Supplement of Geosci. Model Dev., 11, 4537–4562, 2018
https://doi.org/10.5194/gmd-11-4537-2018-supplement

Geoscientific
Model Development
Open Access

Supplement of

A protocol for an intercomparison of biodiversity and ecosystem services models using harmonized land-use and climate scenarios

HyeJin Kim et al.

Correspondence to: Henrique M. Pereira (hpereira@idiv.de) and HyeJin Kim (hyejin.kim@idiv.de)

Supplement

Supplementary Methods: Description of the post-processing (downscaling) of LUH2 using GLOBIO 4

GLOBIO 4 discrete land-use allocation routine

The GLOBIO4 land-use allocation procedure requires two main inputs: regionally aggregated totals or demands ('claims') of each land-use type and, for each land-use type, a layer quantifying the suitability of each grid cell for that land-use type (10 arc-seconds resolution; ~300 m). Claims can be derived from national or regional statistics or from models that estimate demands based on socio-economic developments, for example integrated assessment models (IAMs). All claims are expressed in terms of area (km^2). The allocation algorithm then prioritizes candidate grid cells according to their suitability values and allocates the claims of each land-use type in each region starting from the cells with the highest suitability until the total claim is allocated. In the allocation a predefined order is followed, where urban land takes precedence over cropland (Bren d'Amour et al., 2017) and cropland in turn takes precedence over pasture (Hasegawa et al., 2017). If for a given land-use type in a given region there are multiple cells with the same suitability, the allocation is done randomly. Non-allocated areas are assigned the primary vegetation type from a natural land cover map. If the area of land use allocated in a given time step is smaller than the area allocated in the preceding time step, the cells that fall free are assigned secondary vegetation.

Suitability layers

Urban

Urban claims are first allocated to existing urban area, from the centre outward, and then to non-urban area with the probability decreasing with increasing distance from urban areas. We further assume that within protected areas no further urban expansion takes place (beyond the current urban area in PA). To achieve this, the urban suitability layer is calculated as follows, based on the ESA CCI-LC map for 2005:

- For each urban cell (class 190; see Table A2), calculate the Euclidian distance to the nearest other cell (such that cells in the city centres get higher values than cells near the edges). Normalize such that each value ranges between 0 and 1, and add +1 to all values. This gives layer 1.
- For each non-urban cell, calculate the Euclidian distance to the nearest urban cell. Invert the distances (such that cells closer to urban get higher suitability) and normalize such that each value ranges between 0 and 1. Set values within protected areas to zero. This gives layer 2.
- Sum the two layers and normalize again such that each cell gets a value between 0 and 1. This gives a layer where suitability within urban is always higher than beyond urban, and with suitability decreasing from the existing city centres outward.

Cropland

Similar to urban, cropland is first allocated to existing cropland and then with increasing distance to it (based on ESA CCI-LC map for 2005). We assume that homogeneous cropland cells in the ESA CCI-LC map represent more suitable areas than mosaic croplands. We further assume that within protected areas no further cropland expansion takes place (beyond the current cropland within PA). To achieve this, the suitability layer is calculated as follows:

- For each homogeneous cropland cell in the ESA CCI-LC map for 2005 (classes 10, 11, 12 and 20), calculate the Euclidian distance to the nearest other cell (such that cells in the centres of cropland areas get higher values than cells near the edges). Normalize such that each value ranges between 0 and 1, and add +2 to all values. This gives layer 1.
- For each mosaic cropland cell in the ESA CCI-LC map for 2005 (classes 30 and 40), calculate the Euclidian distance to the nearest other cell (such that cells in the centres of cropland areas get higher values than cells near the edges). Normalize such that each value ranges between 0 and 1, and add +1 to all values. This gives layer 2.
- For each non-cropland cell, calculate the Euclidian distance to the nearest cropland cell (classes 10, 11, 12, 20, 30 and 40). Invert the distances (such that cells closer to cropland get higher suitability) and normalize such that each value ranges between 0 and 1. Set values within protected areas to zero. This gives layer 3.
- Sum the three layers and normalize again such that each cell gets a value between 0 and 1. This gives a layer where suitability within cropland is always higher than beyond cropland, with homogeneous cropland being more suitable than mosaic cropland, and with suitability decreasing away from existing cropland.

Pasture and rangeland

For pasture and rangeland, we assume that suitability can be inferred from the density of grazing livestock species, which we retrieve from FAO's gridded livestock of the world (30 arc-seconds). We establish the suitability layer as follows:

- Retrieve the densities (head per km^2) of each of three ruminant livestock species (cattle, goat, sheep) from the FAO's gridded livestock of the world, resolution 30 arc-seconds (https://livestock.geo-wiki.org/download/).
- To correct for differences in body mass among livestock species, convert heads to so-called tropical livestock units (TLU) by assuming that goat/sheep = 0.1 TLU and cattle = 0.6 TLU per individual (Petz et al., 2014).

- Sum the TLUs per grid and normalize the resulting values to achieve suitabilities ranging from 0 to 1.

Forestry

In a recent review it was found that six factors were consistently associated with higher deforestation (roads, urban areas, population, soil suitability, agricultural activity, and proximity to agriculture) (Busch and Ferretti-Gallon, 2017). We assume here that the last five factors primarily reflect deforestation for urban and agricultural development, which is covered in the allocation of urban and cropland, and that forestry/wood harvest is primarily determined by elevation and the proximity to infrastructure needed to transport wood (FAO, 2000). The review further found that protected areas consistently result in lower deforestation. Suitability for forestry (within forest) is therefore calculated as follows:

- Calculate the Euclidian distance to roads from PBL's GRIP database (Meijer *et al.*, accepted) or, in South-America, the distance to either roads or rivers (FAO, 2000), using the Digital Chart of the World (DCW) combined with the Global Lake and Wetland Database (GLWD) to delinate the rivers. Invert and normalize the distances to arrive at suitability values between 0 and 1. This gives layer 1.
- Invert and normalize elevation to arrive at suitability values between 0 and 1. This gives layer 2.
- Multiply the layers and normalize again to arrive at an overall suitability between 0 and 1.

