models (ANN) may also be helpful in situations in which a response variable should be estimated or its behavior predicted as a function of one or several predictor variables. ANN models have been conceptualized as non-parametric statistical

techniques because they do not require the fulfillment of the theoretical assumptions of parametrical statistics. They are also considered as non-linear regression techniques.

One valuable source of information is local and indigenous peoples who have a wealth of traditional knowledge. They often possess ample knowledge of the behavior of complex ecological systems that was accumulated and transmitted from generation to generation, since they are dependent on their local environment. In these communities, the knowledge of the ecosystems and their resources use and conservation practices are related to cultural aspects and religious beliefs (Gadgil 1993). Hence, they may not trust persons outside their community sufficiently to share their knowledge. Overcoming this requires the development of participation channels through the experience of anthropologists. Efforts should be made to systematically gather and organize such information. It is clear that research is needed on developing robust methods to elicit local and indigenous knowledge that are, in many situations, key to the development of models and scenarios. There are some lessons to be learned from climate science and efforts to include traditional ecological knowledge in mitigation and adaptation strategies (Dewulf et al. 2005; Smith & Sharp 2012; Brugnach et al. 2014).

The input data for biodiversity and ecosystem services models and scenarios are often uncertain and are specified as a range of values or as statistical distributions. Uncertainty analysis aims to quantify the overall uncertainty of model results in order to estimate the range of values the output could take (Regan et al. 2002). In recent years there has been an increasing interest in uncertainty analyses, partly motivated by the goal of keeping imperfect data in data-poor model environments instead of discarding them. Uncertainty and dependence modeling, model inferences, sampling design, screening and sensitivity analysis, and probabilistic inversion are among the most active research areas (Kurowicka & Cooke 2006). To date, despite few positive examples and the awareness that different algorithms likely result in different projections, biodiversity and ecosystem services models are too often used without clear reporting of the underlying uncertainty in parameter estimation or the uncertainty resulting from the input data.

Better integration of statistical analyses into parameter estimation of mechanistic models could foster appropriate characterization and reporting of uncertainty. Promising approaches for doing so include inverse modeling or Bayesian computation, which produce a probability distribution of the estimated parameters (the posterior distribution) that are relevant for the reporting of uncertainty (Hartig et al. 2012). So far, however, a full treatment of uncertainty has been considered too time-consuming and complex to be achieved in biodiversity and ecosystem services models, and a full integration and partitioning of the uncertainty originating from different sources (such as climate or land-use models) is difficult to achieve. To meet this challenge, there is a need for mathematical, statistical and computational skills that extend beyond the range of standard ecological expertise, and include novel techniques mixing deterministic and random concepts that are usually considered as independent skills and expertise. For instance, Bayesian calibration, comparison and averaging can be used in biodiversity and ecosystem service models to be used in IPBES assessments. These methods require a capacity of integrating process and parameter uncertainty and incorporating prior, even qualitative, knowledge. These approaches have mostly been tested with forest-gap models (van Oijen et al. 2011, 2013) but they could certainty be extended to many other types of biodiversity and ecosystem service models.

Pragmatic approaches are encouraged, for instance by sub-sampling alternative climate projections for the same scenario to obtain a basic representation of the uncertainty; or by considering that parameters in mechanistic models should not be fixed to one value but rather sampled from probability distributions representing uncertainty. While climate research has long started to produce such kinds of ensemble projections, this is not often done in biodiversity models, e.g., land use models. This situation poses serious challenges when modelers have an ensemble of climatic data and only few discrete scenarios of land use as input for deriving biodiversity scenarios into the future.

8.3. Improving Scenarios

Scenarios help decision makers to explore the impact of a broad range of policy options and socio-economic pathways on biodiversity, ecosystem services and human well-being (Abdelgalil et al. 2001). Quantitative models are one of the main tools used in scenarios to assess such impacts. In this section we identify areas for improvement of scenarios at each step of the scenarios development iterative cycle (Figure 8.1). We first examine how to best engage stakeholders in scenario development. Next we discuss how to improve the links between models and policy options in scenarios. We examine how the results of scenarios can be better communicated to policy-makers and other stakeholders. Finally, we propose avenues for improving the relevance of scenarios to policy makers.

