6 Linking and harmonizing scenarios and models across scales and domains

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Key findings

For assessments of biodiversity and ecosystem services, linking models and linking scenarios increases our ability to capture complex dynamics of social-ecological systems, but at the same time increases the uncertainty of model outcomes (6.1). It may not be necessary to explicitly account for all the interconnections such as across scales, or between biodiversity, ecosystem services and human well-being for some decision-making contexts. However, many real-world decisions need to account for these interconnections. Thus, exploring them as well as the associated uncertainty may be desirable (see chapter 2).

"Output-input" approaches link models by passing outputs from one model as inputs to another model. Existing families of approaches include one-way (information is passed in one direction between two or more models), two-way (information is passed in both directions between models allowing for feedbacks), loose (meaning that model output can be computed separately) and tight (integrated, requiring simultaneous processing of multiple models) coupling (6.2). One-way loose coupling (quantitative and/or qualitative) is used most frequently, because it is relatively straightforward and often meets the desired objectives. Two-way coupling is more complex, but needed and beneficial in some situations to explore and capture feedbacks. Integrated assessment models (IAMs) are examples of frameworks that include coupling of a broad range of models to represent social-ecological systems.

A common method for linking scenarios of similar spatial and temporal scales or that are developed independently for different purposes or scales is to first group the scenarios according to the scenario family or archetype that they belong to, then combine scenario descriptions (qualitative or quantitative) that belong to the same family or archetype (6.3). Families of existing scenarios for assessments of global and regional environmental changes exist. Scenarios can be coupled loosely either upfront or after scenarios are developed, while links for tightly coupled scenarios are usually established upfront by a team of scenario developers.

Multi-scale scenarios that link global and regional-scale scenarios have been useful for informing environmental assessments that need to consider drivers at different scales (6.3). Approaches for developing multi-scale scenarios include using global-scale scenarios as boundary conditions for

regional-scale scenarios, translating global-scale storylines into regional storylines, using standardized scenario families to independently develop scenarios across scales, and the direct use of global scenarios for regional policy contexts. However, approaches and examples for up-scaling regional scenarios for global assessments are lacking.

Key recommendations

The IPBES Task Force on Capacity Building should foster the development of communities of multi-disciplinary researchers and practitioners to harmonize and link across models, scales, domains and elements (6.1). This would encourage shared learning from experience gained from different approaches employed in different parts of the world – e.g. across different regions/countries.

The IPBES Global and Regional Assessments should not limit their work to a particular scale, but use multi-scale scenarios (6.3) that are coupled both loosely and tightly (6.1). The loose-coupling approach is particularly suitable for framing stakeholder issues, while the latter also allows consideration of feedbacks among scales, elements and domains and promote more detailed system understanding.

The IPBES Task Force on Knowledge, Information and Data should work with the scientific community to define a set of standard conditions and components for "IPBES compatible" model and scenario components that share a common ground (6.3). This could be similar to the approach that has successfully been implemented through coordinated efforts between the IPCC and the scientific community.

The IPBES Task Force on Knowledge and Data should encourage the incorporation in integrated assessment models (IAMs) of ecological processes (e.g., population dynamics or biogeography of groups of animals) into IAMs (6.3). This would allow these classes of models to address a broader range of questions related to biodiversity and ecosystem services.

The IPBES Global and Regional Assessments should explore the use of existing scenario archetypes (families) to link and harmonize scenarios that best respond to their questions. Common scenario families include economic optimism, reformed markets, global sustainable development, regional competition, regional sustainable development and business-as-usual (6.4).

To facilitate linkages and harmonization of models and scenarios for assessing ecosystem services, human well-being and policy options, the IPBES Task Force on Knowledge, Information and Data should develop an open source data infrastructure to share multi-disciplinary data, toolkits and tested methods, and promote the use of common terminology (6.4). This would allow informed linking and harmonization of scenarios and models, as well as model benchmarking.

6.1 Importance of linking and harmonizing models and scenarios

6.1.1. Point-of-departure

Models and scenarios are important tools to understand and communicate effects of natural and

human drivers on biodiversity and ecosystem services (Chapter 3, 4 and 5). The temporal, spatial, and social organization scales that modelling and scenario assessments focus on are generally specific to particular policy contexts (Chapter 2). However, biodiversity and ecosystem services and their drivers are interconnected, and span multiple spatial and temporal scales, domains and elements of the IPBES framework (see Chapter 1 and Glossary). Thus, linking models and linking scenarios at different scales and across domains and elements is an important step in advancing our understanding of how the human subsystem may sustainably operate within planetary and social boundaries (Steffen *et al.* 2015; Mace et al. 2012; Raworth 2012; Dearing et al. 2014). This chapter builds upon Chapter 2 to 5 to assess the availability of tools and methods for linking and harmonizing scenarios and models of drivers of biodiversity (Chapter 3), impacts of these drivers on biodiversity, ecosystem functions (Chapter 4) and benefits to people (Chapter 5) in order to inform policy-making at specific spatial and temporal scales (Chapter 2).

Specifically, this chapter aims to: a) summarize existing approaches and initiatives that link and harmonize models and scenarios across scales, domains and elements; b) discuss relevance to policy-making; c) identify knowledge gaps; d) propose possible ways for IPBES to undertake multi-scale/domain/element linkages and harmonization to assess biodiversity and ecosystem services. Models for biodiversity and ecosystem services run at a wide variety of time scales (from hours to days, seasons, years, decades and millennia) depending on the elements, domains and processes that they represent (Figure 6.1, see section 6.2). Similarly, they cover a variety of spatial scales. Our discussion focuses on both short (10 – 15 years) and long (multi-decadal) time scales, and on global, regional and national (sensu IPBES) spatial scale. We present case studies selected across a wide variety of elements and applications to showcase approaches to tackle complex issues.

6.1.2. Linking and harmonizing models and scenarios: why and why not

Decision makers, from individuals to global institutions, are unlikely to have knowledge about the entirety of impacts of their chosen actions within an element and across multiple, interconnected elements (Chapter 2). Models and scenarios can be used to understand the (positive and negative) impacts of an action across interconnected elements, by unveiling the interactions and feedbacks across multiple elements and domains of social, economic and natural systems. An action may impact individual elements in different and often unexpected ways across spatial and temporal scales, as well as potentially affecting multiple elements. For example, damming a river impacts fish up- and down-stream of the dam (migration barrier; *spatial impacts*), immediately and in the longer term (altered water flow, sediment accumulation in reservoir; *temporal impacts*), and impacts fish, aquatic and terrestrial plants, and people (*multiple organizational scales*). Models and scenarios that integrate feedbacks and tradeoffs across temporal and spatial scales and among dynamic social, economic and natural systems can help address complex environmental challenges and guide decision making (Carpenter *et al*. 2006). To bring models or scenarios together, they need to be made compatible or consistent with one another; such process is referred to as 'harmonization'. Harmonization is related to the concept of interoperability, or the ability of different information technology components, systems, and software applications to communicate and exchange data accurately, effectively, and consistently, and to use the information that has been exchanged (Heubusch, 2006, Matott et al. 2009,

Laniak *et al*. 2013). Harmonization also enables comparisons across models and scenarios, which is a necessary step to understand the uncertainty around possible outcomes of the complex interactions between drivers, biodiversity and ecosystem services and the other elements of the IPBES framework.

For some decision contexts, multiple models and scenarios exist, or could be developed, that provide different information to decision makers (Chapter 2). Models or scenarios may differ because they (a) were developed to address subtly different questions for different audiences (e.g. composition and function of biodiversity, temperature and precipitation for climate) and therefore produce different outputs (e.g. carbon ecosystem service models may output carbon stocks or carbon sequestration); (b) use different input data (e.g. different biophysical layers for species distribution modelling); (c) represent different components/elements within the model/scenario (e.g. biodiversity models may incorporate metabolism, reproduction, growth, dispersal, mortality); (d) use different methodologies or techniques (e.g. quantitative, qualitative, inductive, deductive, statistical, process-based); or (e) cover different spatial and/or temporal scales.

The main reason to link and harmonize across models and scenarios is to aid decision makers to evaluate multiple and potentially contradictory outputs. Harmonizing model/scenario inputs and outputs enables their intercomparison. In the Coupled Model Intercomparison Project (CMIP, results directly feeding into the IPCC assessment reports), for example, climate models explore the same sets of greenhouse gas emission scenarios and other forcings to produce common outputs such as annual mean atmospheric temperature (Taylor *et al*. 2011). Recently, the climate impact modelling community attempted to compare projected impacts across different sectors (e.g. agriculture, hydrology, carbon cycling and biome shifts) using one common set of driving variables and modelling protocol within the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP, Schellnhuber *et al*. 2011). Additional sectors will be included in the next phase, also including impacts on biodiversity and ecosystem services such as fisheries (https://www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip). Comparing among models helps to identify differences and their causes, and assess the model/scenario quality. Models and scenarios can be harmonized in multiple ways, by using: standardized inputs (e.g. all Integrated Assessment Models used in IPCC AR5 use the same harmonized land use data, Hurtt *et al*. 2011), agreed output metrics, evaluation or benchmarking against common observational data sets (e.g. GCMs to be included in IPCC need to be able to hindcast historic temperature trends, derived from multiple sources), or specifying the key components and elements that need to be represented in the model/scenario.

The main challenges of linking across multiple models are a) output-input chains and feedbacks of models are often complex, difficult to debug and potentially result in error propagation and uncertainty, and b) each model comes with separate and sometimes incompatible assumptions (Laniak et al. 2013). Careful assessment of feasibility and potential effects of linking multiple models on uncertainty and error propagation need to be conducted, as well as assessing the appropriateness/relevance to decision context.

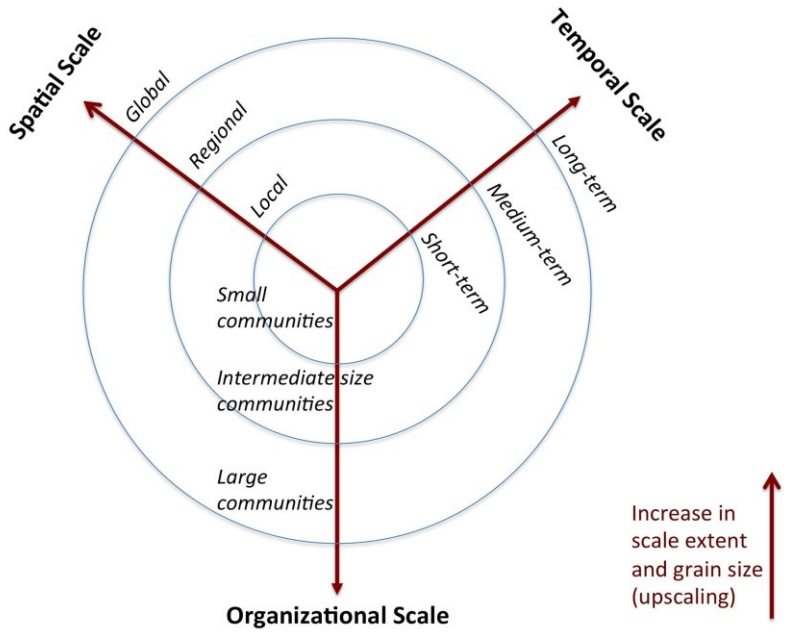

Figure 6.1: Spatial, temporal and organizational scales are usually correlated, thus the consequences of changing the scale of analysis (upscaling or downscaling) in any of these three dimensions need to be carefully considered. Upscaling is related to an increase in scale extent and grain size, while downscaling is the inverse process. Note that the organizational scale, here represented by social organization, is also relevant to biodiversity (e.g. genes, species, ecosystems) and ecosystem services (e.g. provisioning, regulating, cultural).

Linking and harmonizing models/scenarios may not be appropriate in every decision context, for instance when the causality of links across elements is poorly understood. Linking too many components either statically or dynamically may create complex models. These become unhelpful for decision making when error propagation increases uncertainty to an unacceptable level (par. 6.5). Voinov and Shugart (2013) caution that in some cases the software engineering approach of mechanically connecting models as software can result in conceptually ambiguous products or 'integronsters', which seem to be technically correct but make little sense as realistic system models and decision support tools. It is important that in addition to data integration that checks that the data passed from one module to another is consistent with the model assumptions and is quantitatively meaningful (units, time-space scales and synchronization), there are also proper semantic integration checks that operate within extensive ontologies matching the concepts and assumptions used in various models that are connected. Thus, the amount of linkage among models/scenarios needs to be tailored to the decision at stake (Figure 6.1). Scenarios may differ also because they do not share the same values, or the same worldviews, and it may important to present

these differences clearly. Although standardising likely reduces the uncertainty around estimates (e.g. by using standardized model inputs or by removing outliers), many models/scenarios will give similar outputs which may be more precise but not necessarily accurate and therefore less policy relevant. By *a priori* standardising inputs and components as well as ensuring validation against a standard dataset, models/scenarios that are projecting the "unknown unknowns" (low frequency, high impact events) will be excluded (Levin 2003) (e.g., the 2008 financial crisis or abrupt climate change).

6.2. Approaches for linking and harmonizing models and scenarios

Models or scenarios developed for different spatial and temporal scales, different domains (e.g. biomes, organizational domains) and for different elements can be linked or harmonized using different approaches (Table 6.1). Specifically, different models are linked together across spatial and temporal scales, and across elements and their domains. Linking (also referred to as coupling) works by feeding outputs of one model as input to another model, which can be done iteratively (two-way or tight coupling) or off-line (one-way or loose coupling). Scenarios (plausible descriptions of how the future may develop) cannot be readily linked because they do not have quantitative outputs. Only models applied to scenarios produce these outputs. Models and scenarios can also be linked qualitatively (e.g., through narratives or description of storylines). For example, each of the Millennium Ecosystem Assessment scenarios of socio-economic development is linked to scenarios of climate change (Millennium Ecosystem Assessment 2005). Models and scenarios describing different elements may also be combined quantitatively or qualitatively to provide a more holistic assessment, as done by integrated assessment models (IAMs), and more generally, Integrated Environmental Modelling (IEM) approaches (Laniak *et al*. 2013). IEM broadly refers to modelling approaches that represent holistic system-level thinking by using quantitative and participatory methods for defining, selecting, integrating, and processing the combination of environmental, social and economic information needed to inform decisions and policies related to the environment (Laniak *et al*. 2013). Note that frequently links are being made across spatial and temporal scales, and elements may act on one another at different scales (also see IPBES Deliverable 2(a), Chapter 2). For example, historic global climate data may be used as input for modelling the current distribution of species at national scale, which then are used to estimate a provisioning ecosystem service (blue arrows in Figure 6.2).

Table 6.1: Summary of different approaches to linking and harmonizing models and scenarios.