Perform the following post-processing steps:

- Set suitability values within protected areas to zero.
- Clip the global suitability layer to land cover with trees from the ESA CCI-LC map for 2005 (classes 50-110; see Table A2). This contains both closed and open forest, in order to accommodate wood harvest from areas with different tree densities (forested and non-forested in LUH2).

Post-processing LUH2 data with the GLOBIO 4 land allocation routine

Step 1 | Discrete allocation of urban, cropland, pasture and forestry

We use the GLOBIO routine to post-process (downscale) the LUH2 data (http://luh.umd.edu/data.shtml) and refine for cropland, as follows:

1) We aggregated the areas of urban, cropland, pasture, rangeland and forestry across the LUH2 cells to IMAGE region level to obtain the claims. The cropland claim consists of the sum of the five cropland types (c3ann + c3per + c4ann + c4per + c3nfx). The forestry claim is the sum of the wood harvest from forested cells and non-forested cells with primary vegetation (primf_harv + primn_harv), as this is most important for the biodiversity impact. We compiled five sets of claims: three scenarios SSP1-2050, SSP3-2050 and SSP5-2050), the base year (2015), and a starting year (2005) to calculate the initial map.
2) We create an initial land-use map by allocating urban, cropland, pasture, rangeland and forestry with GLOBIO 4 land allocation routine, using the claims for 2005 and, for the primary vegetation, the ESA CCI-LC map for the same year. For pasture and rangeland, we use the same suitability layer. By allocating pasture first and rangeland thereafter, the pasture (more intense use) will be allocated to the most suitable areas. Post-process the initial map to remove any remaining urban (class 190) or cropland (classes 10-40) from the ESA CCI-LC map by reclassifying into secondary vegetation.
3) We then allocated the LUH2 'claims' for the years 2015 and 2050 with the GLOBIO 4 allocation routine, using the map from step 2 as initial land-use map.

Step 2 | Differentiate cropland

After allocation, we differentiate cropland intensities based on the amount of fertilizer:

1) We created a total fertilizer map layer (0.25 degree resolution; kg N per ha) as weighted average over the crop types: (fertl_c3ann * c3ann + fertl_c4ann * c4ann + fertl_c3per * c3per + fertl_c4per * c4per + fertl_c3nfx * c3nfx)/(c3ann + c4ann + c3per + c4per + c3nfx)
2) We classified intensity per cell: low intensity = 0–100 kg N-input/ha, medium intensity = 100–250 kg N-input/ha and high intensity = >250 kg N-input/ha (Temme and Verburg, 2011).
3) We combined the intensity layer with the map resulting from the discrete allocation to classify cropland based on intensity (post-processing step).

Table S1: Sources and characterization of input data in BES-SIM.

BES-SIM model	Land-use data - re-categorization of LUH2 land-use classes in the model	Climate data - data sources with variables used in the model	Other data
Species-based models of biodiversity			
AIM-biodiversity	Cropland (c3ann, c4ann, c3per, c4per, c3nfx) Pasture (pastr) Built-up area (urban) Forest (primf, secdf) Other natural land (primn, secdn, range)	ISIMIP2a (IPSL-CM5a-LR) - monthly mean maximum temperature, monthly mean minimum temperature, monthly precipitation	Species occurrence records (GBIF)
InSiGHTS	Cropland (c3ann, c3per, c3nfx, c4ann, c4per) Forest (primf, secdf) Non-forest (primn, secdn, range) Pasture (pastr) Urban (urban)	WorldClim v1 - annual mean temperature, diurnal range (mean of monthly), isothermality, temperature seasonality, max temperature of warmest month, minimum temperature of coldest month, temperature annual range, mean temperature of wettest, driest, warmest quarter, and coldest quarters, annual precipitation, precipitation of wettest and driest months, seasonality, wettest, driest, warmest, and coldest quarters	Global mammal habitat suitability models (Rondinini et al., 2011) Mammal range maps (IUCN)
MOL	Forest (primf, secdf) Grassland/shrubland/wetland (secdf, secdn) Rangeland (pastr, range) Urban (urban) Crops (c3ann, c3per, c3nfx, c4ann, c4per)	WorldClim v2 (present), v1.4 (future) - annual mean temperature, temperature seasonality, annual precipitation, precipitation seasonality, precipitation of driest quarter	Expert maps (IUCN) Species land cover preferences drawn from the literature
BIOMOD2		CHELSA (1979-2013 for present, and 2041-2060, 2061-2080 for future) - annual mean temperature, annual temperature range, annual sum of precipitation and precipitation seasonality (coefficient of variation in monthly sum of precipitations)	Expert maps for mammals and amphibians (IUCN) Bird data (Birdlife International)
Community-based models of biodiversity			
cSAR-iDiv	Primary vegetation (primf, primn Secondary vegetation (secdf, secdn) Pasture (pastr, range) Urban (urban) Cropland (c3ann, c4ann, c3nfx) Permanent (c3per, c4per)		Bird species occurrence data (Birdlife International) Coefficients for affinities (PREDICTS)