8.3.1. Engaging stakeholders

8.3.1.1. Who are the stakeholders and the users of assessments?

"Stakeholders" are any individuals, group or organization who affect, or could be affected (whether positively or negatively) by a particular issue and its associated policies, decisions and/or actions (Grimble & Wellard 1997, UNEP & IOC-UNESCO 2009, Lucas et al. 2010). Stakeholders can be organized or unorganized; they can be at any level or position in society from local, regional, to global spatial scale. Some categories of stakeholders are useful to identify key stakeholders for the issue. "Active" stakeholders are those who are actively involved and interact with each other. "Influential" stakeholders are those who have power and are influential on the decision and outcomes of the issue. "Important" stakeholders are those whose needs and interests are priorities of the issue (Grimble & Wellard 1997, Lucas et al. 2010). "Actors" and "agents" are sometimes used in a similar way to stakeholders but with particular emphasis. The word "actors" is a synonym of active stakeholders usually with a neutral connotation, while agents indicate that the stakeholders are representatives of a group or an organization according to a common interest. "Users" are stakeholders who use the products and/or receive the services related to the issue.

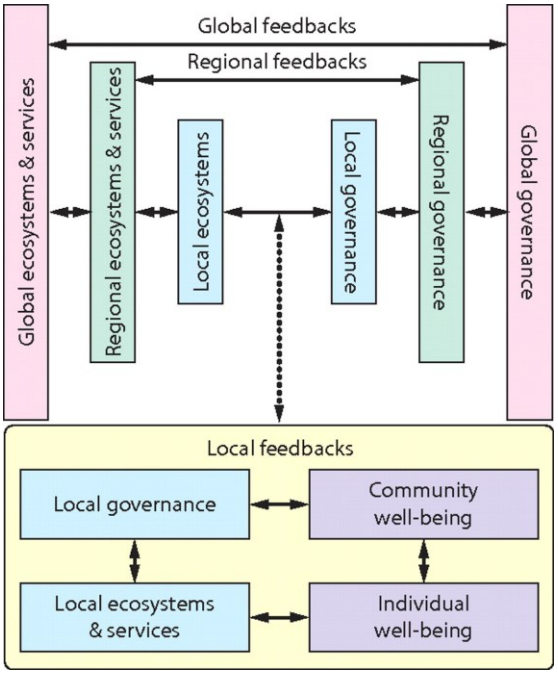


Figure 8.3: Governance and ecosystem services are interlinked at multiple scales, in ways that may or may not be effective for building or maintaining ecosystem services and human well-being. Reprinted from Carpenter et al. 2009.

The focal issue of IPBES is assessments on biodiversity and ecosystem services. IPBES has a large and varied group of stakeholders including international agencies, national and local governments (policy makers), NGOs, local communities, companies, and researchers. The spatial scale of assessments ranges widely from local to regional and global (Figure 8.3), but IPBES focuses on the latter two. Stakeholders dispersed over the assessment region have different interests according to their ways of knowing reality and of framing issues and problems. For instance, biodiversity and ecosystem services can have a variety of uses that are not always compatible and which may be valued differently by different stakeholders. Therefore, the active, influential and important stakeholders could differ depending on the scope and objective of the assessment, its targeted spatial & temporal scales and the kinds of ecosystem services addressed (UNEP & IOC-UNESCO 2009, Lucas et al. 2010, Wittmer et al. 2013). Governance and ecosystem services should be matched at the appropriate scales in an assessment, in ways that are effective for building or maintaining ecosystem services and human well-being (Carpenter et al. 2009).