	Approaches	**Model**	**Scenario**
Linking	Output-input, one-way coupling	x	
	Output-input, two-way coupling	x	
	Combining outputs qualitatively	x	x
Harmonizing	Standardization of metrics (input and/or output), classification schemes, taxonomies	x	x
	Scaling (upscaling, downscaling) in time and space	x	x
	Converting across dimensions, domains and organizational levels and spatial and temporal scales	x	x
	Benchmarking	x	

Harmonization of models and scenarios occurs across domains and spatial and temporal scales *within* an element. In particular, harmonization involves the standardization of metrics (e.g. output metrics of models, conditions for scenarios i.e. CO2 concentration, agricultural production) and input data (e.g. land use, temperature) or both. For nominal variables, this can be achieved through the adoption of standard classification schemes (e.g. the unified classification of species threats and conservation actions, Salafsky et al. 2008). Harmonization often involves upscaling and downscaling models and scenarios in space and time, as well as model benchmarking. Benchmarking is not applicable to scenarios because these are by definition alternative to each other. Harmonized models and scenarios and their outputs facilitate model linking, error detection and uncertainty estimation and ultimately decision making.

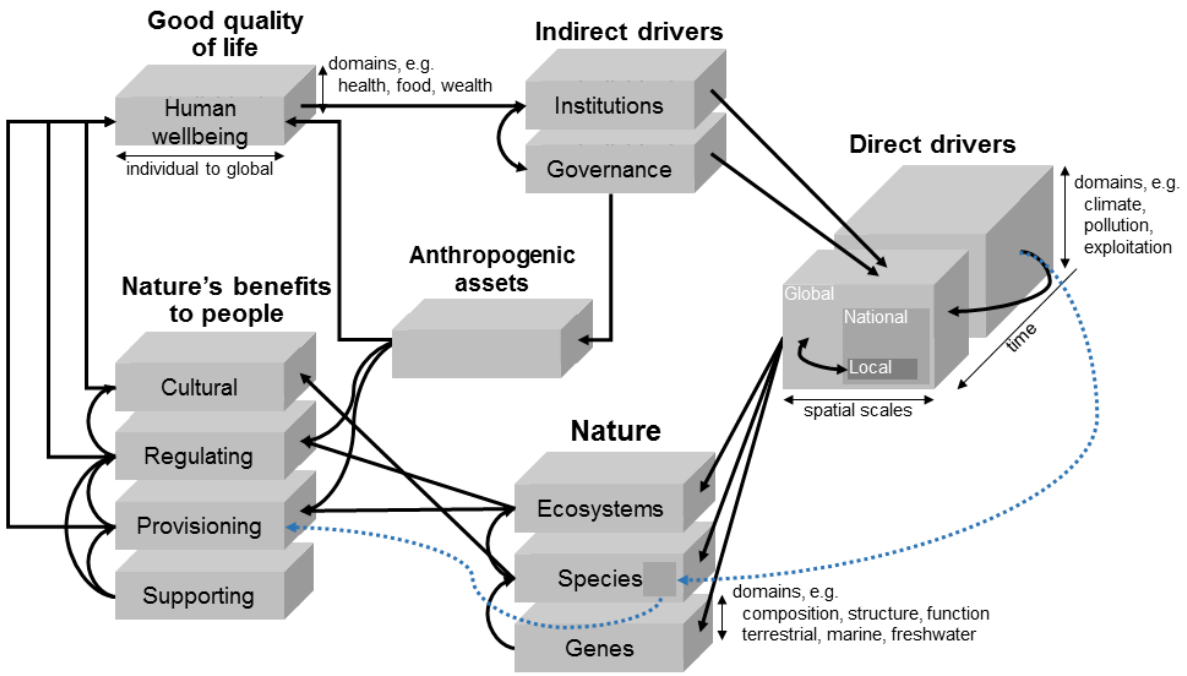

Figure 6.2 Linking models among the six elements of the IPBES conceptual framework (straight arrows) and within domains (vertical axis), spatial (horizontal) and temporal (Z dimension) scales of each element (curved arrows). Each element has multiple dimensions (examples shown) including temporal and spatial scales, and disciplinary and organizational domains. Blue arrow explained in text.

6.3 Linking models and scenarios of biodiversity and ecosystem services

6.3.1 Model coupling through input-output

Models representing different components of the social-ecological system that are related to biodiversity and ecosystem services and their drivers are linked through either one-way (off-line) or two-way coupling (which allows feedback). In both cases, outputs from one model feed into another model as inputs. For example, in modelling the effects of changes in ocean conditions (temperature, primary productivity, oxygen level and acidity, and the resulting species range shifts) on marine

ecosystems in the Northeast Pacific coasts, Ainsworth *et al*. (2011) took simulated changes in ocean conditions from a coupled ocean-atmospheric earth system model and projected range shifts from species distribution models as inputs (forcing factors) in trophodynamic foodweb models to simulate the effects of multiple CO_2-related drivers on marine ecosystems and fisheries yields. Visconti *et al*. (2015) used scenarios of climate and land use change to project species distributions into the future, and assembled these projections into policy-relevant indicators of biodiversity change (Box 6.1). In contrast, two-way coupling includes feedbacks of inputs-outputs between models. For example, a marine ecosystem model, Atlantis (Fulton *et al*. 2011), links model components describing ocean biogeochemistry, lower-trophic level ecosystem, upper-trophic level ecosystem and human activities (with a focus on fishing) in which outputs from the components mutually affect one another directly or indirectly over space and time.

The choice of coupling methods depends on the dynamics of the modelled systems and the objectives of the models. One-way coupling is simpler to implement than dynamic two-way coupling, because the models can be run sequentially. The responses of the modeled system are also more predictable, because feedbacks are not allowed (e.g., predicting changes in tree species distributions driven by climate model outputs vs tightly-coupled system dynamic models, where changes in tree species distributions have a feedback on local climate). On the other hand, non-linear system dynamics and feedback between model domains cannot be directly revealed with models that are coupled one-way. Two-way coupling is more realistic for understanding social-ecological systems where feedbacks and resulting non-linear responses are common among domains and elements. However, it is technically more difficult, particularly if components operate at different temporal and spatial scales. The model responses are also less predictable and may result in large internal variability.

Regarding potential linkages between models representing different aspects of biodiversity (from the genetic to the ecosystem level, Chapter 4) and models or modelling frameworks adopted to develop ecosystem service scenarios (Chapter 5), only a fraction of the available biophysical model types has been extensively used in ecosystem service modelling work (Table 6.2). Ecosystem service models have often been based on rather simple proxies or indicators for biodiversity and the associated ecosystem services. Rather few ecosystem service models tackled the demand side of the service, i.e., modelled the realized ecosystem service (Turner et al. 2012) (Chapter 5). Proxy-based approaches, however, have the advantage that they are easier to handle and amenable to participatory processes. Furthermore, quantitative model results and qualitative expert knowledge can be integrated (Chapter 5).

Many natural-science-based biodiversity model types have rarely or never been used in ecosystem service modelling. Models that simulate ecosystem functions or services directly, such as models of fisheries, agricultural and timber yields, have been used most widely (table 6.2, chapter 5). However, in these models the focus is not on representing biodiversity (e.g. number of species in a habitat or region). Amongst biodiversity models that represent biodiversity in a stricter sense, only species distribution models (SDMs) have, to our knowledge, been used in ecosystem service modelling. Hanewinkel *et al*. (2013), for example, used SDMs to project future range shifts for major tree species and associated changes in economic revenues across Europe, and Cheung et al. (2010) applied SDMs

to project future changes in fisheries catch potential and Lam et al. (in press) combined SDM outputs with a bioeconomic model to assess the implications of climate change and ocean acidification for the economics and livelihood of Arctic fisheries in the future.

Species-habitat relationships based on expert knowledge have been used to create maps of the extent of suitable habitat for species, similar to SDMs (Rondinini et al. 2011, Iglecia et al. 2012, Ficetola et al. 2015), but the models rely less on statistical inference of species habitat requirements (Chapter 4). In combination with models of future habitat changes, such as land cover models or dynamic global vegetation models (DGVMs), such approaches have been used to develop scenarios for the future distribution of species (Visconti et al. 2015, Rondinini & Visconti in press), which could then also be linked to ecosystem services.

Species richness patterns can be simulated with a variety of approaches (see Chapter 4 and table 6.2). As in the case of functional trait models, the results of such models have not been interpreted in terms of ecosystem service supplies. DGVMs simulate a number of ecosystem functions that represent ecosystem services (e.g. carbon storage) or are closely linked to these (e.g. vegetation type – provisioning of habitat), and the results have been interpreted in terms of ecosystem service supplies (e.g. Doherty *et al*. 2009). The DGVM LPJmL (which includes major global crop types) has also been implemented in IMAGE3.0, but we are not aware of any DGVM application within a more social-science-based ecosystem service scenario framework. This partly reflects a scale mismatch; most ecosystem service scenario work concerns smaller scales. DGVMs that are adapted to the regional scale (e.g. Hickler *et al*. 2012, Seiler *et al*. 2014) would be more suitable for smaller scale ecosystem service scenario development. Crop and hydrology models have been widely used in ecosystem service scenario work (Table 6.2), but these models don't focus on biodiversity, even though hydrology models increasingly account for the effects of vegetation or plant functional type composition on hydrological cycling (e.g. Rost *et al*. 2008).

Table 6.2: Examples of major model types and models that can be used to project future changes in biodiversity (from the species to the ecosystem level), most common inputs and outputs, examples of specific widely used models or modelling studies, main associated ecosystem services, and models or modelling frameworks that have been linked to the outputs of biodiversity models. The ecosystem service model categories have been adopted from Crossmann et al. (2013). Note that some of the models are intermediate between categories and that we only aim at listing representative examples, not an exhaustive list. More models are discussed in chapter 4 and 5.

Biodiversity models	**Inputs**	**Outputs**	**Examples**	**Ecosystem services**	**Ecosystem service scenario examples**
Species distribution models	Climate, land cover, soil types, ocean biophysics and biogeochemistry	Species ranges	BIOMOD (Thuiller et al. 2009), Maxent (Phillips and Dudík 2008), Aquamaps (Kashner et al. 2006), DBEM (Cheung *et al*. 2011)	Provisioning[1] Cultural and Amenity[2]	Exploited marine species (Cheung *et al*. 2010), forestry revenues (Hanewinkel et al. 2011)
Expert-knowledge-based species-habitat relationships	Vegetation/ land cover types	Local occupancy of particular species	Rondinini et al. 2011, Iglecia *et al*. 2012, Ficetola et al. (2015)	Cultural and Amenity	-
Abundance models	Land cover or land use intensity	Changes in species abundances	PREDICTS (Newbold et al. 2015)	Provisioning Cultural and Amenity	-
Community-based biodiversity change models	Multiple environmental layers, including, e.g., land cover and use, climate and vegetation type	Groups of species and community characteristics	Ferrier and Guisan (2006)	Provisioning Cultural and Amenity	-
Population dynamics models	Multiple environmental layers	Population dynamics of individual species	Kramer-Schadt *et al*. (2005)	Cultural and Amenity	-
Richness models	Multiple environmental layers (at smaller scales) or available habitat area (species-area relationship) or as for species distribution models (stacking results from individual species)	Species richness	Ferrier and Guisan (2006), van Vuuren *et al*. (2006), Rahbek *et al*. (2007), Algar *et al*. (2009), Calabrese *et al*. (2014), PREDICTS (Newbold et al. 2015)	Provisioning Cultural and Amenity	-
Functional trait models	Climate, soil types, atmospheric CO_2	Trait composition/diversity Biogeochemical cycles	JEDI (Pavlik et al. 2013), aDGVM2 (Scheiter *et al*. 2013), Barton et al. (2015)	Provisioning Regulation[3] Habitat[4]	-

Landscape models	Climate, soil types, land use	Landscape-level land cover and vegetation structure	Landclim (Schumacher and Bugmann 2006)	Provisioning Regulation Habitat	Habitat for biodiversity (Bryan and Crossmann 2013)
Forestry models	Climate, soil types, land use	Timber yield, C cycle, habitat quality	3-PG (Landsberg and Waring 1997), EFISCEN (Verkerk *et al*. 2011)	Provisioning Regulation	Carbon Sequestration and wood production (Verkerk et al. 2011, Boettcher et al. 2012, Bryan and Crossmann 2013, Paul *et al*. 2013)
Dynamic Global Vegetation Models	Climate, land cover and use, soil types, atmospheric chemistry (e.g. CO2 concentration, nitrogen deposition)	Biome distribution, vegetation structure, plant functional type diversity, NPP, C, N, P and water cycles	LPJ (Sitch *et al*. 2003), SDGVM (Woodward and Lomas 2004), MC1 (Gonzalez *et al*. 2010)	Provisioning Regulation Habitat	-
Ecosystem or Biogeochemistry models	Climate, soil types, land cover, atmospheric composition (e.g. CO2, nitrogen deposition), Climate, land cover, soil types, atmospheric chemistry, ocean biogeochemistry and food web	NPP, C, N, P and water cycles	Century (Parton *et al*. 2010), TEM (McGuire *et al*. 1992) Ecopath with Ecosim (Christensen and Walters 2004), Atlantis (Fulton *et al*. 2011), TOPAZ (Bertino et al. 2008)	Provisioning Regulation and provision services	Fish yields (Blanchard et al. 2012, Christensen *et al*.2015) Carbon cycle (Wenzel *et al*. 2014)
Agricultural models	Climate, crop management, soil types, atmospheric chemistry	Crop yields	GEPIC (Liu *et al*. 2007), APSIM (Keating *et al*. 2003), LPJmL (Bondeau *et al*. 2007)	Provisioning	Food production (Keating *et al*. 2003, Bryan and Crossmann 2013)
Hydrology models	Climate, land cover, soil types	Water cycle	WaterGap2 (Alcamo *et al*. 2003)	Provisioning Regulating	Fresh water supply (Bryan and Crossmann 2013)

[1] Food, water, raw materials, genetic, medicinal and ornamental resources

[2] Aesthetic information, opportunities for recreation and tourism, inspiration for culture, art and design, spiritual experience, information for cognitive development

[3] Air quality, climate, moderation of extreme events, water flows, waste treatment, erosion prevention, maintenance of soil fertility, pollination, biological control

[4] Maintenance of life cycles and genetic diversity, cultural and amenity services

The question of whether biodiversity and ecosystem service models should be directly linked depends on the research objectives and policy context. Nevertheless we think that not all useful linkages have been utilized and more direct linkages have great potential. The ARIES ecosystem service modelling framework (Chapter 4.2.1) presents an important advance as it allows linking a variety of models in a

very flexible framework, which also allows for feedbacks between changes in ecosystem services and biodiversity via, e.g., land use decisions (Villa *et al*. 2014). Also among biodiversity or biophysical models based on natural science (first column in Table 6.2), not all potential links have been utilized. Most species distribution models, for example, use climatic variables, land cover, and in rare cases, soil types as input, but a biome shift could influence the occurrence of species much more than the a change in climate. In spite of this obvious link, projected changes in biome distribution or vegetation structure, as simulated, by DGVMs, have only rarely been used in species distribution models (Linder *et al*. 2012). Recently, it has also been shown that species distribution models in riverine systems should and can be improved by using hydrological variables derived from hydrological models as inputs (Jähnig et al. 2012, Kuemmerlen et al. 2014).