BES-SIM model	Land-use data - re-categorization of LUH2 land-use classes in the model	Climate data - data sources with variables used in the model	Other data
cSAR-IIASA-ETH	Urban (urban) Annual cropland (c3ann, c3nfx, c4ann) Perennial cropland (c3per, c4per) Pasture (pastr) Extensive forest (range, secdf, secdn) Pristine (primf, primn)		cSAR model parameters (Chaudhary et al. 2015; Frischknecht and Jolliet 2016)
BILBI	Primary vegetation (primf, primn) Mature secondary vegetation (secdf, secdn) *if older than 50yrs* Intermediate secondary vegetation (secdf, secdn) *if 10-50 years old* Young secondary vegetation (secdf, secdn) *if younger than 10yrs* Rangelands (range) Managed pasture (pastr) Urban (urban) Perennial croplands (c3per, c4per) Nitrogen-fixing croplands (c3nfx) Annual croplands (c3ann, c4ann)	WorldClim v1.4 – BIO6 and BIO12 Climate variables derived by integrating Worldclim monthly temperature and precipitation estimates with radiative adjustment for terrain, and with soil water-holding capacity (Ferrier et al., 2013): max temperature of warmest month, max diurnal temperature range, actual evaporation, potential evaporation, min monthly water deficit, max monthly water deficit	Plant species occurrence records (GBIF) Soil attributes: pH, Clay %, Silt %, Bulk Density, Depth (Hengl et al., 2014) Terrain attributes: Ruggedness Index (G. Arnatulli, Yale University), Topographic Wetness Index (WorldGrids) MODIS Vegetation Continuous Fields (NASA) Global Human Settlement Population Grid Coefficients: impact of land use on local native-species richness (PREDICTS)
PREDICTS	Primary vegetation (primf, primn) Secondary vegetation (secdf, secdn - split into three age bands: Mature, Intermediate and Young) Managed pasture (pastr) Rangeland (range) Urban (urban) Annual (c3ann, c4ann) Nitrogen-fixing (c3nfx) Perennial (c3per, c4per)		PREDICTS database (Hudson et al., 2014) Human population density (GRUMP v1., HYDE (historical) and the corresponding SSPs as developed by Jones and O'Neill 2016 (future projection)). Agricultural suitability (Zabel et al., 2014)
GLOBIO - Aquatic	Primary forest (primf) Primary other vegetation (primn) Secondary forest (secdf) Pastures (pastr) Rangelands (range) Cropland (c3ann, c4ann, c3nfx) Perennials (c3per, c4per) secdn urban	IMAGE model (MAGICC 6.0) - daily precipitation and evaporation, monthly precipitation and evaporation. ISIMIP2a (IPSL-CM5a-LR) - water temperature	River flow compared to natural river flow (global hydrological model: PCR-GLOBWB or LPJ) Water temperature (PCR-GLOBWB model) Nutrient loads to aquatic systems (Global Nutrient Model) Drain direction network (Döll and Lehner, 2002) Global map of rivers, lakes and wetlands ((Lehner and Döll, 2004) Lake depths (Kourzeneva, 2010) River dam database (Fekete et al., 2010; Lehner et al., 2011)
GLOBIO - Terrestrial	GLOBIO downscaled LUH2 data (see Annex 1 in Supplementary Materials)	IMAGE model (MAGICC 6.0) - global mean temperature increase (°C)	Nitrogen deposition (IMAGE model) Roads (GRIP dataset, Meijer et al., 2018)

BES-SIM model	Land-use data - re-categorization of LUH2 land-use classes in the model	Climate data - data sources with variables used in the model	Other data
			Settlements in tropical regions (Humanitarian Data Exchange, Open Street Map)
Ecosystems-based model of biodiversity			
Madingley	*States* Primary (primf, primn) Secondary (secdf, secdn) Grazing (pastr, range) Cropland (c3ann, c4ann, c3per, c4per, c3nfx) Urban (urban) *Transition*s Primary losses (all transitions beginning with primf or primn) Secondary losses (all transitions beginning with secdf or secdn) Secondary gains (all transitions ending with secdf or secdn)	ISIMIP2a (IPSL-CM5a-LR) - temperature, precipitation	Soil characteristics (Smith et al., 2013) Modis Net Primary Productivity (NASA, 2012) Human Appropriation of Net Primary Productivity (Haberl et al., 2007) Human population densities (Jones and O'Neill, 2016; Klein Goldewijk et al., 2016)3
Models of ecosystem functions and services			
LPJ-GUESS	Primary natural vegetation (primf, primn) Secondary natural vegetation (secdf, secdn) Pasture (pastr, range) C3 crops (c3ann, c3per, c3nfx) C4 crops (c4ann, c4per) Urban (modelled as natural vegetation)	ISIMIP2a (IPSL-CM5a-LR) - monthly min/max T, precipitation, shortwave radiation; atmospheric CO_2, N-input, fractional land cover (crop irrigated yes/no, pasture, managed forest, natural)	Crop irrigated and biofuel fraction (LUH2 dataset) Wood harvest estimate (LUH2 dataset) Nitrogen deposition (Lamarque et al., 2011)
LPJ	Primary natural vegetation (primf, primn) Secondary natural vegetation (secdf, secdn) Pasture (pastr, range, c3ann, c3per, c3nfx, c4ann, c4per) urban (modelled as natural vegetation)	ISIMIP2a (IPSL-CM5a-LR) - monthly T, precipitation, shortwave radiation or cloudiness; atmospheric CO_2, fractional land cover (pasture, managed forest, natural)	
CABLE	Primary natural vegetation (primf, primn) Secondary natural vegetation (secdf, secdn) Grass (pastr, range) Crops (c3ann, c3per, c3nfx, c4ann, c4per, c4nfx)	ISIMIP2a (IPSL-CM5a-LR) - daily min/max T, precipitation, shortwave radiation, longwave radiation, humidity, windspeed, atmospheric CO_2, N-deposition, land-use transitions (crop, pasture, secondary forest, natural)	Wood harvest estimate (LUH2 dataset) Nitrogen deposition (Lamarque et al., 2011)
GLOBIO-ES	Primary forest (primf) Primary other vegetation (primn) Secondary forest (secdf) Pastures (pastr) Rangelands (range) Cropland (c3ann, c4ann, c3nfx) Perennials (c3per, c4per) secdn urban	IMAGE model (MAGICC 6.0) - aggregated monthly precipitation, monthly wet day frequency	Population size, GDP per capita, soil data, altitude range, slope (IMAGE model) Population density in river floodplains Water demand for electricity, industry and households (Bijl et al., 2016)

BES-SIM model	Land-use data - re-categorization of LUH2 land-use classes in the model	Climate data - data sources with variables used in the model	Other data
InVEST	GLOBIO downscaled LUH2 data (see Annex 1 in Supplementary Materials)	*Nutrient delivery* WorldClim v1.4 - precipitation *Coastal Vulnerability* CMIP5 AOGCMs - sea level rise	*Nutrient delivery* Digital elevation model (ASTER) Biophysical table (InVEST database) Rural population scenarios (Jones and O'Neill, 2016) Population raster (GPWv4, 2018) *Coastal Vulnerability* Natural Habitat polygons for mangrove, corals, and eel grass (WCMC) Continental Shelf polygon (COMARGE, Census of Marine Life) Digital elevation model (ASTER) Wind and wave exposure (WAVEWATCH III) Population raster (GPWv4 - 2018) *Pollination* Yield raster for 115 crops (Monfreda et al., 2008) Nutrient content of 115 crops (table; USDA 2011) Pollination dependence of 115 crops (Klein et al., 2007) Dietary requirements (Allen et al., 2006; BNF, 2016) Demographic population data (GPWv4 Age Dataset – 2018) *Crop production* -Yield raster for 115 crops (Monfreda et al., 2008)
GLOSP	12 original land states in LUH2	ISIMIP2a (IPSL-CM5a-LR) - precipitation	Fractional vegetation cover (Filiponi et al., accepted) Topography (GMTED2010) Soil type and physical properties (Hengl et al., 2014)

Table S2: Model description, modifications and assumptions made to published models in BES-SIM.