8.3.1.2. Why is adequate stakeholder involvement indispensable?

The early engagement of stakeholders in scenarios development is crucial to enhance the legitimacy, salience, and credibility of the results of an assessment (Cash et al. 2003; UNEP & IOC-UNESCO 2009, Lucas et al. 2010). *Legitimacy* means that the relevant stakeholders are included in the assessment and perceive the process as unbiased and meeting standards of political and procedural fairness (Cash *et al*. 2002; UNEP & IOC-UNESCO 2009, Lucas et al. 2010, Wittmer et al. 2013). For instance, early discussion of the features of the Access and Benefit Sharing protocol of the CBD were marred by exclusion of indigenous people's representatives from the negotiation. *Saliency* means that the features of an assessment must be relevant for the decision makers. It is useless to develop a very sophisticated map or assessment if its features or outputs are legally, economically or culturally irrelevant to the policy makers. For instance, some results of the

Millennium Ecosystem Assessment will never be used at the scale of municipalities in many countries simply because they lack the links to the specific problems, ecological details or legal frameworks there. *Credibility* means that the stakeholders are willing to accept the features of the assessment as believable, performed with at least acceptable standards of rigor. If stakeholders belonging to a traditional or indigenous culture are part of the assessment, credibility often becomes a very difficult issue due to non-overlapping perceptions about local vs. global contexts, non-shared values and differences in ontological assumptions like the object/subject dichotomy (Agrawal 1995). One approach is to address this problem, is to ensure that the local and indigenous knowledge used in the assessment that has been appropriately validated and reviewed by local knowledge holders (Brook and Lachland 2008).

As number and/or variety of stakeholders increases, conflict of interests is likely to occur, especially as regards engagement of private sectors (Hochkirch et al. 2014). Inappropriate selection of stakeholders loses legitimacy by excluding adequate agents of common interest groups, decreases its relevance and credibility to the issue. However, adequate participation of stakeholders under well-organized governance can provide human resources necessary for the issue, achieve a balanced and comprehensive understanding of the different perspectives, enhance legitimacy of the assessment, make it relevant to the stakeholders' priorities, and ensure credibility for decision-making through enhancing communication, individual and social learning (UNEP & IOC-UNESCO 2009, Lucas et al. 2010, Wittmer et al. 2013). Adequate participation of stakeholders fosters mutual understanding, trust and empowers participants toward the assessment goal.

Participatory methods and tools constitute important channels to collectively define complex problems related to the governance of particular biodiversity and ecosystem services (Palacios-Agundez et al. 2013; Carvalho-Ribeiro et al. 2010; see also Chapter 3). Models and scenarios can be used to improve the transparency and relevance of policy making, by incorporating necessary demands and information of each stakeholder. These tools allow comparing multiple options, and making assumptions, trade-offs and potential conflicts of interests between stakeholders explicit. The information incorporated in models and scenarios through the collaboration of stakeholders could strengthen the credibility and usefulness of these tools, however, models and scenarios are not the only means (UNEP & IOC-UNESCO 2009, Lucas et al. 2010, Wittmer et al. 2013).

When we identify and engage stakeholders effectively, identification of potential providers and users of information on relevant issue at different scales and a list of stakeholders who are potentially affected by the assessment are indispensable. "User needs assessment" and "stakeholder analysis" are such methods recommended to adopt at the beginning of the assessment for the purpose (Ash et al. 2010, Grimble & Wellard 1997). In identifying and recruiting stakeholders, transparency of the process should be kept in such that all stakeholders have the opportunity to be heard and to participate (Wittmer et al. 2013).

An assessment is an empowering process where stakeholders do not feel as if they are contributing to an academic study of researchers but that the researchers help them answer questions of their own and find out answers. Collaboration of stakeholders should be designed in such manner that researchers work with the stakeholders to identify what the questions, opportunities and challenges are and help them to concentrate on the opportunities (Wittmer et al. 2013).

The utility of scenarios as assessment tools and products, and the capacity of the stakeholders to act on the best policy and management options are expected to improve progressively in an iterative participatory process (Figure 8.1). This cycle enables stakeholders not only to improve models and scenarios but also simultaneously help themselves enhance technical capacity as it provides access to data-sets, software tools for scenario analysis, and opportunity for better incorporation of local data and knowledge.

8.3.2. Linking scenarios and policy options to models

8.3.2.1. Identifying policy needs and integrating social dynamics in models and scenarios

The development of scenarios requires a full consideration of policy options and actions. The participations of stakeholders on the co-design of inputs, parameters and outcome of models and scenarios is essential (Future-Earth 2013). Feedbacks through the ecological and physical earth system both constrain and moderate the future options of decision makers. From the outset, policy makers can help identify topics, questions and approaches that are relevant to them. This approach will constitute a mutual learning experience whereby the modeling community will learn about the more imperious challenges and operative options on biodiversity from stakeholders, while stakeholders will gain from scientists a better understanding of the environmental challenges faced and the solutions that science can provide.