Most examples above concern one-way coupling between models. Two-way coupling or full socio-ecological systems modelling has only rarely been achieved. The rare examples include Integrated Assessment Models (IAMs), such as IMAGE3.0 (Box 6.2), which only represent very general system characteristics and are of limited use for regional or local policy making or stakeholders. Integrated assessment models combine components (sub-models) representing the future development of human societies, including major sectors such as energy use, industrial development, land use, that are important for making projections about the future of human and natural ecosystems (Harfoot *et al*. 2013). Currently, the main applications of IAMs are on modelling climate change and effects of climate mitigation. In most IAMs, their sub-models, including both natural and human subsystems, are linked although dynamic linkages are not commonly represented in most IAMs (Harfoot *et al*. 2013). An example of natural systems sub-models in an IAM is the linkage between hydrological models providing inputs regarding water and nutrient supply into terrestrial vegetation models. For human systems sub-models it includes, for example, component representing the energy sectors that capture the demand and supply of energy as links to industrial development, population demand and commodity prices. There are also components that link natural-human systems such as food production, linking vegetation and land-use with societal demand, energy sources (particularly from bio-energy crops) and commodity prices. IAM provides a framework for linking models to represent complex social-ecological systems, however there are gaps in the application of IAMs to address questions related to biodiversity and ecosystem services (Harfoot et al. 2013). Currently, representation of biodiversity in IAMs is only limited to terrestrial ecosystems (Chapter 4). Thus, using the IAM framework to address a broader range of questions related to biodiversity may require further works in incorporating model components that represent more ecological processes e.g., population dynamics or biogeography of groups of animals.

6.3.2. Combining model and scenario outputs

Outputs from models and scenarios that are complementary in representing different domains and scales can be combined qualitatively so that each provides descriptions, projections or narratives of different axes of the biodiversity and ecosystem services assessment framework. The projections or narratives generated by models and scenarios representing different domains can be combined to more holistically describe potential changes in social-ecological systems or a subset of the systems.

Such linkages would be simple if the models or scenarios are coherent across scales and have the same analytical frameworks and logics. However, in many cases, models and scenarios may be constructed to be largely independent at different scales or domains, but connected by the same issues they address; or conversely, they may be at the same scales but addressing different issues. An iterative process is generally necessary to incorporate feedbacks and maintain storyline consistency, although feedbacks are seldom considered in this type of linkages. In order for the outputs to be compatible with one another, they should first be harmonized by categorizing them into the same scenario archetype or family based on their drivers, assumptions, scenarios logics and boundary conditions (Zurek and Henricks 2007; see 6.4).

6.4 Harmonizing models and scenarios

6.4.1. Harmonizing models across scales and domains

Harmonizing models to assess the status and trends, and project future changes in biodiversity and ecosystem services require synthesizing biophysical and socio-economic data and results that are available at different spatial, temporal and organization scales and domains (Table 6.3).

Spatial, temporal and organizational scales can be defined considering two main dimensions: *grain* and *extent*. Grain refers to the resolution of the dataset, while extent is the size of the observation. More specifically, the *spatial grain* is the size of the sampling unit, the *temporal grain* is the frequency of data observation, and the *organizational grain* is the resolution of the social, human or built capital information. The extent refers to how large is an area (*spatial extent*), period of time (*temporal extent*) or human system considered (*organizational extent*). For example, with an Enhanced Thematic Mapper Plus sensor, the spatial grain is 30 meters (for bands 1 to 5), the temporal grain is 16 days (the satellite makes an image of the same place each 16 days), the spatial extent corresponds to a track 183 km wide, and the temporal extent is the duration of the study (for example, few days, one season, several years). Within the framework of IPBES, we will refer to three spatial extents (global, regional, and national/subnational/local scales) and to short (around 10 years) and long-term (e.g. several decades) temporal extents or time series data. Global extent considers the whole planet, regional extent encompasses several countries, specific ocean basin or large marine ecosystem (for example, the South African region is composed by South Africa, Mozambique, Zimbabwe, Namibia and Botswana), national to local scales refer to space in the same country.

Table 6.3. Scale typology: scale types, examples of levels, extent and grain.

Scale types	Levels of scale	Extent	Grain
Spatial	- *Geographical*: local, regional, global - *Geophysical*: watersheds, geomorphological units, continents - *Biophysical*: vegetation types, ecosystems, ecoregions, biomes - *Governmental* (administrative boundaries): municipalities, departments, provinces, regions, countries	The size of the focal area	The finest level of spatial resolution
Temporal	- Years, decades, centuries	Duration of time under consideration	Frequency of observations
Organizational	- *Social*: Individuals, communities, societies, ethnic groups - *Cultural*: indigeneity - *Biodiversity:* composition, structure, function; and genes, species, ecosystem - *Ecosystem services:* provisioning, regulating, cultural	Size of the human/social system considered	Level of details of the information on the human/social system

Space, time and organization scales are usually correlated (Fig. 6.1): the assessment of large human systems or communities will require data at large spatial and temporal scales (but with low resolution), and inversely data on specific local communities will require more detailed temporal and spatial information, with high resolution. The correlation between spatial and temporal scale is particularly well-known. There is an intrinsic relationship between space and time, which makes processes acting in more local scales more dynamic (local fast changes are more likely), while those operating at larger spatial scales require larger temporal observation. For example, global scale population dynamic models of fishes do not resolve fine scale behavior shift of individuals because of changing local ecological or environmental conditions. As a consequence of this spatial-temporal interaction, models with coarse spatial resolution usually do not resolve processes that operate at fine temporal scale, while models at a more local scale will require more fine-grained spatial and temporal resolution data. There is thus an optimal temporal domain of scales to understand the natural dynamics of systems operating at a focal spatial scale (Figure 6.3). In this sense, very detailed models, representing for example the local dynamics of a given population, will not be informative for understanding the dynamics of a metacommunity on a broader time and spatial scale, or vice versa. There are thus appropriate scales to analyze certain processes, and a first challenge (for scientists and practitioners) is to identify those scales, avoiding building too much detail or coarse models. Additionally, biodiversity dynamics and ecological processes acting at a particular domain of scales are also indirectly affected by processes acting in other scales. Particularly, local biodiversity pattern or ecosystem services, such as stocks and flows of water and other living resources, are mainly controlled by proximate factors acting locally, but are also affected by indirect global drivers of change (Levin 1992), which would require data on large spatial extension and for an extended period of time. Inversely, local actions affect the environment globally, and as a consequence the success of global scenario projections will

depend on the congruence of scenarios and goals planned at more local scales (Cash *et al*. 2006).

Scaling is thus needed and is a widely used method in environmental science to modify the prediction of phenomena at different scales from its initial record or model. Scaling can be done in two different directions: upscaling information from local, fine-grained resolution to global, coarse-grained resolution, or vice-versa, downscaling the information. Upscaling usually leads to an increase in the extent, and decrease in the resolution, while downscaling increases the resolution of the data, while losing the extent (Figure 6.3). In both directions, predictions are associated with errors and uncertainty, which are explored in the next section (6.5). Environmental studies involve dynamic modeling with data sources at various spatial and temporal scales which need to be integrated. Furthermore, the output of the model often needs post-processing treatment to modify its scale to fit it to the resolution required for policy decisions. Each component of the research cycle has its own temporal or spatial scale. Scaling methods refers to the transfer of information on spatial and temporal scales.

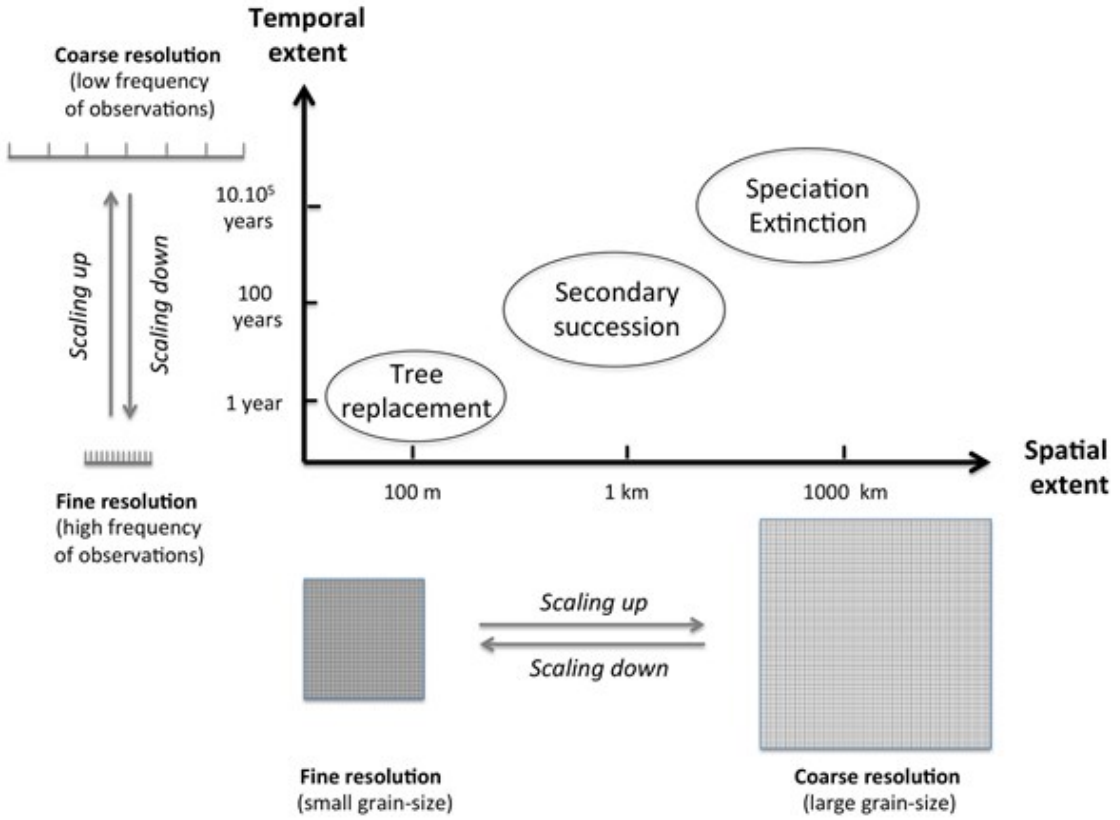

Figure 6.3. Four ecological processes (tree replacement, secondary succession, speciation and extinction) and their respective space-time domains. Large spatial and temporal extents are usually related with coarse spatial and temporal resolution data, in contrast to small spatial and temporal extents. Consequently scaling up is usually associated with an increase in spatial and temporal extent and decrease in resolution, while scaling down has as consequence a reduction in extent, which should be followed by an increase in resolution.

Scaling is inevitable when modeling biodiversity and ecosystem services, and is necessary for both global and local ecological and environmental planning and adaptive management (Holling

1978). There is frequently a mismatch between availability and the scale of data, model outputs or scenario descriptions that are needed for biodiversity and ecosystem services assessment at global and regional scales. Available data, models or scenarios are often obtained from sporadic studies, unevenly distributed spatially, cover a short period of time (e.g., snapshot samples), and are collected with inconsistent methodologies. Thus, understanding how patterns revealed from these models and scenarios change across scales and how to transfer information among scales is crucial to integrate different components of the social-ecological systems that operate at different spatial scales (Wu and Li 2006).

6.4.1.1. Organizational scale (social aggregation and biodiversity levels)

Any form of modelling and scenario development and usage stems from and affects a social, organizational context. The desire to understand and make better decisions with regard to this relationship between the human and natural systems causes us to consider linkages between models and scenario for and from models. Following an ecological economics convention, the human sub-system is roughly comprised of social, human and built capital and embedded within the natural system (i.e. natural capital, ecosystems, nature) (Costanza et al., 1997a, see Chapter 1). However, the underlying (often deeply engrained and unspoken) assumptions and mental models that people hold about this human-natural systems relationship drives the type of models and scenarios being accepted and developed (Hamilton, 2011) (see also IPBES Deliverable 3d on 'diverse values and valuation').

Several models have been proposed and adopted to provide knowledge about human-natural systems in a range of spatial-temporal-organizational dimension (Dietze *et al*. 2011). Some of these models are static, with snapshot changes (e.g. Computable General Equilibrium), linear with projected changes over time [e.g. VISIT, Integrated Valuation of Environmental Services and Tradeoffs (InVEST) (Goldstein et al., 2010; Kaveira et al., 2011; Dean et al., 2012) and system based models [e.g. World3 (Meadows et al., 1972), Global Unified Meta-model of the Biosphere (GUMBO) (Boumans et al., 2002), Multi-scale Integrated Modeling of Ecosystem Services (MIMES) (Boumans and Costanza, 2007; Boumans and McNally, 2012; Altman et al, 2014)].

Issues of scale relating to space and time needs to be 'fit for purpose' in an organizational context. As models refer to 'any abstract reflection of reality' (including mental models) we confine this section to ecosystem services models; i.e. the models that stem from the desire to highlight and make visible the benefits and well-being people derive from natural capital. An ecosystem services approach can be considered an organizing principle linking natural and human systems (Costanza et al., 1997b; Daily, 1997; Millennium Ecosystem Assessment, 2005; Braat and de Groot, 2012). As a trans-disciplinary approach, the ecosystem services concept and its associated tools, including modelling approaches, have undergone a rapid evolution since the 90's (see Chapter 5).

Economic 'benefit transfer methodology' was effectively used to highlight value from ecosystems that is not visible in the market and therefore often neglected. For example, Costanza et al. (1997, 2014) calculated an annual flow of value of ecosystem services derived from the stock of global natural capital to conservatively be twice that of global Gross Domestic Product (GDP). Turner et al. (2012)

also provide another example of modification of benefits-transfer approaches to address some of the limitations of ecosystem service measurement and mapping. In addition, the values resulting from Costanza et al. (1997, 2014) were spatially displayed on a global map. While the authors never claimed robustness or accuracy, this global ecosystem service value in relation to GDP, drew attention from policymakers, business and a wider audience and sparked a fierce debate. In fact, Costanza et al. (1997) laid out the many challenges that would have to be overcome for this value to be identified and captured for management purposes. Since then, numerous data bases have been developed to support valuation of ecosystem services, for example Earth Economics (http://www.eartheconomics.org/). For example, the draft chapter 3 on 'Ecosystem Services' of the 1st World Oceans Assessment identified 14 databases that are directly or indirectly in conjunction with ecosystem services approaChapter For terrestrial and freshwater ecosystems, no such compilation does yet exist. Given that the marine ecosystems are lagging in application of ecosystem services approaches, the vast amount of databases and information available for other ecosystem (often unconnected) can be assessed. While basic value transfer assumes that value per ecosystem type remains constant (e.g. Costanza et al. 1997b, 2006), expert modified value transfers adjust values for local conditions of ecosystems (e.g., Batker et al. 2010) and Natural Capital Project (http://www.naturalcapitalproject.org). Involvement of stakeholders and their different mental models / interests in understanding local dynamics and non-spatial trade-offs between bundles of ecosystem services has been explored through systems thinking and system dynamics e.g Mediated Modelling (van den Belt et al. 2012). Values may also be adjusted based on statistical models of spatial and other dependencies (meta regression analysis e.g. de Groot et al. 2012). This rapid development has led to spatially explicit dynamic modelling frameworks at multiple scales (e.g. Boumans et al., 2002; Boumans and Costanza, 2007; van den Belt 2009; Boumans and McNally, 2012; Altman et al., 2014).