BES-SIM model	Description
Species-based models of biodiversity	
AIM-biodiversity	The AIM-biodiversity model (Ohashi et al., submitted) predicts potential shifts of suitable habitat of multiple species caused by the projected climate and land-use change, using the ISI-MIP climate and LUH2 land-use data. The model incorporates distribution of 9,025 species with ≥ 30 refined occurrence data in their native region, which has been assessed by the IUCN Red List. This includes species of the least concern in five major taxonomic groups: vascular plants, amphibians, reptiles, birds, and mammals. Native region of each species was specified by database of the IUCN Red List. The distribution of suitable habitat (land) is estimated from climate and land-use data at 0.5 arc degrees spatial resolution using a statistical model on the relationship between species occurrence and climate and land-use classes. This statistical model is calibrated by Maxent (Phillips et al., 2006) using the occurrence data from the Global Biodiversity Information Facility (GBIF), historical climate (WorldClim database) and land-use (Hasegawa et al., 2017) data for 2005. The bias of occurrence data is corrected using bias files for generating a set of background data for a target group of species (Phillips et al., 2009). The shifts in species suitable habitat in 2050 are projected under two common assumptions of dispersal: 'no' (zero) and 'full' (unlimited and instantaneous) migration (Bateman et al., 2013; Midgley et al., 2006). For the past projections, it is assumed that in year 1900 species can distribute in all suitable habitats without any dispersal limitations.
InSiGHTS	The InSiGHTS model (Rondinini et al., 2011; Visconti et al., 2016) forecasts the Extent of Suitable Habitat (ESH) for vertebrates accounting for land and climate suitability, using global mammal habitat suitability models, IUCN range maps, Worldclim climate and LUH land-use data. Bioclimatic envelope models are fitted based on ecologically current reference bioclimatic variables (Visconti et al., 2016). Species' presence records are obtained by regularly sampling within species' ranges, excluding areas outside of known altitudinal limits. Species' pseudo-absence records are obtained by randomly sampling outside of species' ranges, but within the biogeographic realms intersected by the species' range. Presence and pseudo-absence sampling grids match in resolution. Forecasted layers of land use/land cover are reclassified according to expert-based species-specific suitability indexes, which identifies land-wise suitable cells or proportions thereof. The product of the two layers is multiplied by a layer of cell area (e.g., km²) to estimate species-specific cell-wise ESH. InSiGHTS index, which describes the proportional positive and negative contribution of the region (cell to global) to the species' change in ESH compared to a reference year, is calculated. The improvements made to the model since last published methodology (Visconti et al., 2016) include increased number of modelled species and new scenarios used for climate and land use. For both future and past forecasts, the model limits calculations within the current (2011) species range due to the sparsity of historical data – an assumption that the species' ranges remain constant. InSiGHTS index (ii): $$ii_{s,r,t'} = \frac{E_{s,r,t'} - E_{s,r,t}}{\sum_{r=1}^{\lvert R \rvert} E_{s,r,t}}$$ E = ESH s = species r = observed region (from cells to global) R = set of all regions t = reference time (present) t' = observed time (future or past)
MOL	The MOL model (Jetz et al., 2007; Merow et al., 2013) projected potential losses in species occurrences and geographic range sizes given changes in suitable conditions (climate only, land-cover only and climate and land-cover), using Worldclim climate data IUCN expert maps, and species land cover preferences. Climatic niches were estimated using penalized Poisson point process models (similar to Maxent) by extracting presence from the expert maps on a quarter degree grid. Niche were projected under future scenarios and binary maps of predicted presence/absence were obtained. These binary values were then rescaled by the proportion of each cell consisting of habitat where the species in known to occur, leading to maps of the proportion of each cell that is suitable habitat. Species-level losses were aggregated to inform regional trends. For all three projection types – climate only, land-cover only and climate and land-cover – changes in individual species range size and range location