To address current and future policy needs it is important to promote a greater interdisciplinary understanding of the connections between natural and human risks on biodiversity in past, present and future timescales (Costanza, R. et al. 2007). The modeling communities in the natural and social sciences are relatively isolated from each other, and a substantive collaboration effort is needed. Model co-design will promote intellectual fusion between communities, helping them to formalize and integrate different discourses into a consistent framework (Rindfuss, R.R. et al. 2004). Such an effort will necessitate overcoming linguistic, epistemological, technical and other hurdles between the modelling communities.

A key issue is how to manage tradeoffs and also opportunities for synergies between biodiversity conservation, food security and livelihoods across contrasting social-ecological regions. In particular the community needs to: i) identify the nature of these tradeoffs and synergies across social-ecological systems and regions of the world; ii) identify the key ecosystem services that are at stake in these tradeoffs; iii) identify the biophysical and societal drivers that contribute to exacerbating the tradeoffs and those that contribute to reducing them; iv) identify opportunities for synergies between biodiversity conservation, food security and livelihoods that are most suitable for particular social-ecological contexts (McCarthy, Lipper et al. 2012, Smith, Haberl et al. 2013, Klapwijk, J. et al. 2014).

Many biodiversity models emphasize the predictive power of environmental processes, but do not include socioeconomic dynamics. One exception are Integrated Assessment Models (IAM), which were designed for evaluating policy pathways (Vuuren, Isaac et al. 2011, Vuuren, P. et al. 2012). Additionally, models often are not able to reproduce state transitions in the coupled human-environment system, and cannot structurally produce qualitative shifts or collapse such as tipping-

points (Leadley et al. 2014; for exceptions see eg. de Roos and Person 2002 or Figueiredo and Pereira 2012). However, research shows that even simple systems with smooth behavior, when coupled as a co-evolving system, can display strong non-linearity and abrupt transitions (Scheffer, M. et al. 2003, Folke, C. et al. 2004, Leadley, P. et al. 2014). Simple complex systems models address feedbacks and qualitative shifts, but cannot speak to the fuller processess that includes regime shifts and tipping points.

8.3.2.2. Exploratory versus normative scenarios

Scenarios can be developed using a variety of approaches (Kok et al 2011; Alcamo et al. 2001). In exploratory scenarios, the analysis starts in the present and different plausible future trajectories are explored by stakeholders, often across major axes of uncertainty on social-ecological dynamics, and using associated narratives for the unfolding of events from present to the future. In normative scenarios, stakeholders agree on a set of desirable futures, and then a backcasting analysis is performed of the socio-ecological pathways that may lead to those desirable futures.

There are advantages and disadvantages to each approach, and some exercises have tried to combine elements of both approaches (Kok et al. 2011). Exploratory scenarios foster creative thinking and exchange of viewpoints between different stakeholders, but do not always provide clear actions that decision makers should implement to reach desirable outcomes. Normative scenarios are more likely to provide clear policy pathways but have been criticized for being value laden.

Recent large scale environmental scenarios have been following an approach that is perhaps more akin to normative scenarios, and that should be considered by IPBES activities. The new scenarios of IPCC, defined plausible relative concentration pathways (RCP) of greenhouse gases to achieve different levels of radiative forcing for the end of the century (Moss 2010). Then, emission pathways and associated socio-economic scenarios were developed in order to produce those RCP scenarios. In the end, these are integrated with climate models and analysis of impacts. Another approach was followed by the Rethinking Global Biodiversity Strategies scenarios (ten Brink et al. 2010). These scenarios consider a set of policy options aimed at reducing biodiversity loss, such as increase in protected areas, changes in diet and improving forest management. The effects on biodiversity of the implementation of those options are then assessed over time. More recently, the Roads from Rio+20 Scenarios (PBL 2012) defined a vision for biodiversity in 2050, and then examined three pathways, each one with its one set of policy options, that can lead to that vision.