Furthermore, an ecosystem services approach is also inherently multi-scale as ecosystem services can be classified according to their spatial characteristics (Costanza 2008; see Figure 6.4). (1) At a global level, climate regulation, carbon sequestration and storage as well as cultural or existence values do not depend on people's proximity to the ecosystems from where the services originate, whereas (2) local proximity is relevant for disturbance regulation / storm protection, waste treatment, pollination, biological control and habitat. (3) A directional flow characterises water regulation/ flood protection, water supply, sediment retention/erosion control or nutrient regulation. (4) a point of use is relevant for soil formation, food/forest production and other raw material and finally (5) some ecosystem services and the benefits/values derived from them are related to the manner in which users move in space (and time), e.g. genetics resources, recreational potential and cultural values. Bundle of ecosystem services, their possible tradeoffs exist and require pluralism (including multiple modelling approaches) need to acknowledge values (or participation) of stakeholders. Due to its complexity, the scope for approaches aiming for optimization are limited and the process of model building with stakeholders becomes equally important as the model itself (van den Belt, 2004).

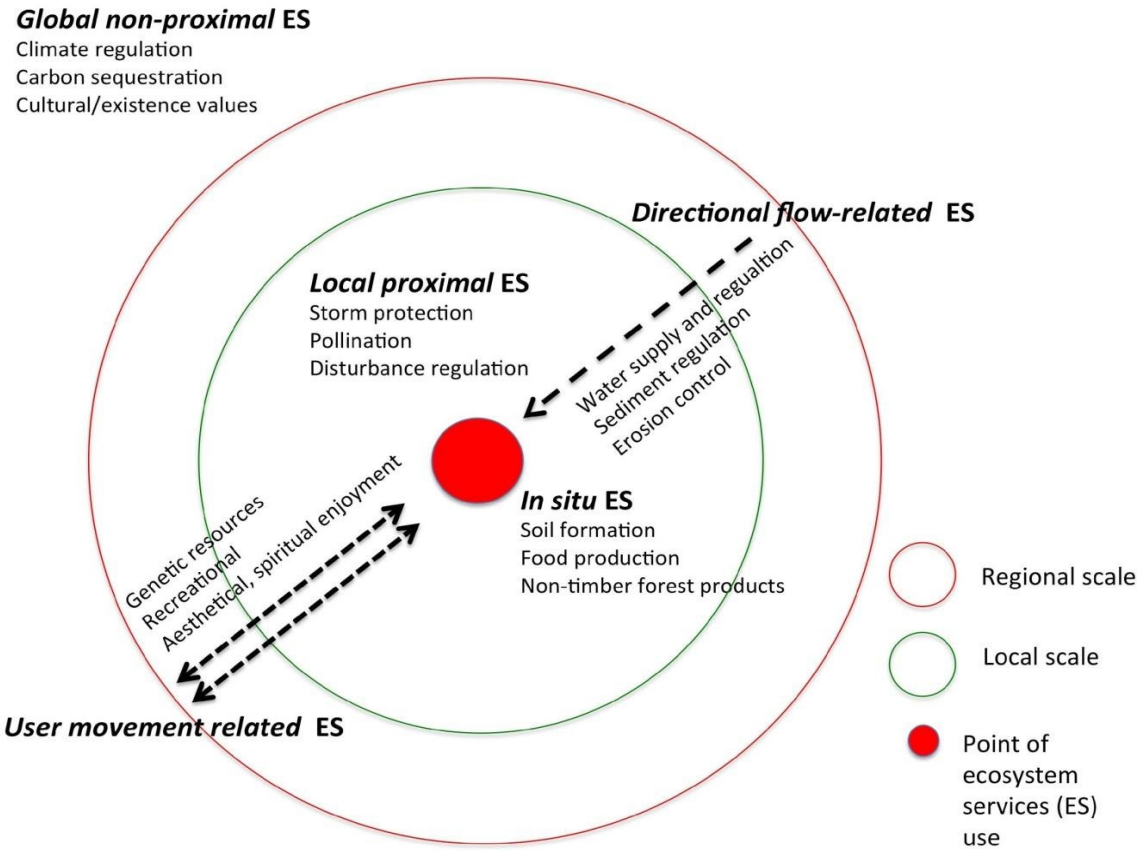

Figure 6.4. Multiscale ecosystem services approach classified according to their spatial characteristics (adapted from Costanza 2008).

Up- and down- scaling along a social organizational scale requires awareness of humanly imposed boundaries and conventions, which often are not following an ecosystem logic (O'Brien and Vickerman 2013). Even the distinction between surface and groundwater leads to different spatial extent. In addition, it is not unusual for governing bodies to be guided by multiple ways in which their constitutions are divided in space; e.g. the Auckland Council identified 30 different ways in which space is divided for water management (including water supply, water treatment, storm water, river/coastal and groundwater protection and various values from interest groups such as people from the Maori culture) (van den Belt *et al*. 2011).

While most decision making time frames are relatively short term (e.g. election and budgetary cycles), the collective human impact is changing ecosystems over decadal to centennial time-scale (e.g. IPCC scenarios of climate change, IHOPE, World3), with local spatial variations. Following an ecosystem services classification provides one option for developing a strategy for harmonizing across time scales (see 6.4.3, Figure 6.5). When developing a model harmonizing strategy that is relevant to decision making, two distinctions may be useful; 1) model building *with* decision makers and model building *for* decision makers; and 2) discrete models which present an isolated point (often more accurate but narrow) and continuous models which aim to simulate pathways (often more intuitive but comprehensive).

Understanding variations in the ecosystem types species and the influence of external factors such as climate change and socioeconomics at different temporal scales require the use of geospatial data. For example, when considering time from a (spatial) data perspective leads to a basic trade-offs between temporal and spatial resolution. It means, for example, if we are looking for high spatial resolution satellite data (e.g. Landsat 30m spatial resolution with repeat cycle 16 days), we might need to compromise with the temporal resolution (MODIS satellite remote sensing data with 500m spatial resolution and daily resolution). This is particularly relevant for in-situ ecosystems services (soil protection, food production). However, directional flow- related (from point of production to point of use, e.g. water regulation/flood protection, water supply, sediment regulation/erosion control, nutrient regulation) has a time dimension of seconds to days, as in the case of hydrology models, to multiple decades in the case of land use/cover change (UK NEA). Ecosystem services which do not depend on proximity of people to a spatial denomination (e.g. climate regulation) can span centuries.

The linkages between scales are useful to study about multi-scale scenarios and it can provide information about the number of scales at which scenarios are developed and the connection between the scales. According to Biggs et al. (2007), scenarios can be divided into three types (a) single-scale scenario exercise (b) loosely linked scenarios and (c) multi-scale scenarios that are tightly coupled across two or more scales. In the case of loosely linked multiscale scenarios, links may be established up front or after scenario development and have varying degree of flexibility. In the case of tightly coupled multi-scale scenarios, links are usually established up front and reinforced by an iterative process of downscaling and upscaling. There is generally a greater emphasis on downscaling because researchers and policy makers haves more interest in how downscaling institutional and economic drivers affect ecosystem services across regions.

Stakeholders are often not familiar with computerized models, which are perceived as a 'black box'. The results may be discarded quickly when stakeholders don't identify with proposed scenarios (Scholes and Biggs, 2004), which can cause unpopularity of tightly coupled, complex models (Kok et al, 2007). The reason why loosely linked scenarios are a success is that it allows a space for both local and global players to interact and allow the exchange of ideas that favour both in long term (Biggs et al. 2007) and provides a way to explore boundary organizations between scales and domains (van den Belt and Blake, in press).

6.4.1.2. Spatial scale

Downscaling

When fine grained-resolution data is not available, *downscaling* is a common technique to provide information particularly for local conservation issues or management needs, such as establishing priority conservation areas (Rondinini *et al*. 2005, Bombi *et al*. 2012, Fernandes *et al*. 2014). With the impossibility or high cost for obtaining fine-grained resolution data, downscaling approaches are a possible cost-effective alternative. For example, downscaling is relevant to incorporating projections of climate models into local conservation planning (Wiens and Bachelet 2010; Walz *et al*. 2014). However, fine scale climate projections that are at spatial scale relevant to conservation is often

lacking. There is a long history of developing downscaling methods for climate data that provides valuable experience for downscaling of biodiversity and ecosystem services models and scenarios (Box 6. 3). The main methods can be categorized into dynamic and statistical approaches.

There are different techniques for downscaling, most of them based on statistical relationships between biological data and environmental attributes. Some of these techniques use hierarchical models (Keil and Jetz 2014, Keil *et al*. 2013), projecting the relationship between coarse-grain species and environmental data to a finer grain using fine-grain environmental (predictor) variables. This method was, e.g., used with success for downscaling exploited fishes and invertebrates' distributions in Western Australia (Cheung *et al*. 2012). A similar approach was used by Barwell *et al*. (2014) to downscale a coarse-grained (> 100 km^2) Odonata atlas data to a more fine-grain (25km^2, 4km^2 and 1 km^2) local scale in mainland Britain (see Chapter 4). Ten different downscaling models were used for 38 species. Results suggest reasonable estimates of fine-grain occupancy, with varying errors according to species traits. High dispersal ability was associated with relatively poor downscaling predictions (Barwell *et al*. 2014). Furthermore, recent studies showed high predictive performance of downscaling models in comparison with field observations of invasive alien species (Fernandes *et al*. 2014), birds (Keil *et al*. 2013), Sardinian reptiles (Bombi *et al*. 2012), and global marine circulation (Sandø *et al*. 2014). Specific approaches such as Hierarchical Bayesian Modelling (HBM) approach is shown to improve the performance of downscaling over other statistical approaches (Keil *et al*. 2013). Those predictions may be further improved when combined with macroecological relationships (e.g. scale area relationships) (Keil *et al*. 2013).

Upscaling

Environmental problems or the consequences of human activities sometimes encompass broad spatial and temporal scales, which need global assessments and policy actions. For this reason, it is often necessary to transfer local high-resolution data to broader scales, which is an upscaling procedure (Flint and Flint, 2012). Upscaling methods seem more intuitive than downscaling, as it involves averaging values extrapolated over a larger time period or space. During this process, it is important to preserve information integrity, otherwise it can contribute to scaling uncertainties (6.5).

Most upscaling approaches use satellite imagery and combines statistical and image processing analyses, with simulation models, and field-based observations (Zhang *et al*. 2007, Chen *et al*. 2010, Fu *et al*. 2014). For example, this has been used to estimate net ecosystem exchange or carbon dioxide fluxes from flux towers to landscape and regional scales (Fu *et al*. 2014), or to upscale leaf area index (LAI) in terrestrial ecosystems from Arctic landscapes. In this last case, a simple exponential relationship between LAI and the Normalized Difference Vegetation Index (NDVI) obtained with a LANDSAT image was used to upscale LAI values (Williams *et al*. 2008). Other methods have been developed to upscale gross ecosystem production (GEP) from leaf or stand levels to larger regions (ca. 12 km^2) taking into account tree canopy structure (Hilker *et al*. 2008), using Light Detection and Ranging (LiDAR) images. Results showed a high correlation (r^2 between 0.75 and 0.91, $p< 0.05$) between estimated and measured ecosystem production. A good fit between upscaled estimated values and field measurements were also obtained with net primary productivity in China, showing that the integration of field data with remote sensing though an ecosystem model can generate

reliable estimates (Zhang *et al*. 2007). Upscaling can result in better estimates than those obtained from coarse-grained resolution images, such as those obtained from satellite remote sensing data from MODIS (Fu *et al*. 2014), possibly because they can integrate the variability observed at finer scales in the coarse-scale evaluation. Similar results were obtained by Hay *et al*. (1997) when upscaling forest stand characteristics with image resampling techniques. They showed that appropriately upscaled satellite imagery can represent a more accurate estimation than an image obtained at the upscaled resolution.

6.4.1.3. Temporal scale

Time is an important characteristic of biodiversity, which helps to understand processes, fluctuations and the distribution of species at a specific period. Temporal change can be cyclical, directional, and/or chaotic. Cyclical change refers to the variation in pattern that can occur with certain frequency, for example seasonal change in food availability. Directional change results from the influence of the past to the future but not the other way round, for example vegetation succession. Chaotic change refers to changes that are driven by random events, for instance fires, contamination, or the introduction of exotic species (Landres, 1992).

Quantifying and modelling processes and patterns in biodiversity inform the development of policies to mitigate biodiversity loss, answer basic ecological questions and identify important ecological issues (Dornelas et al. 2012). However, different phenomena of natural or human systems operate or are perceived (by humans) at different temporal scales. Processes and patterns occurring at very low spatial scale, for instance at individual level, generally occur at short temporal scales and are generally not perceived by humans, e.g., leaf colour change. They only become evident when accumulation of changes have occurred during a longer period of time, e.g., a whole season. Processes at large spatial scales occur at long temporal scales and are more “visible” to us. Given that spatial and temporal scales are correlated, system predictability will depend on an adequate adjustment of observational grain in space and time. If the frequency of observations is too low, it will not be possible to capture adequately the natural dynamics of the system (which will be faster than observations, in this case). On the other side, if the frequency of observations is too high, there will be a high temporal pseudo-replication, and the system will appear more stable than it is. At an adequate scale, it will be possible to capture the natural dynamics of the system (Fig. 6.5).

Temporal data is collected generally by remote sensing platforms and sensors. However, depending on the study’s objective, limiting factors on the use of these time-series data can be data availability and the limitation in resolution and/or extent. For instance, in multi-temporal studies either datasets are incomplete or do not have adequate resolution (both temporal and spatial) or with wrong spatial extent. In those cases, either upscale or downscale data, or modify extent are needed. Also, satellites like IKONOS and QUICKBIRD launched in 1999 and 2001 respectively, have high spatial and temporal resolution, but limited temporal and spatial extent. On the other hand, satellites with adequate extent, and global time series, usually have either coarse spatial resolution (ERS-2 GOME 40 sq km), or coarse temporal resolution (ENVISAT-MERIS every 35 days).