BES-SIM model	Description
	were assessed and summarized for different taxonomic and geographic groupings. Species Habitat Index and Red List Index may be projected with modelled results. All modelling was performed as part of a multispecies workflow that automates production and quality control for range models.
BIOMOD2	The BIOMOD2 model (Thuiller, 2004; Thuiller et al., 2009, 2011) is an R-package that allows running up to nine different algorithms of species distribution models using the same data and the same framework. An ensemble is produced to allow for a full treatment of uncertainties given data, algorithms, climate models and climate scenarios. Based on the species distribution models that link observed or known presence-absence data to environmental variables (e.g. climate), each model is cross-validated several times (a random subset of 70% of data is used for model calibration while 30% is held out for model evaluation). Models are evaluated using various metrics, and produce indicators including change in species range, species loss and gain per pixel, species turnover, functional and phylogenetic diversity.
Community-based models of biodiversity	
cSAR-iDiv	The cSAR-iDiv (Martins and Pereira, 2017; Pereira and Daily, 2006) model assesses the response of biodiversity to land-use change, using LUH2 land use, Birdlife species occurrence and PREDICTS affinities data. It accounts for the persistence of species in human-modified habitats and for the differential use of habitats by species. The model allows to assess the impact of changes in species richness across scenarios of land use in the countryside SAR, the richness of each functional species group *i*, S_i, is given by a function of the area of each habitat *j*, A_j , in the landscape, $$S_i = c_i \left(\sum_{j=1}^{n} h_{ij} A_j \right)^z$$ where n is the number of modified habitats types, h_{ij} is the affinity of species group *i* to habitat *j* and A_j is the area cover by habitat *j*. The parameters *c* and *z* are constants that depend on the taxonomic group and sampling scheme respectively, and will be species group dependent. Species are classified in functional species groups sharing similar habitat preferences using the Birdlife dataset. The h_{ij}, reflecting the relative affinity of a functional species group *i* to a modified habitat type *j* compared to its natural habitat are derived from the PREDICTS dataset. The model calculates the proportion of species of each functional group between two time periods, then multiplies the trend by the actual number of species of the functional group (i.e. as reported by Birdlife) in each sampling unit. Using this approach, the model estimates the trends of local (i.e., grid cells), regional and global species richness of the two functional groups of bird species - forest and non-forest. The improvements made since last published methodology include the use of high-resolution land-use dataset and affinities calculated from the PREDICTS dataset, and application of two functional groups across scales based on habitat types (land classification). For the past projections, the model is applied starting from 1900 with an assumption that the number of species currently present in different areas/sampling units (IUCN/Birdlife data) corresponds to the number of species at the starting point.
cSAR-IIASA-ETH	The IIASA-ETH cSAR model is based on a countryside Species Area Relationship (cSAR) type of model and estimates the impact of time series of spatially explicit land-use and land-cover transitions on community-level measures of terrestrial biodiversity on five taxa (amphibians, birds, mammals, reptiles and plants). It uses LUH2 data and the initial species richness and cSAR model parameters from Chaudhary et al. (2015) and Frischknecht and Jolliet (2016). Regional species loss is weighted by the fraction of range area of all species in every ecoregion and IUCN threat level, to derive an estimate of global extinctions. The original approach of Chaudhary et al. (2015) is not tailored for estimating long-term and large land-use changes because i) it is a linear approximation (contingent to the current land-use patterns) of a non-linear relationship, and ii) although it incorporates a measure of the length of recovery, the approach is not designed to look at the dynamics of LULCC towards a more biodiversity-friendly state. Instead, in the IIASA-ETH-cSAR model the biodiversity impacts of land-use change is estimated directly from the cSAR formula (cSAR relationship and parameters for the model) and applied to the land-use shares for the various LULC classes considered (their affinity values are derived directly for the local characterization factor database based on field records). The link between LULCC and habitat is more detailed by taking the gross transitions directly as input

BES-SIM model	Description
	between LULC classes (instead of net state changes, which ignores the land-use history). The model also accounts for the time dynamics with which a transition generates biodiversity outcomes where the affinity of species for a converted LULC class forgets its origin that is specific to each pair of LULC class. It is typically quick (i.e., lower than one time step) for biodiversity-unfavourable LULC transitions, and long (typically several decades) for biodiversity-favourable LULC transitions. The model is run from 1500 onwards – from the past to into the future – with initial land-use states in year from LUH2 dataset and cumulated transitions from one time step to another.
BILBI	This modelling framework (Hoskins et al., in prep.) couples application of the species-area relationship (SAR) with correlative statistical modelling of continuous patterns of turnover in the species composition of communities as a function of environmental variation (Ferrier et al., 2004, 2007). Generalised dissimilarity modelling (Ferrier et al., 2007) is used to fit models of spatial turnover in vascular-plant composition, based on 52,489,096 occurrence records for 254,145 plant species, extracted from GBIF, and environmental layers covering the entire land surface of the planet at 30-second (~1km) grid-resolution (including climate layers derived from WorldClim; see Table S1). A separate GDM is fitted for each of 61 bio-realms from WWF's ecoregionalisation. In a few cases, data from neighbouring or ecologically-related bio-realms are used to supplement the dataset employed in fitting GDMs for more poorly sampled bio-realms. To accommodate the 'presence-only' nature of much of the biological data assembled from GBIF, GDMs are fitted to observed matches and mismatches in species identity between pairs of individual occurrence records. The modelled probability of a mismatch in species identity is then transformed into the expected compositional similarity between any two cells. Using the approach employed by Blois et al., (2013), Ferrier et al. (2012), Fitzpatrick et al. (2011), Mokany et al. (2012), Prober et al. (2012) and William et al. (2015), space-for-time substitution is applied to the fitted GDMs to project temporal turnover in species composition expected as a result of any given climate scenario based on temperature and precipitation projections for 2050, downscaled by WorldClim. Given that the 'current climate' surfaces from WorldClim, used to fit the GDMs, are averaged over the period 1960-1990, the analysis is effectively projecting the temporal turnover in species composition expected between 1975 (midway between 1960 and 1990) and 2050. This approach allows estimation of temporal turnover for a single location or of spatial-temporal turnover between two different locations. Estimates of the proportional coverage in 2015 of 12 land-use classes within each terrestrial 0.25 degree grid-cell on the planet, from the LUH2, are statistically downscaled to 30-second grid resolution using the approach described by Hoskins et al. (2016) incorporating MODIS Vegetation Continuous Fields, and the Global Human Settlement Population Grid, as additional covariates. Downscaled land use in 2015 is then translated into 'habitat condition' for biodiversity using coefficients fitted in hierarchical mixed-effect modelling undertaken by the PREDICTS project. These coefficients estimate the proportion of local native species richness expected for different land-use classes. This modelling employed the approach described by Newbold et al. (2016b) but with models refitted using the 12 LUH2 land-use classes. Change in habitat condition at 30-second grid resolution is projected for any given LUH2 land-use scenario using a simple delta-downscaling approach of applying the proportional change in habitat condition between 2015 and 2050 to the downscaled 2015 condition values for all 30-second cells within each 0.25 degree cell. The GDM-based modelling of temporal turnover in species composition for the climate scenario of interest, and downscaled habitat condition for the land-use scenario of interest, are used in combination to estimate the proportion of plant species expected to persist over the longer term (i.e. the complement of the proportion of species committed to extinction) employing the SAR. This particular SAR-based approach, as applied recently in two major projects within Australia – the Australian National Outlook (Bryan et al., 2014; Hatfield-Dodds et al., 2015; Brinsmead et al., 2017) and AdaptNRM (Prober et al., 2015) – is an extension of that described originally by Allnutt et al. (2008) and Ferrier et al. (2004). In contrast to more traditional applications of the SAR to estimating levels of species persistence, which work with discrete environmental classes or ecosystem types, this approach views grid-cells as sitting within a continuum of spatial and temporal turnover in biodiversity composition (Allnutt et al., 2008; Ferrier et al., 2004). The proportion of plant species originally associated with cell *i* which are expected to persist over the longer term, anywhere in their range, as a consequence of a given combination of climate and land-use scenarios is calculated as:

BES-SIM model	Description
	$$p_i = \left[\frac{\sum_{j=1}^{n} s_{i_{present} j_{future}} c_{j_{future}}}{\sum_{j=1}^{n} s_{i_{present} j_{present}}}\right]^z$$ where: n = total number of cells on the planet $s_{i_{present} j_{present}}$ = similarity between cells i and j in the present $s_{i_{present} j_{future}}$ = similarity between cell i in the present and cell j in the future $c_{j_{future}}$= condition of habitat in cell j in the future z = SAR exponent (set to 0.25 for the current study) The proportion of species originally associated with any specified region (reporting unit) expected to persist can then be calculated as a weighted geometric mean of the values for all individual cells in that region: $$p_{region} = \frac{\sum_{i=1}^{m} p_i w_i}{\sum_{i=1}^{m} w_i}$$ where: m = total number of cells in the region (reporting unit) of interest The weights employed are: $$w_i = \frac{1}{\sum_{j=1}^{n} s_{i_{present} j_{present}}}$$ where: n = total number of cells on the planet
PREDICTS	The PREDICTS model (Newbold et al., 2015, 2016b) estimates how four measures of site-level terrestrial biodiversity – overall abundance, within-sample species richness, abundance-based compositional similarity and richness-based compositional similarity – respond to land-use and related pressures. These models are combined with global data on past, present or future states of the pressures used in modelling, to make global projections of each variable for each desired time point. The modelling uses data from 767 studies, each of which surveyed multiple sites that faced differing land-use and related pressures, for which version 1 has been published (Hudson et al., 2017), with now more data available from over 32,000 sites and over 51,000 species, which is reasonably representative across different biomes and major animal, plant and fungal taxa. Models also use human population density (HYDE, GRUMP v1, Jones and O'Neill, 2016) and LUH2 land-use data. In addition to the LUH2 land-use data, the PREDICTS model uses secondary vegetation age and use intensity classes. Fractional distribution of secondary vegetation age was compiled for each grid cell by tracking conversions using LUH2 transitions data. Secondary vegetation was classified into young, intermediate and mature using the following thresholds: <30y = young, 30y>50y=intermediate, >50y= mature. Use intensity was classified as Minimal, Light or Intense using Global Land Systems data as in Newbold et al. (2015). Linear mixed-effects models (with study- and block-level random effects to accommodate the heterogeneity in the data, and site-level random effects to account for over-dispersion in species richness models) are used to estimate how local (alpha) diversity is affected by land use, land-use intensity and human population density. Model coefficients are combined with maps of the pressure data to make global projections of the estimated values of the response variables. These projections are then combined to yield the variants of the Biodiversity Intactness Index (BII) shown in Newbold et al. (2016; see Scholes and Biggs, 2005 for the original development of BII). Since last published model, sites in the PREDICTS database were re-curated to incorporate the land-use classes present in LUH2 but not used by Hurtt et al. (2011 Climatic Change), i.e., the refinement of agricultural classes. When modelling abundance, the abundance data were rescaled within each study such that the maximum abundance was the same within each study; this assists with model convergence. The compositional similarity models use the data more fully than previously: whereas previously independent pairwise comparisons were made between sites, the models here are based on the full matrix of pairwise comparisons between sites. This full-matrix approach allows incorporation of human population density in addition to land use (the only pressure variable previously analysed in our models of compositional similarity: (Newbold et al., 2016b, 2016a). Whereas our

BES-SIM model	Description
	previous models of compositional similarity used all primary vegetation sites as the baseline condition, expansion of the database has allowed us to restrict the baseline to minimally-used primary vegetation. Previously, human population density (ln(x+1)-transformed) was fitted as a quadratic term in models of abundance and richness but omitted from models of compositional similarity; here we have treated it as a linear term in all models to improve consistency. The study-level mean of ln(human population density + 1) was also added as a control variable into the models of abundance and species-richness, to avoid possible artefacts that could otherwise arise if studies in more densely-populated areas sample more intensively. Agricultural suitability (Zabel et al., 2014) was also used as a control variable (Gray et al., 2016). These control variables are used as additive terms in modelling but not projections. Our previous models of abundance and richness considered proximity to roads as a pressure, but we have omitted roads from these models because of the lack of future and historical estimates; land use, land-use intensity and human population density – all somewhat correlated with proximity to roads – have the potential to explain some of the variance previously explained by roads. PREDICTS also modelled species richness as a function of land use, in order to provide habitat coefficient estimates to other models in BES-SIM. Separate models were run for areas that would naturally be forested and non-forested (data subset using LUH2/fstnf). Human population density was omitted from the model; otherwise, model structure matched that outlined above.
GLOBIO-Aquatic	The GLOBIO-Aquatic model (Janse et al., 2015) quantifies the impacts of multiple anthropogenic pressures in the past, present and future on freshwater biodiversity and its ecosystem services, using climate (IMAGE model), land use (GLOBIO model), river flow (PCR-GLOBWB or LPJ model), water template (PCR-GLOBWB model), nutrient loads to aquatic systems (Global Nutrient Model), global map of rivers, lakes and wetlands (GLWD), and river dam database. The drivers included are land use, eutrophication, climate change and hydrological disturbance. The model comprises a set of mostly correlative relationships between anthropogenic drivers and biodiversity and ecosystem services of rivers, lakes and wetlands. The model produces biodiversity intactness indicator – Mean Species Abundance (MSA) – of lakes, rivers and wetlands as well as the probability of harmful algal blooms as an indicator for freshwater provisioning services.
GLOBIO-Terrestrial	The GLOBIO model for terrestrial biodiversity (Alkemade et al., 2009) quantifies the impacts of multiple anthropogenic pressures on local biodiversity based on the mean species abundance (MSA) metric. MSA represents the mean abundance of original species in relation to a particular pressure as compared to the mean abundance in an undisturbed reference situation. MSA's responses to a particular pressure are quantified based on a meta-analysis of biodiversity monitoring data reported in the literature, whereby abundance ratios of individual species are calculated as $A_{impacted}/A_{reference}$ for $A_{impacted} < A_{reference}$ and $A_{impacted}/A_{reference} = 1$ for $A_{impacted} > A_{reference}$. Changes in biodiversity are quantified by combining georeferenced layers of the pressure variables with the MSA response relationships. Next, the maps with the MSA values per pressure are combined to arrive at an overall MSA. If a particular pressure is assumed to be dominant, the combined impact (MSA) is assumed equal to the impact (MSA) of this dominant pressure. If pressures act independently, the overall MSA value is calculated by multiplying the MSA values corresponding with the individual pressures. Five pressures are currently included (climate change, land use, roads, atmospheric nitrogen deposition and encroachment/hunting). Climate change, nitrogen deposition, and land-use data are derived from the IMAGE model (Stehfest et al., 2014). Land-use data from IMAGE are downscaled to a higher spatial resolution with the GLOBIO land allocation routine. Roads data are taken from the global road inventory project (GRIP) database (Meijer et al., submitted). Settlement data (required to calculate hunting impacts) are retrieved from multiple open-source datasets, including Open Street Map and Humanitarian Data Exchange. Improvements made to the model since the last published methodology include a new high-resolution, discrete land-use allocation routine and improved response relationships for encroachment/hunting (Benítez-López et al., 2017).
Ecosystems-based model of biodiversity	