8.3.3. Communicating results

8.3.3.1. Understanding model outputs and the limitations in their scope

Models results need to be understood within the context of the data and the assumptions. Here, the users may be those stakeholders involved in the modeling process, but often they could be decision-makers at other levels who may want to use the available information and results, or even NGOs willing to inform the public in general. Keohane et al. (2014) identify five plausible principles to guide communication: honesty, precision of scientific findings, audience relevance, process transparency, and, last but not least in any way, specification of uncertainty about conclusions. It is particularly important that the process of building a dialogue between scientists/modelers and

stakeholders/decision-makers explicitly involves communicating the weaknesses that inevitably appear regarding present knowledge and the way it can be used. Being clear about what the shortcomings are should permit an increase in the confidence between interlocutors.

It should be made clear what the uncertainties in the output are, what the implications are, and also all that is not implied (Janssen et al. 2005). If the users participated in the modeling process, it might be easier to communicate the relative rigor of the results and translate their meaning because of the previous involvement of the users and the understanding of the modeling process. Nevertheless, the results should be presented in a clear, consistent, and precise way, giving preference to graphic forms or to tables that synthesize the main points. If the intended audience was not engaged in the model-construction process, much more attention needs to be given to communicating the outputs in a way that minimizes misinterpretation and does not generate confusion or mistrust. Kloprogge et al. (2007) recommend Progressive Disclosure of Information (PDI), which "*entails implementation of several layers of information to be progressively disclosed from non-technical information through more specialized information, according to the needs of the user*".

The audience needs to make sense of the information that is being provided, so it may be important to give it in the context of the assessment and to include some idea of how it was obtained. Over all, it is essential that the audience perceives the information as being useful for making policy decisions, or for use in political debates, or for forming personal opinions relative to policy advice.

New technologies in computer science and design have made easier to represent in graphic form information on processes and/or data creating a visual image, usually a chart or diagram but also videoclips, movement effects and interactive visualizations. These can become very efficient means of communicating complex concepts in a clear and simple way, particularly among actors with different backgrounds. Although scientists usually use sketches and graphs to explain ideas and results in their work environment, they do not normally have any training on how to use these visualization techniques to better report findings to a wider, less specialized audience (McIrney 2013; McIrney et al. 2014). Infographics and visual representations could be valuable tools to be used from the very beginning of the iterative process of scenarios and model construction and assessment involving scientists and stakeholders, facilitating the understanding of complex processes and identifying uncertainties, and thus building confidence and empowering participants. Moreover, it would be advisable to explore how planning of final visual outputs can be embedded into the development and production stage of modelling and scenario activities. A more extensive assessment of the role of visual communication for model and scenario outputs seems necessary. As examples, it can be mentioned that in order to explicitly account for uncertainty related to data gathering, Elith, J. et al. (2002) propose methods for developing realistic confidence intervals and visualization of information for use by decision-makers, while Ronchini et al (2011) propose the creation of "maps of ignorance" to provide information on where the mapped distributions are reliable and where they are uncertain.

The process of constructing models, proposing scenarios and analyzing them as means of learning in advance about the effects and implications of policies on biodiversity and ecosystem services is

not only a technical matter. The whole process is embedded in the cultural setting of the societies that are part of those ecosystems and use their resources. Communicating effectively with those stakeholders requires the participation of interdisciplinary professionals with diverse skills and broader intellectual capabilities, in particular social scientists who understand the institutions and the social structure in the region, helping modelers to notice relevant issues, but who can also contribute in helping society better understand and solve environmental problems. The Task Force on Capacity Building and Task Force on Local and Indigenous Knowledge could consider the proper ways to train and involve interdisciplinary professionals in these communication processes.