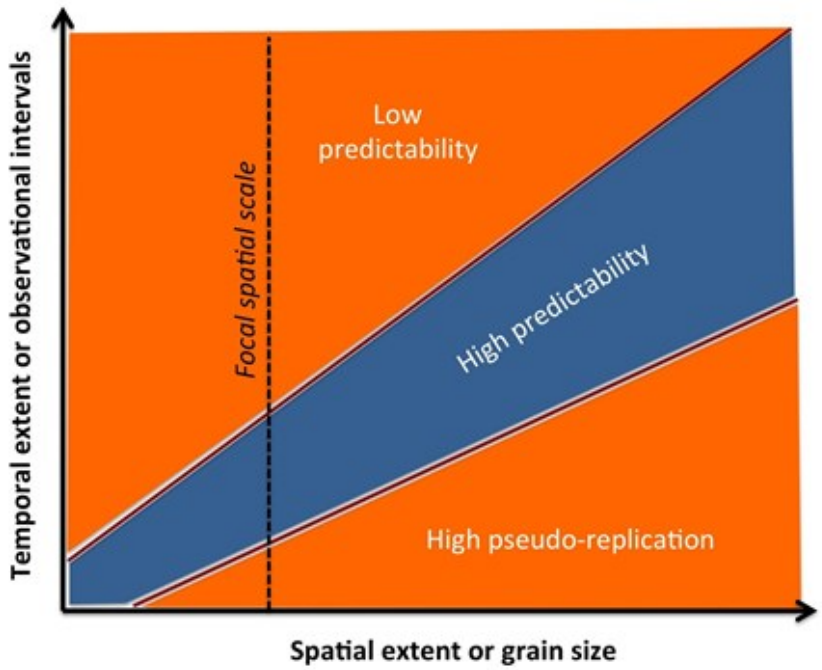

Figure 6.5.: Relationship between spatial and temporal grain of observations and predictability of ecological phenomena (adapted from Wiens 1989).

Temporal scale is also important to monitor the shifting of priorities from one ecosystem service to another ecosystem service and also changes with the change in supply of and demand for ecosystem services. Therefore, in assessing the trade-offs between ecosystem services, it is important to consider the temporal dimension because trade-offs at temporal scale allows policy makers to understand the long-term effects of one ecosystem service over another and have enormous impact on future ecosystem services (Rodriguez *et al*. 2006). Some models are developed at a large temporal scale while some exists within the short time scale (at higher time resolution). Linking and transforming between scales are necessary for holistic understanding of the ecosystem.

Upscaling

Upscaling approaches for temporal data use a combination of statistical methods and remote sensing analysis. The most common application of this approach is to address land cover change issues, including habitat loss, fragmentation and implications to biodiversity in general at all levels. In Millington et al. (2003) for example, forest fragmentation patterns in central Bolivia were identified and quantified using an incomplete set of LANDSAT imagery in order to determine whether spatial resolution affects the performance of certain landscape metrics. At national level, Greenberg et al. (2004) quantified annual rate of rainforest deforestation in Ecuador using a multitemporal satellite imagery dataset. Further, based on deforestation patterns, the authors estimate future forest loss. At global level, initiatives like the “Global Forest Change” project (Hansen et al. 2013) uses thirteen years of LANDSAT imagery to measure extent, loss and forest gain for the whole planet.

Other approaches for upscaling temporal data have been focused on development of methods and algorithms. For example, Ryu et al. (2011) proposed BESS (Breath Earth System Simulator), using the

sensor MODIS (spatial resolution of 1-5 km and a temporal resolution of 8 days). This approach, the first of its kind, allows the harmonization and use of MODIS products and the quantification of global gross primary productivity and evapotranspiration. In Du et al (2002), a new procedure for radiometric normalization between multitemporal images was developed to ensure the preservation of radiometric resolution. This procedure is in particular necessary for land cover change detection, where standard methods like ground reference data collection become costly and subjective.

Downscaling

Downscaling temporal data is primarily based on numerical models such as GCMs, (Meehl et al. 2007), statistical analysis and stochastic algorithms. Other methods look for alternatives to traditional approaches. For instance, Rebora et al. (2006), developed a new spatial-temporal downscaling procedure, called RainFARM to flood forecasting, as alternative to stochastic algorithms. RainFARM generates small scale rain rate fluctuations that preservers the spatio-temporal evolution of rainfall patterns. Mendes et al. (2010) proposed an alternative to numerical models, and developed a temporal neural network for downscaling global climate outputs (downscaling daily precipitation time series).

6.4.1.4. *Cross*-scale interactions

Cross-scale interactions are defined as interacting processes across scales (spatial, temporal or organizational), resulting in nonlinear dynamics (Peters et al. 2007, Box 6.5). Many processes or organisms interact with their environment at different spatial scales, and then multiple scale models perform better than single scale models. Indeed, Boscolo and Metzger (2009) showed that multiscale models (which considered pattern-process relationships at different extents in a unique model) always performed better than single-scale model to predict the occurrences of bird species in a tropical forest, probably because extinction and recolonization processes that control species occurrences simultaneously act at different scales. However, with cross-scale interactions it can be even harder to model accurately some processes. For instance, forest dieback in New Mexico (USA) depends on factors occurring at global scales (severe drought and unusual warmth), regional scales (insect mortality agents and fire that move throughout the landscape) and local scales (environmental stress operating on individual trees), and their interactions (Allen 2007). Vegetation dieback interacts with fire activity by modifying fuel amounts, and insect herbivore populations interact with the stress operating at the plant hosts, sometimes resulting in nonlinear pest outbreak dynamics. There are many other examples of important ecological processes that are modulated by processes that interact across scales, such as bark beetle eruptions (Raffa et al. 2008), parasitism (Tompkins et al. 2011), fire disturbances (Falk et al. 2007), runoff and erosion processes (Allen 2007).

Cross-scale interactions can involve both human and natural systems. The management of salmon resource in the Columbia River Basin, USA, is a good example (Peterson 2000). Conflict within and among groups of individuals and organizations that have different interests, values, and power can be viewed as an interacting hierarchical structure. Particularly, the interests of local loggers, fishers and environmentalists are in conflict with the interests of those who are planning hydropower utilities, as well as pitting native fishers against offshore fishermen and environmental groups (Peterson 2000). Those social or organizational scale interactions are thus particularly relevant for salmon management.

Those different interacting spatial, temporal and organizational scales can generate emergent behavior or nonlinear dynamics with thresholds that could not be predicted at single or multiple independent scales (Peters et al. 2004, 2007). If those cross-scale interactions are not considered, our ability to understand and identify those nonlinearities and threshold behaviors are limited. As a consequence, cross-scale interactions make interacting multiscale modelling approaches particularly important in order not only to consider the different factors that impact species distribution or ecological processes at different scales, but also to integrate their interactions across scales (see also section 6.5). Due to the complexity and the uncertainty involved in both upscaling and downscaling, an intermediate but integrated framework or model that can provide solutions to the problem of scaling would be necessary.

An issue that is related to cross-scaling is the consideration of boundaries between scale. Boundaries are defined as transition zones between observational units (e.g., ecosystems, human or social systems). In ecology, boundaries have been shown to play an important role in the dynamics and functioning of landscapes (Forman and Godron 1981, 1986, Wiens et al. 1985, 1993, Holland 1988, Holland et al. 1991, Naiman et al. 1988, Naiman and Décamps 1990). Particularly, boundaries can act as semipermeable membranes, controlling biotic and abiotic flows (Wiens et al 1985, Pinay and Décamps 1988), and affecting species composition and diversity, acting in the balance between edge species and core area species (Lovejoy et al. 1986, Hansen and di Castri 1992, Décamps and Tabacchi 1994, Tabacchi 1995). Boundary frequency and type also have been used for quantitative descriptions of landscape patterns, as in the case of the patchiness index (Romme 1982), the landscape contagion index (Li and Reynolds 1993) and several fragmentation indices (Li et al. 1993, Zipperer 1993). Two approaches are often used to detect boundaries. When using continuous variables, boundaries between system elements are placed where the variables show an important rate of change (Fortin 1994). Boundaries are thus critical thresholds, i.e. points at which there are abrupt changes in the structure or functioning of the studied system. In the second approach, discrete or categorical system units are used and boundaries are defined as limits of those more homogeneous areas (Johnston and Bonde 1989, Johnston et al. 1991), and can be characterized by two adjacent units.

6.4.2. Harmonization of scenarios

Scenarios that are related to biodiversity and ecosystem services are produced from a number of international, national and local assessments. Each of them was developed for a specific set of objectives, such as greenhouse gas emission or sustainable development. Most of them employed different methodologies in developing the scenarios, even between different iterations of the assessment, depending primarily on the goals, spatial scales, social-economic and policy context, and resources available for the scenario development exercises (Biggs et al. 2007).

Approaches for harmonizing scenarios for biodiversity and ecosystem services across scales are not yet well developed. Existing reviews on this topic (e.g., Biggs et al. 2007) suggest that the first step in harmonizing scenarios is to identify the number of scales and/or domains that need to be linked and the strength of links that are anticipated between scales and domains.

To downscale scenarios (see Biggs et al. 2007), scenario pathways at large scale can be used as boundary conditions to frame developments of finer-scale scenarios. This ensures that outcomes of the regional scenarios do not conflict with those of the global scenarios. Also, in some case, the entire large scale scenario pathway can be translated into regional pathway. Moreover, scenarios at different scale may be developed without much reference to one another but they can then be mapped together (see section 6.4). Finally, large scale scenarios can be applied directly to examine regional policies without the need for development of complete regional scenarios. Some of the methods for downscaling scenarios can be applied to upscale scenarios from finer to broader spatial scales. Generally, to upscale finer scale scenarios to large spatial scale, scenario pathways should not conflict with one another at the larger scale. Also, teams of developers of finer scale scenario could collaboratively develop consistent regional and global scale scenarios. However, existing examples of scaling of scenario have greater emphasis on downscaling than on upscaling, limiting the available experience that could be drawn on.

Available literature on standardizing and harmonizing scenarios for environmental assessments suggested three main steps: (1) identify and discuss the application of the scenarios and their main characteristics (2) compare the key assumptions and storylines behind the scenarios, and (3) compare the trends observed in the main scenario methodology in relation to policy making (van Vuuren *et al*. 2012). Scenarios can be categorized into “scenario families” or archetypes according to their underlying assumptions, storyline, logic, and characteristics. Some of the key elements in which these scenarios differ include risk-perception and resulting policy actions to environmental change, spatial scale of drivers and systems, trends relative to the past, and degree of cooperation in the society (van Vuuren *et al*. 2012). Scenarios belonging to the same archetype or family can be linked together to provide more comprehensive descriptions of possible futures across scales and domains (Biggs et al. 2007).

Mapping of scenarios onto archetypes or families could be facilitated using tabular or graphical representation. For example, existing scenarios for global environmental assessments include the Global Scenario Group (GSG)’s work on Great Transitions (Raskinet *et al*. 2002, 2005), the IPCC Special Report on Emission Scenarios (SRES) (Nakicenovic *et al*. 2000), UNEP’s Third Global Environmental Outlook (GEO3) (UNEP 2002) and the World Water Vision work (Cosgrove and Rijsberman 2000, van Vuuren *et al*. 2012) (Table 6.4). To harmonize these scenarios, firstly, they are characterized by eight broad attributes: economic development, population growth, technological development, main objectives, environmental protection, trade, policies and institutions, and vulnerability to climate change (rows in Table 6.4). Based on these attributes, they can be categorized into different archetypes or scenario families: Global Sustainable Development, Business As Usual, Regional Competition, Economic Optimism, Reformed Markets and Regional Sustainability (different columns in Table 6.4). For example, the IPCC has developed multiple sets of socio-economic scenarios for different assessment reports (ARs) e.g., Special Reports on Emission Scenarios (SRES, developed in AR4) and Shared Socio-economic Pathways (SSPs, developed in AR5) (O’Neill *et al*. 2013). These IPCC scenarios can be characterized and mapped graphically according to the underlying socio-economic challenges for mitigation and adaption of each scenario (Figure 6.6).

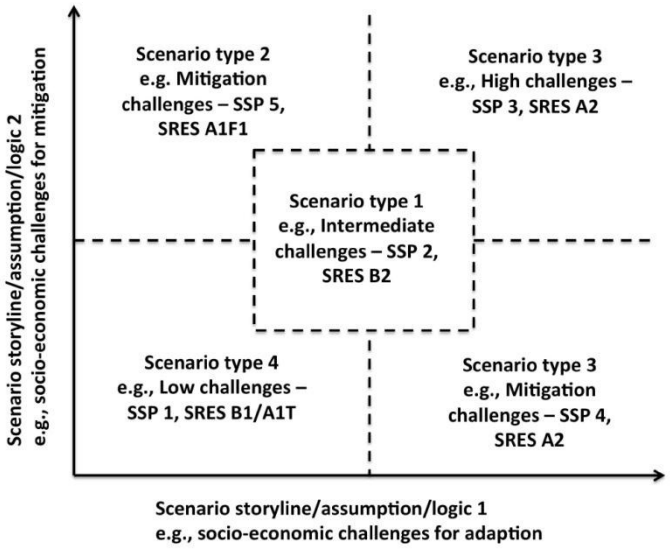

Figure 6.6. An example illustrating the mapping of scenarios onto scenario familiies or archetype based on the storyline, assumption and logic of the scenarios. The example is on mappying the Special Reports on Emission Scenarios (SRES) and Shared Socio-economic Pathways (SSPs) developed by the IPCC. (based on O'Neill *et al*. 2013).

Table 6.4. Archetypes or families of scenarios from previous global environmental assessments and their key characteristics and assumptions (adopted from van Vuuren *et al*. 2012).

Archetype/scenario family	Global sustainable development	Business as usual	Regional competition	Economic optimism	Reformed markets	Regional sustainability
Economic development	Ranging from slow to rapid	Medium	Slow	Very Rapid	Rapid	Medium
Population growth	Medium	High	Low	Low	Low	Medium
Technological development	Ranging from medium to rapid	Medium	Slow	Rapid	Rapid	Ranging from slow to rapid
Main objectives	Global sustainability	Not defined	Security	Economic growth	Various goals	Local sustainability
Environmental protection	Proactive	Both reactive and proactive	Reactive	Reactive	Both reactive and proactive	Proactive
Trade	Globalization	Weak globalization	Trade barriers	Globalization	Globalization	Trade barriers
Policies and institutions	Strong global governance	Mixed	Strong national governments	Policies create open markets	Policies target market failures	Local action
Vulnerability to climate change	Low	Medium	Mixed – varies regionally	Local action	Low	Low
Examples						
SSP	SSP1	SSP2	SSP3/SSP4	SSP5		
SRES	B1 (A1T)	B2	A2	A1F1		B2
GEO3/GEO4	Sustainability First		Security First	Market First	Policy First	
Global Scenario Group	New Sustainability Paradigm		Barbarization	Conventional World	Policy Reform	Eco-communalism
Millennium assessment	Techno-garden		Order from Strength		Global Orchestration	Adapting Mosaic

6.4.3 Benchmarking of models

Benchmarking is the process of systematically comparing sets of model predictions against measured data in order to evaluate model performance. It should also help identifying processes that may be poorly represented in models (McCarthy et al. 2012). Model inputs are commonly harmonized across several models. Benchmarking is common practice in fields other than ecology: for example, Global

Circulation Models included in the IPCC need to be able to hindcast historic temperature trends, derived from multiple sources. In scenario work, model predictions are sometimes weighted by the model performance in relation to the benchmarks (e.g. Rammig et al. 2011). General guidelines for benchmarking environmental models have been developed by Bennett et al. (2013) and a particular framework for land (ecosystem) models by Luo et al. (2012), but we are not aware of any multi-model benchmarking activity with biodiversity models at the species level or ecosystem service models. The framework proposed by Luo and colleagues as part of the International Land Model Benchmarking (ILAMB) project includes 1) targeted aspects of model performance to be evaluated, (2) a set of benchmarks as defined references to test model performance, (3) metrics to measure and compare performance skills among models, and (4) model improvement. To improve the credibility of species-based biodiversity and ecosystem service models, benchmarking should be further developed. Species distribution models, for example, could be tested against observed historical changes in species ranges (Chen et al. 2011).