BES-SIM model	Description
Madingley	The Madingley Model (Harfoot et al., 2014) is a mechanistic, or process-based, model of whole ecosystems developed to synthesize and advance our understanding of ecology, and to enable mechanistic prediction of the structure and function of whole ecosystems at various levels of organisation, whether on land or in water. Using data from ISI-MIP, soil characteristics (Smith et al., 2013), Modis Net Primary Productivity (NASA, 2012), Human Appropriation of Net Primary Productivity (Haberl et al., 2007), and LUH2 (land use), Madingley simulates the dynamics of autotrophs, and all heterotrophs with body masses above 10 μg that feed on living organisms. In the model, organisms are not characterised by species identity but grouped according to a set of categorical functional traits, which determine the types of ecological interactions that modelled organisms are involved in whilst a set of continuous traits determine the rates of each process. Plants are represented by stocks, or pools, of biomass modelled using a terrestrial carbon model. Biomass is added to the stocks though the process of primary production, the seasonality of which is calculated using remotely sensed Net Primary Productivity (Harfoot et al., 2014). This production is allocated to above-ground/below-ground, structural/non-structural, evergreen/deciduous components and Madingley assumes that above-ground, non-structural matter is available for heterotrophic organisms to consume. Biomass is lost from plant stocks through mortality from fire and senescence, as well as through herbivory. Production, allocation and mortality in the plant model are all determined by environmental conditions (temperature, number of frost days, precipitation and the available water capacity of soils). Heterotrophic animals are represented as agents, termed cohorts, which are collections of individual organisms occurring in the same modelled grid cell with identical categorical and continuous functional traits. This approach enables the model to predict emergent ecosystem properties at organisational scales from individuals to the whole ecosystem. Heterotroph dynamics result from five ecological processes: metabolism, eating, reproduction, mortality and dispersal. Predator-prey interactions (including herbivory) are based on a Holling's Type III functional response (Denno et al., 2012), and for predation on a size-based model of predator-prey feeding preferences (Williams et al., 2010). Metabolism is based on empirical relationships between energy consumption and ambient temperature taking into account the body mass of the organism (Brown et al., 2004). Endotherms are assumed in the model to thermoregulate perfectly, and thus are active for 100% of each time step. Ectotherms in the model do not thermoregulate, and thus are only active for the proportion of each time step during which ambient temperature was within their upper and lower activity temperature limits, estimated following (Deutsch et al., 2008). Reproduction can occur once a cohort has achieved its adult body mass and results from the allocation of surplus mass to reproductive potential followed by reproductive events once a threshold ratio of reproductive potential to adult body mass is reached (Harfoot et al., 2014). Mortality (in addition to predation mortality) arises from three causes: a constant background rate, starvation if insufficient food is obtained, and senescence, which increases exponentially after maturity with a functional form similar to the Gompertz model (Pletcher, 1999). Dispersal in the terrestrial realm is either random diffusive dispersal of juvenile organisms or directed dispersal of organisms in response to starvation or low densities of individuals (Harfoot et al., 2014). The model produces total biomass and abundance of above ground heterotrophs, total biomass of autotrophs, total biomass and abundance of functional groups (trophic levels, metabolic pathways, reproductive strategies), trophic and food web structure, biomass structure, age structure, functional diversity (richness, evenness, divergence), functional dissimilarity, net secondary productivity, biomass turnover rates, herbivory, predation, mortality and reproduction rates. The improvements made to the model since last published methodology include incorporation of temporally changing climate as well as natural and human impacted plant stocks to better represent the LUH2 land-use projections and calculation of functional diversity and functional dissimilarity to represent community changes. To make historical reconstructions back to 1900 we first run an ensemble of six simulations from pseudo-random initial conditions for 100 years until it reaches quasi steady state for the year 1901. This spin up used land use and HANPP for 1901, and 100 years of climate randomly recycled from the years 1951 to 1960 of the ISI-MIP IPSL climate reconstruction. The quasi-steady state conditions from these simulations were then ran forward to 2005 using the time series of land-use change, climate change (where the period 1901 – 1950 was constructed using randomly recycled years from 1950 – 1961) and HANPP.
Models of ecosystem functions and services	
LPJ-GUESS	The LPJ-GUESS model (Lindeskog et al., 2013; Olin et al., 2015; Smith et al., 2014) is a "demography enabled" dynamic global vegetation model using historical and future climate, CO_2, nitrogen deposition and fertilizer, land