8.3.3.2. The importance of communicating uncertainty

A critical challenge in communicating the results of scientific research arises when those results contain uncertainties. It is highly important that the various types of uncertainties that will necessarily appear in the modeling process, as well as in the scenario analysis, be clearly communicated to all stakeholders and decision-makers so that there is full understanding of the relative weight of the output, their implications and the risks involved. Uncertainties need to be set in the context of the key messages that are being conveyed, and the implications of the uncertainties need to be explained. It may also be important to offer information on how the uncertainties can be or may be treated or dealt with. However, decisions can be made even when gaps in information appear, or data are not totally reliable, or ample variability is observed and risks are identified (see Section 8.2.2).

Recent experience, mostly related to the communication of uncertainties related to climate change (Box 8.5) or to potential pandemics, has opened the way to a more systematic analysis of how people perceive the uncertainty inherent to scientific research. These problems have captured the attention of both climate and social scientists (Janssen et al., 2005; Handmer & Proudley, 2007; Kloprogge et al., 2007; Pidgeon & Fischhoff, 2011). Research communities have emerged in which people from different fields, such as climate and environmental scientists, historians, social scientists, philosophers, examine issues of uncertainty with respect to global environmental problems with the purpose of improving the capacity to discuss and weigh related policy recommendations (e.g. www.princeton.edu/piirs/research-communities/communicating-uncertainty/).

Box 8.5 An example of the importance of communicating uncertainty in a science-policy interface.

Keohane et al (2014) focus on the ethics of scientists' communication with policy makers relative to assessments of issues such as climate change. As a case study, they analyze the treatment of possible sea level rise as a result of melting of ice sheets in Antarctica and Greenland in the Fourth Assessment of the IPCC. Sea level rise can be projected using computer simulations of global climate models and focusing on three processes: thermal expansion of the oceans, mountain glacier melt, and ice sheet disintegration via melting and dynamical loss (or sliding of ice sheets into the ocean). Sliding is considered the major contributing factor in Antarctica; however scientists did not have models to estimate future changes in sliding which resulted in a high degree of uncertainty in the projections. The IPCC Working Group I assessing the physical scientific aspects of

the climate system and climate change (IPCC 2007) gave uneven treatment to this third factor relative to the other two, creating confusion with projections lacking clarity and transparency. Thus, the misuse of projections led to significant differences in the estimation of sea level rise to be used in infrastructure planning by coastal communities, making it difficult to take practical, long-term steps under a risk-based approach. It can also be noted that Working Group I and Working Group II (assessing impacts, vulnerability, and adaptation) chose different approaches to deal with uncertainty. O'Reilly et al. (2012) suggest that the decision to use one approach in Working Group I and another in Working Group II was partly a function of the particular set of authors involved in each group, how they were selected for and how they worked together. Working Group II used a risk management approach to frame its findings which gave decision makers as comprehensive a basis as possible on which to make decisions.

8.3.3.3. The need to improve the communication of probabilistic results

All biological dynamical systems evolve under stochastic forces. In a stochastic or random process there is some indeterminacy. Even if the initial condition or starting point is known, there are several directions in which the process may evolve. Translating the meaning of output from stochastic models to persons without professional or specialized knowledge in the subject often generates confusion because there is a whole set of possible outcomes and the results are given in terms either of averages or probabilities. As mentioned earlier, and depending on the context, it is advisable to use multiple models, of differing complexities and types, to compare the outputs and help comprehend their meaning.

Normally information involving probabilities is susceptible of biases and misinterpretations, as people have different perceptions of what is really being meant. For instance, different levels of comprehension of weather forecasts given in probabilistic terms were detected depending on gender and age (Handmer & Proudley, 2007). Social and cultural factors may influence the interpretation of the probability of occurrence of a given outcome and the perception of the seriousness of possible non-desirable consequences. Research on cognitive biases and prospect theory (behavioural economic theory that describes the way people choose between probabilistic alternatives that involve risk) indicates that people have difficulty in correctly interpreting risks because they are more likely to act to avoid a loss than to achieve a gain (Kahneman & Tversky 1979; Kahneman et al. 1982; Kahneman 2011). Stakeholders and policy makers may not have a technical or scientific training that could help reduce subjectivity or asymmetry in the interpretation. Research focused on better understanding both the cognitive and the psychological processes involved when a person interprets information containing uncertainties, particularly in cases which involve appraising risks which are given in probabilistic terms, either numerically or linguistically, could be extremely useful. Based on this research, IPBES could set standards for communication through Task Force on Capacity Building.