Benchmarking should be accompanied by standardized model documentation and archiving of model source codes, input data, model results and model result processing tools. For biogeochemical models, such as global terrestrial carbon cycle models, guidelines for developing standardized archives were suggested by Thornton et al. (2005). The current situation is unsatisfactory. Even though the results from numerical models should in principle be 100% reproducible, this is often not the case, e.g. because complex models are often under constant development, implying that references to published model descriptions are outdated. Archives for this purpose still have to be developed (Thornton et al. 2005).

6.5 Uncertainty in linking and harmonizing models

6.5.1 Cascade of uncertainty from models linking biodiversity and ecosystem services

Uncertainty in model projections for any time horizon and spatial scale arises from three sources: (1) internal variability, (2) model uncertainty and (3) scenario uncertainty (Figure 6.7). Internal variability is caused by natural physical, ecological and social processes that are intrinsic to systems. It arises even in the absence of any human drivers. Model uncertainty is comprised of parameter and structural uncertainty (Tebaldi and Knutti, 2007) and uncertainty from model assumptions (Platt *et al*. 1981). Parameter uncertainty relates to the specific parameter values used in given equations that determine the behavior of a model (Tebaldi and Knutti, 2007; Knutti *et al.*, 2010). Structural uncertainty relates to different ways in which ecological, social and economics interactions can be mathematically represented. Scenario uncertainty relates to the many possible futures that may happen due to differences in the natural and/or anthropogenic forcing that drive the model simulation. In modelling biodiversity and ecosystem services, it may be an explicit goal to maximize scenario uncertainties because scenarios are useful ways to take into account uncertainties and to link between them various scales and dimensions (Carpenter 2002; Swart *et al*. 2004). Uncertainties from one model component can carry on into other components, and in some cases, be magnified when

they are linked.

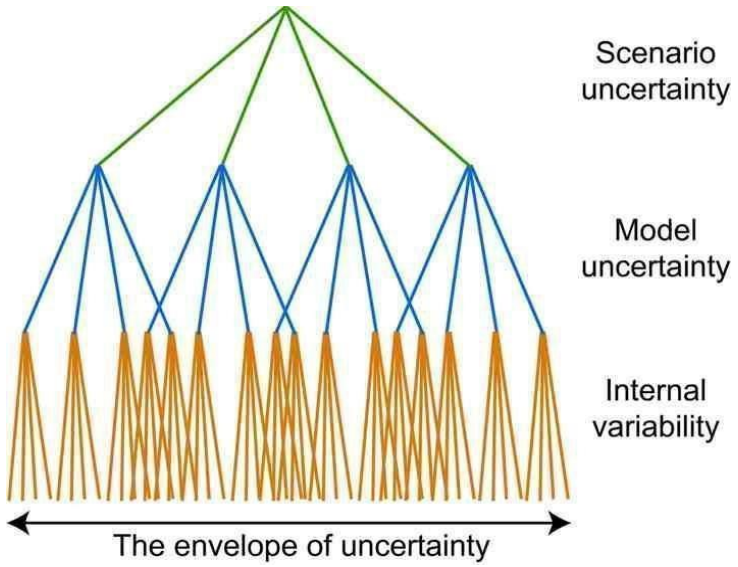

Figure 6.7: Cascade of uncertainties of linking biodiversity and ecosystem services models.

Linking models across spatial and temporal scales and domains may potentially enlarge the envelope of uncertainty from the different types of uncertainties. To assess confidence in model projections, we suggest three possible tiers of evaluation: (1) consistency with mean spatial patterns and temporal patterns across the scales of interest; (2) consistency with past observed responses to variability; and (3) consistency with attribution of observed temporal and spatial trends to particular drivers. Representative model metrics are needed to evaluate different aspects of model projections.

The first tier of evaluation can be applied to all biodiversity and ecosystem service projections so that implausible projections can be identified. Model simulations that do not reproduce the broad mean spatial and temporal patterns of change suggest that the models may not sufficiently represent the biophysical and socio-economic components that are important for the aspects of biodiversity or ecosystem services and scale of interest. Also, data are generally available for such broad-scale evaluation (Table 3). This is consistent with the description of Overland *et al.*(2011) of a coarse "culling" of models if they are in very stark disagreement with observations.

Limited availability of data sets may make it impossible to evaluate models for at all three tiers. In particular, data is challenged by issues of consistency between timeframe and spatial scales and confounding effects of multiple human pressures such as climate and fishing. These limitations of available data should not prevent application of the models and deem all model projection unreliable, as projections also gain credibility through their reliance on robust ecological and physiological principles. It should, however, temper interpretation of results.

6.5.2 Scaling errors and uncertainty

Downscaled and upscaled predictions can differ from observed values for different reasons, including nonlinearity in scaling properties (or in the functional relationships between processes and environmental variables; Jarvis 1995), species spatial aggregation or patchiness and cross-scale

interactions. As a consequence, the higher the order of magnitude of scaling predictions, the higher is the risks of propagating errors (Jarvis 1995).

The first potential source of error and uncertainty in extrapolating pattern across scales is scale variance (Figure 6.8). It is reasonable to think that the larger the extent (with a constant grain) or the higher the grain (with a constant extent), the larger will be the heterogeneity observed, and the higher will be the probability of having discontinuity in the properties of the observed object with the change in scale. For example, temperature and precipitation in mountain areas are highly affected by the heterogeneity of the relief, which is unevenly distributed spatially. As a consequence of this local aggregated heterogeneity, there are sharp differences in mountain areas between original (field-based) temperature and precipitation values and downscaled data sets provided by global climatic models (Karynand and Williams 2010). Those abrupt changes or transition zones in system properties delimit "domains of scale". Inside each domain, scale variance is linear (i.e., the functional relationships among studied components are constant), while in between domains, properties change abruptly. Scaling inside the same domain of scale, or for objects or systems that present scale invariance (such as fractal systems), is usually simple and can be done with relatively simple regression functions. For example, it is well known that the size and frequency of disturbances are inversely related (e.g., large-scale disturbances are less frequent than small-scale disturbances), and this can be easily represented by a power-law function (White *et al*., 2008). However, scaling between two or more domains of scale, where non-linear relationships occur, may be much more challenging to apprehend with simple mathematical models, and thus can lead to significant errors propagation. For some authors, extrapolations across domains of scale are not recommended (Wiens 1989).

A second significant source of scaling errors is related to species' distributional features, such as species spatial aggregation, which may bias estimates if the scaling process is nonlinear (Stoy *et al*. 2009). Errors are commonly more severe when projecting the location of species, compared to the global range. Indeed, downscaling usually tends to lead to an overestimation of species distributions (Sardà-Palomera *et al*. 2012). However, precise information on species distribution at a local level is crucial for local decision making (Franklin *et al*. 2013), such as for identifying biodiversity hotspots (Sardà-Palomera *et al*. 2012). In those cases, a more complex framework, combining niche and spatial models with spatially explicit fine-grain approaches is necessary to reduce errors when modeling species locations (Azaele *et al*. 2012). Different techniques have been proposed to deal with species' spatial aggregation, such as the scale transition theory (Melbourne and Chesson 2006) and the shot noise Cox processes (SNCP), which allow a better prediction of population estimates at fine scales starting from coarser ones (Azaele *et al*. 2012).

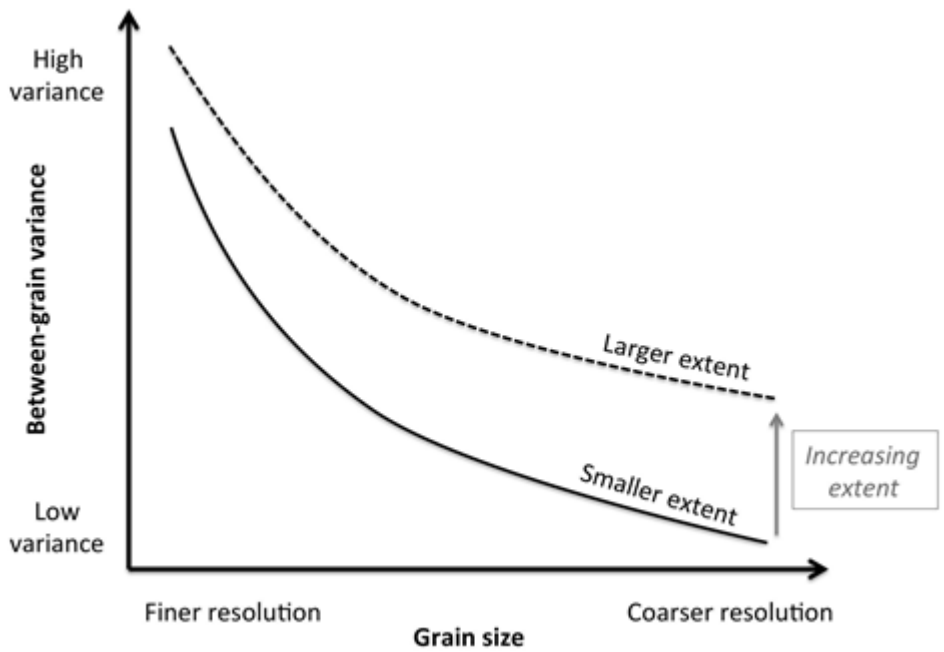

Figure 6.8. Expected relationship between spatial (or temporal) resolution and between-grain (or between temporal observation) variance in heterogeneous landscapes (adapted from Wiens 1989). As resolution decrease (increase in grain size), variance between sampling or observational units (i.e. grains) should decrease (but variance inside sampling units, not represented here, will increase). An increase in the temporal or spatial extent will also expand the potential observed heterogeneity, increasing thus between-grain variance. The higher is this variance (i.e. the higher is the resolution and the extent), the higher will be the error and uncertainty in extrapolating pattern across scales.

Another additional source of error is related to cross-scale interactions, when processes interact at different spatial or temporal scales. Errors and uncertainty are thus inherent to any scaling procedure. Carbon flux from woody debris, for example, is simultaneously affected by climate, site environment and species-specific variations in wood characteristics (Weedon *et al*. 2009), and by the interactions of those processes that occur at different spatial and temporal scales. As a consequence, any upscaling or downscaling framework will need to consider interactions among those processes to properly model carbon dynamics. In this sense, it could be useful to consider species traits that regulate wood and decomposition characteristics at a more local (plot) scale even in global terrestrial carbon cycle models (Weedon *et al*. 2009). To reduce this problem, it is first crucial to identify “domains of scale” and theirs respective scaling thresholds, which should reflect fundamental shifts in underlying processes that regulate the studied system (Wu and Li 2006), and to deal with caution with any extrapolation across domains. It is thus necessary to identify cross-scale interactions and to develop multiple- scaled models that allow integrating those interactions across scales.

Ground observations and global models on coarse spatial resolutions are important sources for data of simulating changes of biodiversity and ecosystem services (Box 6.3). However, too sparsely distributed ground observations are often unable to satisfy the data requirements of regional or local stakeholders and decision makers. One major problem is how to estimate values for locations where reliable estimates can not be generate by interpolation. Many global models are difficult to be used at

regional and local levels because their spatial resolutions are too coarse or region-specific important processes are missing. Global models have to be down-scaled and regionally tested or region- and site-specific models have to be developed (e.g. Hickler et al. 2012, Seiler et al. 2014). High-quality ground observation data and model benchmarking at the desired scale is crucial for any of the two approaches.

6.6. Conclusions

Because of the complexity of systems relevant for assessing the current status and trends of biodiversity and ecosystem services and for developing future scenarios, it is often necessary to link models or scenarios representing different components of the relevant social-ecological systems. Multiple parallel efforts for modelling and assessing biodiversity and ecosystem services for different domains and at different scales exist. Models and scenarios that integrate feedbacks and tradeoffs across temporal and spatial scales and among dynamic societal economic and natural systems can address complex challenges and guide decision making. However, the question of whether biodiversity and ecosystem service models should be directly linked depends on the research objectives and societal demands. Nevertheless, we think that not all useful linkages have been utilized and more direct linkages have great potential.

To facilitate the development of methods for linking and harmonizing scenarios and models, we need to build communities of multi-disciplinary researchers and practitioners to support such research and decision support. The rapidly growing number of model intercomparison projects facilitate the harmonization of models and cultivate a community to make advancements in the long-term. However, existing intercomparison projects are sectorally focused, e.g., for carbon cycling, forest productivity, agriculture or fisheries. Strengthening the linkages between biophysical and human domains is a major challenge. There are increasing efforts in this area such as IAMs and ecosystem services assessments. However, more extensive development and application of these approaches should be encouraged to accelerate the state-of-the-art in linking models and scenarios across social and natural domains.

Box 6.1 Using scenarios of global change to project species distributions and biodiversity trends into the future

Visconti *et al*. (2015) projected trends of ca. 400 species of terrestrial large mammals in two widely used indicators of population abundance (the Living Planet Index; LPI) and extinction risk (the Red List Index; RLI) under different climate and land-use change scenarios. These two complementary indicators have been adopted by the CBD to measure progress towards global biodiversity targets.

The impact of climate change on species' geographic range was quantified by fitting bioclimatic envelope models to the present-day species' distributions, and projecting these under future climate associated with two scenarios of socio-economic development until 2050. The two scenarios, developed for the Rio+20 conference held in Rio in 2002 represent business-as-usual production and

consumption patterns and rates, or reduced consumption (PBL 2012). For each socio-economic scenario, three species responses to climate change were tested: 1) species cannot disperse into new climatically suitable areas; 2) species can expand their distributions each generation by a median dispersal distance estimated using statistical models; or 3). Species adapt locally (their geographic ranges are not affected by climate change). Projected species ranges were further assessed for compatibility with species' fine-scale ecological requirements with habitat suitability models (Rondinini et al. 2011, Visconti et al. 2011) based on species' land cover and altitudinal preferences and sensitivity to human disturbance. These models were applied to projected land-use maps from the IMAGE model (Bouwman et al. 2006) under each scenario, to quantify for each species the extent of suitable habitat (ESH). The distribution projected under each climate change scenario was taken as the extent of occurrence (EOO). The ESH was treated as the maximum potential value of area of occupancy (AOO). The number of mature individuals of a species was estimated by multiplying the AOO by population density from observed and modelled data. These parameters were applied to Red List criteria to evaluate each species' Red List category for each year under each scenario, from which the overall RLI was calculated following Butchart et al. (2007) (Fig. B6.1). The uncertainty around the proportion of mature individuals and proportion of suitable habitat occupied (AOO/ESH) was incorporated into RLI projections by randomly sampling these parameters from a distribution with intervals gathered from the literature and performing a Monte Carlo simulation. Estimates of mature individuals for each species and each year were used to generate the LPI for each scenario following Collen et al. (2009). The methodology was validated through hind-casting species distributions and biodiversity indicators from 1970.

Testing these on terrestrial carnivore and ungulate species, Visconti and colleagues found that both indicators decline steadily, and by 2050, under a business-as-usual scenario, the LPI declines by 18-35% while extinction risk increases for 8-23% of the species, depending on assumptions about species responses to climate change. Business-as-usual will therefore fail CBD target 12 of improving the conservation status of known threatened species. An alternative sustainable development scenario reduces both extinction risk and population losses compared with Business-as-usual and could lead to population increases.

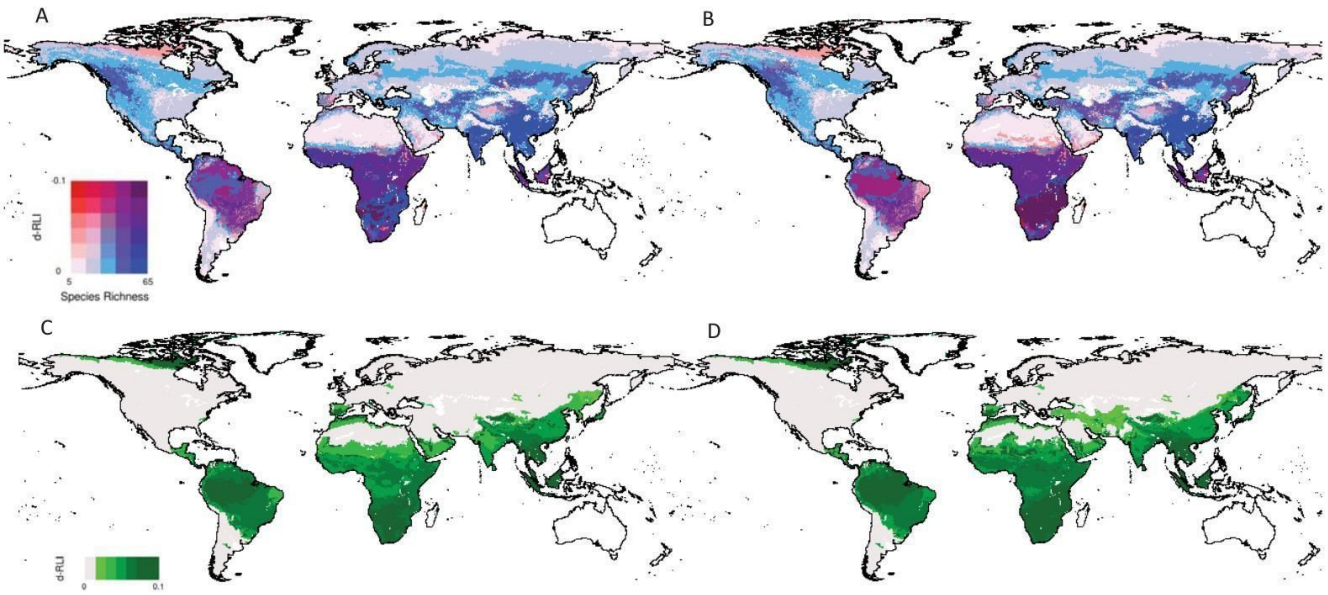

Figure B6.1 Spatial patterns of trends in Red List Index. (A,B) Bivariate plot showing spatial pattern in species richness and trends in the Red List Index (d-RLI) between 2010 and 2050 under the business-as-usual scenario, with land use and climate change and assuming maximum dispersal (A) and no dispersal (B). (C-D) Relative improvements in d-RLI for the reduced impact scenario relative to business-as-usual for year 2050 under maximum dispersal (C) and no dispersal (D). Areas in white contain fewer than 5 species per grid cell modeled in 2010.

Box 6.2: Integrated assessment model - The IMAGE 3.0 Framework

The IMAGE integrated assessment modelling framework has been developed to understand how global, long-term environmental change and sustainability problems develop over time, driven by human activities, such as economic development and population growth (Fig. B6.2). Similar to other integrated assessment models, IMAGE can be used to identify problems of global environmental change, and to advise on possible response strategies. Earlier versions of the IMAGE model have been used to support various international assessments, including IPCC assessments, UNEP's Global Environment Outlooks, OECD's Environmental Outlooks and the Millennium Ecosystem Assessment. Moreover, the model has been extensively used in the scientific literature.

IMAGE assesses the impacts of socio-economic drivers on the environment, such as climate change, land-use change and pollution, and these provide inputs to the GLOBIO3 model to help evaluate impacts on biodiversity. GLOBIO3 was developed to provide information to policy makers at the international level on current biodiversity status and future trends (Alkemade *et al*. 2009). The model delivers quantified results on the impact of environmental drivers and potential policy options on biodiversity. Potential trends in biodiversity are addressed in future scenarios, including the expected outcome in the absence of additional policies to prevent biodiversity loss. GLOBIO3 delivers output in terms of MSA (species abundance relative to the natural state of original species), land cover and land use (high resolution land use and land use intensity based on GLC2000 and IMAGE), SRI (species richness index) and Wilderness area.

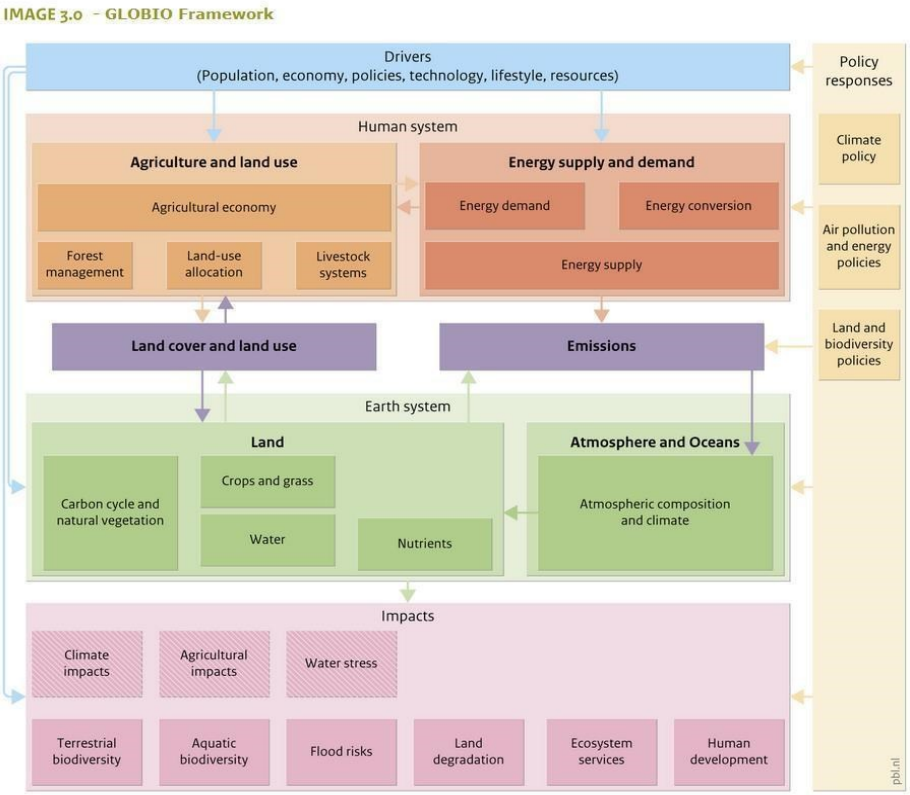

Figure B6.2.1. Framework of the IMAGE 3.0 Integrated Assessment Model.

Box 6.3 Interpolation of local information with extracted global information

Ground observation, a significant source of local information, can obtain high accuracy data at observation points, but observations at fixed positions are confined within some limited dispersal points. Sparsely distributed data are often unable to satisfy the data requirements of most ecosystem change studies. One major problem is how to estimate values for locations where primary data is not available (Akinyemi and Adejuwon 2008). An earth surface (a region) is controlled by a combination of global and local factors, which cannot be understood without accounting for both the local information and global information (Yue, 2011).Introduction of global information by establishing statistical transfer functions (STFs) is an efficient approach to improve the estimation error of ecological variables for locations where primary data is not available.

For instance, a spatial interpolation of mean annual precipitation (MAP) in China changes spatially as a function of latitude, longitude, and topographic variation (Yue et al., 2013). MAP shows spatial non-stationarity and must be estimated with a geographically weighted regression (GWR). In fact, most atmospheric moisture is derived by the evaporation of ocean water and controlled by the transportation of air masses from the tropics to the polar areas. During this transportation, air masses cool down, leading to continuous condensation and rain-out from low to high latitudes on both hemispheres (van der Veer et al. 2009). Latitude and longitude can be used to reflect the influence of general circulation and continentality on precipitation. Spatial variability of precipitation in complex

terrain is caused by the dependence of precipitation on altitude and windward effects (Franke et al. 2008).

A statistical analysis of precipitation data from the 661 meteorological stations (Fig. 1a) demonstrates that precipitation has a close relationship with topographic aspect, latitude, longitude and elevation. The STF of MAP under a BOX-COX transformation was derived as a combination of minimized residuals output by HASM with a GWR using latitude, longitude, elevation, impact coefficient of aspect and sky view factor as independent variables. The MAP transfer function is abbreviated as HASM-GB. Let $\mathbf{x} = (1, Lo, La, Ele, ICA, SVF)$, in which La represents latitude, Lo refers to longitude, Ele is elevation, ICA the impact coefficient of aspect on precipitation, and SVF the sky view factor. Then the STF of MAP under a BOX-COX transformation can be formulated as,

$$\Psi_\alpha\left(Ps_i(t)\right) = \boldsymbol{\theta}_{gwr} \cdot {}^{T} + HASM\left(\Psi_\alpha\left(P_k(t)\right) - {}_{gwr} \cdot {}^{T}\right) \quad (1)$$

$$\begin{aligned}\boldsymbol{\theta}_{gwr} \cdot {}^{T} &= \left(\theta_{i,0} \quad \theta_{i,1} \quad \theta_{i,2} \quad \theta_{i,3} \quad \theta_{i,4}\right)\left(1 \quad Log_i \quad Lat_i \quad Ele_i \quad ICA_i\right)^T \\ &= \left(\theta_{i,0} + \theta_{i,1}Log_i + \theta_{i,2}Lat_i + \theta_{i,3}Ele_i + \theta_{i,4}ICA_i\right)\end{aligned} \quad (2)$$

$$MAP_i(t) = MAX\left\{MAP_i(t)\right\} \cdot \left(\alpha \cdot \Psi_\alpha\left(Ps_i(t)\right) + 1\right)^{\frac{1}{\alpha}} \quad (3)$$

where $Ps_i(t) = \frac{MAP_i(t)}{\mathrm{MAX}\left\{MAP_i(t)\right\}}$, $MAP_i(t)$ is the simulated result of MAP at the grid cell i ($i = 1, 2, \ldots, 19606916$) in the period of t; $P_k(t) = \frac{MAP_k(t)}{MAX\left\{MAP_k(t)\right\}}$, $MAP_k(t)$ is the observed value at meteorological station k in the period of t; $\Psi_\alpha\left(P_k(t)\right) = \left(P_k^\alpha(t) - 1\right)/\alpha$ is a BOX-COX transformation of annual mean precipitation $P_k(t)$ at observation station k in the year t, in which 〈 is a parameter to be determined and equals to 0.475 for the special case of China; Log_i refers to longitude of grid cell i; Lat_i represents latitude; Ele_i is elevation; ICA_i is the impact coefficient of aspect on precipitation; $\theta_{i,j}$ ($j = 1, \ldots, 5$) are coefficients to be simulated.

The introduction of spatial non-stationarity analyses into the interpolation of meteorological stations has greatly improved the interpolated climate surfaces (Fig.1c). For instance, IDW was applied to interpolation of MAP in Chinaduring the period from 1960 to 2010, taking a digital elevation model (DEM) as secondary data (Fig. 1b); mean absolute error of the MAP was 102.23 mm. The mean relative error of the interpolated MAP decreased by 3% due to the combination of Geographically Weighted Regression with IDW; in addition, when a method for high accuracy surface modelling (HASM) is used, which has much better performance comparing with the classical methods such as IDW, Kriging and Spline (Haber, 2012; Jorgensen, 2011), the accuracy of the interpolated MAP has been increased by 3% (Yue *et al*., 2013).

Figure B6.3 a) Spatial distribution of the meteorological stations with location information in China, b) Digital elevation model of China, c) Surface of mean annual precipitation in China.

Box 6.4: Case study – Manawatu watershed, New Zealand

The Manawatu River watershed is located in the North island of New Zealand. The river itself is unique in that it cuts through a mountain range to reach the sea. The watershed is home to about 200,000 people and the land intensively used for agriculture, particularly dairying. Historically, steep hills were forested, but forest is now down to 20% of the original cover (Dymond et al, 2010). Wetlands have also been reduced with 97% converted to other land use types (Dymond et al, 2010). Māori, the indigenous peoples of New Zealand, have been settled in the Manawatū for centuries.

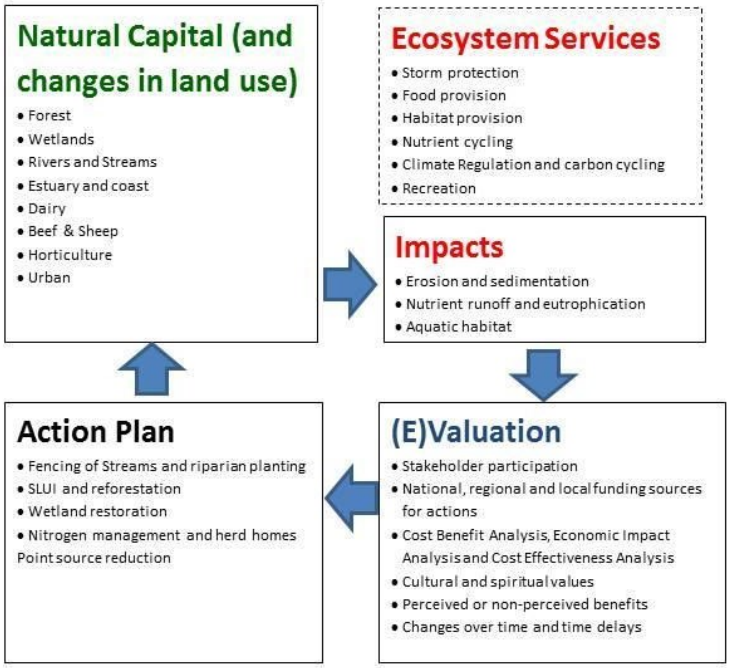

Figure B6.4.1 Generic overview of interlinking issues from an Ecosystem Services perspective, providing a start point for stakeholder dialogue.

In 2009, a newspaper article labelled the Manawatu the 'river of shame'. Researchers had ranked it as the worst of 300 rivers tested for daily change in dissolved oxygen (Clapcott & Young, 2009). In

response, the regional government initiated a collaborative process to bring together stakeholder which became the Manawatu River Leadership Forum. This coincided in timing with MBIE funding Ecological Economics Research New Zealand to undertake the 'Integrated Freshwater Solutions' (IFS) action research project.