8.3.4. Linking Outputs to Policy

8.3.4.1. The role of Boundary Institutions

The process whereby stakeholders engage in a modeling assessment includes the definition of the relevant variables, assumptions, methods and parameterization, all the way to communicating results, uncertainties and caveats, in the appropriate language, to different audiences (Cash et al. 2003; Folke et al. 2005). This is a two-way process, and there is a variety of science-policy "interfaces" (van der Hoven and Chabason 2009), but most have in common the existence of some institutional way of facilitating or enabling the above functions, over the usually long periods of time that are necessary for effective communication to be established among knowledge holders and decision makers, either a government, or a group of governments, or local decision-makers. Such institutions have been called boundary or bridging institutions (Cash et al. 2003; Folke et al. 2005; Cash et al. 2006). The role of boundary institutions in facilitating the science to policy process is crucial given the multiscale features of most realistic biodiversity-governance problems (see 8.3.1), the variety of stakeholders (section 8.3.2), and the serious problem of communicating the assumptions and the results of "boundary objects" (section 8.3.3). Boundary objects are the result of the process between stakeholders and can be maps, models, scenarios and assessments (Cash et al. 2003). A Boundary Institution simply provides the space, experience and credibility, and facilitates the process in which the stakeholders will need to engage to create objects (like scenarios) with the features we now suggest.

8.3.4.2. Features of effective science to policy processes.

Problems with the multi-scale features of many governance processes often arise in biodiversity policy-making (Cash et al. 2006). From a governance perspective, important factors changing with scale are political and jurisdictional units, the characteristic time-frames for decision making, institutional arrangements and the scopes of different types of knowledge systems (formal scientific claiming to be general and abstract, whereas local and indigenous knowledge tends to be specific and experiential). The challenges of producing boundary objects that are relevant across scales is a very difficult one, since it is easy to fail to recognize the heterogeneities in the way that scales are perceived by different stakeholders (Cash et al. 2006). A successful science to policy process then should be aware of the scale problems and be able to tackle those challenges, maybe by focusing on some part of the hierarchy of stakeholders, for instance by choosing representative stakeholders at different scales or by choosing a single scale and associated stakeholders for analysis.

Finally, the BOs resulting from a science to policy process should be communicated actively using the right translation of terms, and concepts, and, if needed, a mediation between stakeholders with different languages, usages and histories (Cash et al. 2003). Such demanding and complicated tasks are better performed institutionally. An institution is more likely than individuals to develop the credibility, memory and experience needed to facilitate the process of developing appropriate boundary objects. Boundary organizations, mandated to act as intermediaries between the worlds of knowledge and policymaking can specialize in organizing legitimate, salient and credible science to policy processes, can be accountable to different groups and can translate and communicate in appropriate ways the boundary objects resulting from the processes. There are many examples of such organizations, working at very different levels of the biodiversity governance scales. For

example, several of the United Nations organizations or programs, the Consultative Group on International Agricultural Research, many bodies of the International Union for the Conservation of Nature and other international centers (Cash et al. 2003), research bodies of the Multilateral Environmental Agreements (van der Hoven and Chabason 2009), international or large national NGOs, and national research centers and universities (Sarukhán et al. 2014). Many of these have been proved to communicate rather complex boundary objects, for instance, the result of sophisticated modeling (Guisan et al. 2013).

8.3.4.3. What should IPBES do to become a successful boundary institution?

In order to become a successful boundary institution, IPBES should facilitate and create conditions, frameworks and infrastructure for the development of policy relevant biodiversity scenarios. This can be achieved by:

- Identifying key global biodiversity questions to which assessments can develop robust answers;
- Overcoming disciplinary barriers in modeling, data collection, selection and management;
- Identifying co-design and co-development of best practices that respond to policy needs;
- Defining modelling methodologies appropriate for the different social contexts and policy needs
- Identifying robust model integration techniques that respond to current and future development requirements;
- Establishing a permanent dialogue between modelers and decision-makers to address issues such as common understanding of concepts, transdisciplinarity, and infrastructure for resource and knowledge sharing.

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