The IFS project worked with the Manawatu River Leadership Forum. Stakeholders took part in a Mediated Modelling (MM) process which can be described as model building *with* rather than *for* stakeholders (van den Belt, 2004). MM was used to support the collaborative effort to understand the underlying systems driving poor water quality, specifically those causing eutrophication, erosion and habitat destruction. System dynamics (using STELLA software) was the modelling approach used in the workshops. A scoping model (Costanza & Ruth, 1998) was constructed. A detailed description of model context, process and content can be found in (van den Belt, Forgie, Singh, & Schiele, 2011). The results of the merged stakeholder process were mixed (see van den Belt et al, 2013). The overview of the MM model is illustrated in Figure B6.4.1.

The MM scoping model was used to 'play out' some of the scenarios associated with the detailed 'Action Plan' signed off by the Manawatu River Leaders Forum. An example is funding to reduce erosion by retiring land and planting trees as part of the the Sustainable Land Use Initiative (SLUI). Figure 6.4.2 illustrates sediment loading in tonnes per year when the impact of the Sustainable Land Use Initiative is taken into account.

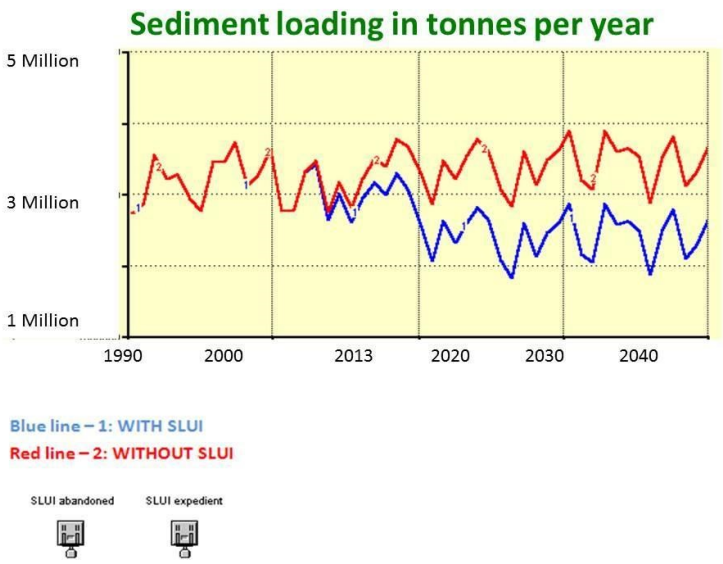

Figure B6.4.2 Sediment loading in tonnes per year taking the impact of the Sustainable Land Use Initiative into account.

The MM effort *with* stakeholders was subsequently translated and enhanced to develop a spatially explicit, dynamic Multi-scale Integrated Model for Ecosystem Services (MIMES) (Altman, Boumans, Roman, Gopal, & Kaufman, 2014). This involved scientists from different disciplines and research organizations. MIMES uses Simile software and links multiple data bases in a way that allows the bundling and trading of ecosystem services over time and space. An overview of MIMES for the Manawatu watershed is shown in Figure B6.4.3.

MIMES can be used to output scenarios as shown in Figure B6.4.4. Here erosion control (as undertaken for example by the SLUI programme) is mapped to highlight the change in 'hotspots' over time and space (Crossman and Bryan, 2009). There was no research funding available to fully validate and ground-proof the Manawatu MIMES model.

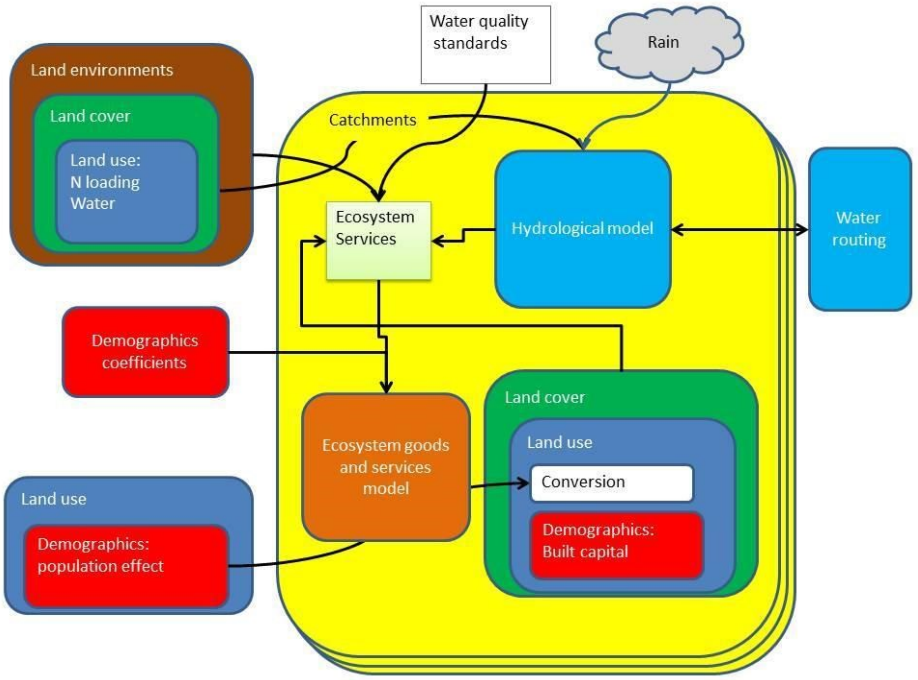

Figure B6.4.3 Overview of MIMES Manawatū.

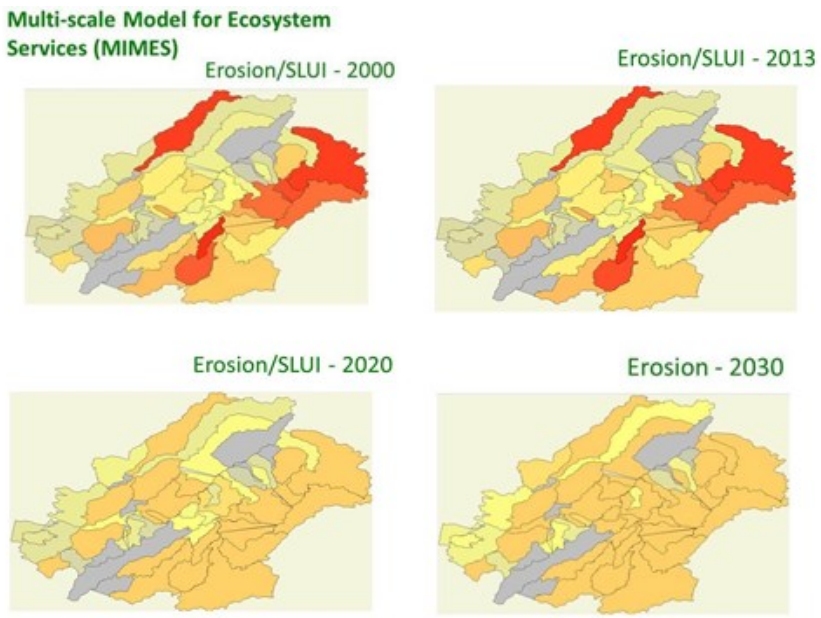

Figure B6.4.4 MIMES scenario outputs at Manawatu.

The progression of model development from MM to MIMES required a transition from interpreting stakeholder perceptions to more data-intense, specialist, modelling by the science community. Figure B6.4.5 shows Figure B6.4.1 upgraded to reflect this. Figure B.6.4.5 emphasizes the gap between the supply and demand of ecosystem services. Value is based on whether there is an abundance or a shortage of ecosystem services over time and space, taking the views of both market and non-market stakeholders into account (van den Belt & Cole, 2014) (van den Belt et al 2012; van den Belt and Cole 2014; van den Belt et al in press 2015).

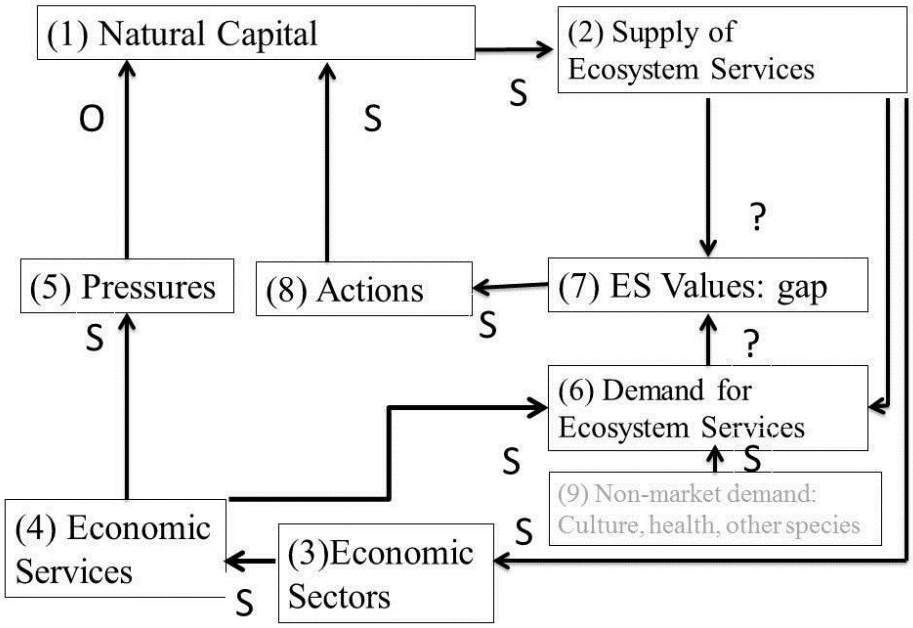

Figure B6.4.5 Upgraded overview of interlinking issues from an Ecosystem Services perspective, emphasizing the gap between the supply and demand of ecosystem services.

Box 6.5. Regional assessments should account for both global information and local information

Ecosystem services are controlled by a combination of global and local factors, which cannot be understood without accounting for both the local and global components (Wilson & Gallant, 2000). The system dynamics that generate the ecosystem services cannot be recovered from the global or local controls alone (Phillips, 2002). In terms of the fundamental theorem of surfaces (Somasundaram, 2005), a surface is uniquely defined by the first and the second fundamental coefficients. The first coefficients express the information about the details of the surface that is observed when we stay on the surface and the second coefficients express the change in the surface observed from outside the surface itself (Yue, 2011).

Ground observation is a source of local information, from which interpolation methods such as Kriging (Krige, 1951) and thin plate splines can be used to create a surface of carbon stocks. Satellite observation is an important source of global information for the simulation of carbon stocks. Ground

forest inventory is able to accurately estimate forest carbon stocks at sample plots, but these sample plots are too sparse to support the spatial simulation of carbon stocks with required accuracy. Satellite remote-sensing can supply spatially continuous information about the surface of forest carbon stocks, which is impossible from ground-based investigations, but their description incorprorates considerable uncertainty. An efficient fusion of local information and global information can considerably reduce the uncertainty of carbon stock simulations.

In this box, we validate the results produced respectively by a satellite-data-based approach (SBA) (Piao *et al*., 2009) and a local-information-based approach (Fang *et al.*, 2001) with the results from fusing local and global information by means of high accuracy surface modelling (HASM) (Yue, 2011). China's national forest inventory database from 2004 to 2008 includes 160,000 permanent sample plots and 90,000 temporary sample plots scattered over the land surface of China. The cross-validation was comprised of four steps: (i) 5% of the sample plots of each forest type in each province were removed for validation prior to model creation; (ii) the spatial distribution of average forest carbon stocks (CS) in China during the period 2004-2008 was simulated at a spatial resolution of 5km×5km using the remaining 95% of the sample plots; (iii) the mean absolute error (MAE) and mean relative error (MRE) were calculated using the 5% validation set; and (iv) the 5% validation set was returned to the pool of available sample plots for the next iteration, and another5 % validation set was removed. This process was repeated until all of the sample plots were used for validation at least one time and the simulation error statistics for each sample plot could be calculated.

The MAE and MRE are respectively formulated as

$MAE = \frac{1}{n}\sum_{i}^{n}|o_i - s_i|$ and $MRE = MAE/(\frac{1}{n}\sum_{i}^{n}|o_i|)$, where o_i represents forest carbon stocks at the *i*th control point for validation; s_i represents the simulated value at the *i*th control point for validation; and n_i is the total number of control points for validation.

MAEs of the carbon stock surfaces, generated by the SBA global-information-based method (Fig 1a) and the Kriging local-information-based method(Fig.1b), are respectively 1.9 and 2.0 kg·m^{-2}. When the local information is combined into SBA by means of HASM, which is denoted below as HASM-SBA, the MAE is decreased to 1.3 kg·m^{-2}. The MREs of both the global and local- information-based methods have been reduced by at least 16% because the local and global information were fused by means of HASM (Table B6.5.1).

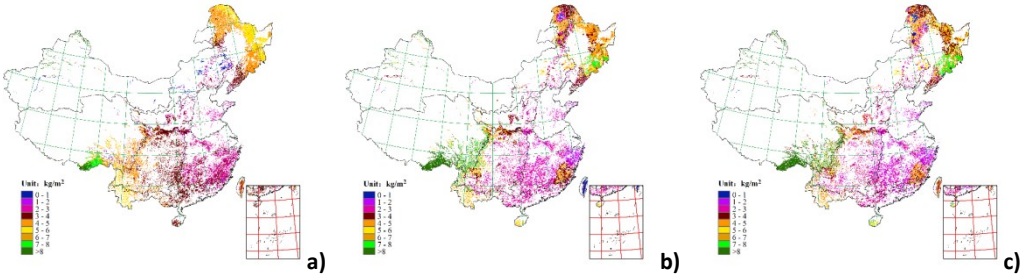

Figure B6.5.1.: Surfaces of carbon stocks created by different methods: a) SBA, b) Kriging and c) HASM-SBA

Table B6.5.1. Comparison of errors from different methods.

Methods	MAE (Kg·m^{-2})	MRE (%)
SBA (based on global information)	1.9	49
Kriging (based on local information)	2.0	50
HASM-SBA (based on both local and global information)	1.3	33

In terms of HASM-SBA, annual mean carbon stocks (AMCS) of all forest types in China was 7.1 Pg during the period 2004-2008, given contributions of 2.7, 4.0, and 0.4 Pg from coniferous, broadleaf and mixed forests, respectively (Table B6.5.2). Similarly, the annual mean carbon density (AMCD) was 4.6 kg/m^2 during the period 2004-2008, with contributions of 4.4, 4.7, and 4.2 kg/m^2 from coniferous, broadleaf, and mixed forests respectively. SBA underestimates AMCS, whereas Kriging overestimates the AMCS of China (Table B6.5.2).

Table B6.5.2. Estimated annual mean carbon stocks and carbon densities from different methods.

Forest type	SBA		Kriging		HASM-SBA	
	AMCS (Pg)	AMCD (kg/m^2)	AMCS (Pg)	AMCD (kg/m^2)	AMCS (Pg)	AMCD (kg/m^2)
Coniferous forests	2.5	3.9	2.8	4.4	2.7	4.4
Broadleaf forests	3.6	4.3	4.1	4.9	4.0	4.7
Mixed forests	0.5	4.9	0.4	4.2	0.4	4.2
Totals	6.6		7.3		7.1	

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