BES-SIM model	Description
	cover change, irrigated fraction, and wood harvest estimate data. The model computes vegetation and soil state and function, and distribution of vegetation units dynamically in space and time in response to climate change, land-use change, atmospheric CO_2, and N-input. It combines an individual- and patch-based representation of vegetation dynamics with ecosystem biogeochemical cycling from regional to global scales. In LPJ-GUESS, the dynamics of vegetation result from growth and competition for space, light, and soil resources from herbaceous understorey and woody plant individuals in each patch replicated for each simulated grid cell. The suite of simulated patches represents the distribution within a landscape representative of the grid cell as a whole of vegetation stands with different histories of disturbance and stand development (succession). Individuals for woody plant functional types (PFTs; trees and shrubs) are identical within a cohort (age/size class) and patch. Photosynthesis, respiration, stomatal conductance and phenology (leaves and fine roots turnover) are simulated on a daily time step. The net primary production (NPP) accrued at the end of each simulation year is allocated to leaves, fine roots and, for woody PFTs, sapwood, following a set of prescribed allometric relationships for each PFT, resulting in diameter, height, and biomass growth. Population dynamics (establishment and mortality) are represented as stochastic processes, influenced by current resource status, demography and the life-history characteristics of each PFT (text from Smith et al., 2014). The modelled outputs include carbon pools in vegetation, soil, gross primary productivity, heterotrophic respiration, net primary productivity, runoff, leaf area index, crop yields, area burnt, fire emissions, carbon to nitrogen ratios, and nitrogen loss. The improvements made since last published methodology include an upgrade in the fire model and accounting for wood harvest. To provide climate input before 1951 random years out of the period 1951 to 1960 are chosen to generate/recycle the climate data for years 1901 to 1950.
LPJ	LPJ is a big leaf model (Poulter et al., 2011) that simulates the coupled dynamics of biogeography, biogeochemistry and hydrology under varying climate, atmospheric CO_2 concentrations, and land-use land-cover change practices, using historical and future climate, CO_2 level, land cover change transitions, and wood harvest estimate data. LPJ represents demography of grasses and trees in a simplistic manner, where a 'representative individual' is used to scale from individuals to landscapes. Physiological processes are applied to the representative individual and integrated over the landscape, i.e., a grid cell, based on the density of individuals. Land cover change includes explicit representation of deforestation and reforestation, as well as harvesting of managed grasslands. Natural fires are included. The LPJ model has a hierarchical representation of the land surface where within a grid cell, tiles represent primary forest, secondary forest, and managed lands (crops or pasture), and within a tile are either plant functional types (PFTs) or crop functional types (CFTs). On an annual time step, establishment, mortality, fire, carbon allocation, and land cover change are implemented, and on a daily time step, photosynthesis, autotrophic respiration, and heterotrophic respiration are calculated. The carbon cycle is coupled to the hydrologic cycle via stomata, which must be open to assimilate atmospheric CO_2 but simultaneously lose water. Stomatal conductance is determined as the minimum between potential evapotranspiration (demand) and soil plant water availability (supply). Photosynthesis and radiation follows the Farquhar biochemical model and distributes photosynthetic active radiation vertically through the canopy following Beer's Law. The LPJ model is fully prognostic, meaning that PFT distributions, phenology, and carbon dynamics are simulated based on physical principles within a numerical framework. The typical variables of model outputs are (either per grid cell simulated, or per PFT): C pools in veg., soil, GPP, heterotrophic respiration, NPP, runoff, LAI, crop yields, area burnt, and fire emissions. The land cover change and land-use transitions have been upgraded to include the dynamics from the Land Use Harmonization product by George Hurtt and Louise Chini. This development means that LPJ represents the full set of states and transitions represented in LUH v2 and has an improved estimate of carbon fluxes from land-cover change. The model is spun up to pre-industrial equilibrium conditions by using an atmospheric CO_2 concentration of 280 ppm and recycling the first thirty years of meteorological data (1901-1930) for 1000 years.
CABLE	CABLE is a "demography enabled" global terrestrial biosphere model (Haverd et al., 2017) that computes vegetation and soil state and function dynamically in space and time in response to climate change, land-use change and N-input, using historical and future daily climate data downscaled to 3-hourly, annual CO_2 levels in the atmosphere, N-deposition, land-cover change, irrigated faction, and wood harvest area. It combines a patch-based representation of vegetation structural dynamics with ecosystem biogeochemical cycling from regional to global scales. CABLE consists of a 'biophysical' core, the CASA-CNP 'biogeochemistry' module (Wang et al., 2010) and the POP module for woody demography and disturbance-mediated landscape heterogeneity. The biophysical core (sub-diurnal time-step) consists of four components: (1) the radiation module describes radiation

BES-SIM model	Description
	transfer and absorption by sunlit and shaded leaves; (2) the canopy micrometeorology module describes the surface roughness length, zero-plane displacement height, and aerodynamic conductance from the reference height to the air within canopy or to the soil surface; (3) the canopy module includes the coupled energy balance, transpiration, stomatal conductance and photosynthesis and respiration of sunlit and shaded leaves; (4) the soil module describes heat and water fluxes within soil (6 vertical layers) and snow (up to 3 vertical layers) and at their respective surfaces. The CASA-CNP biogeochemistry module (daily time-step) inherits daily net photosynthesis from the biophysical code, calculates autotrophic respiration, allocates the resulting net primary production (NPP) to leaves, stems and fine roots, and transfers carbon, nitrogen and phosphorous between plant, litter and soil pools, accounting for losses of each to the atmosphere and by leaching. POP (annual time-step) inherits annual stem NPP from CASA-CNP, and simulates patch-scale woody ecosystem stand dynamics, demography and disturbance-mediated heterogeneity, returning the emergent rate of biomass turnover to CASA-CNP. The model outputs C pools in veg., soil, GPP, heterotrophic respiration, NPP, runoff, LAI, combined crop and pasture yields, wood harvest, C:N ratios, either per grid cell simulated, or per PFT. The land-use and land-cover change module, driven by gross land-use transitions and wood harvest area extend the applicability of CABLE for regional and global carbon-climate simulations, accounting for vegetation response of both biophysical and anthropogenic forcing. Land-use transitions and harvest associated with secondary forest tiles modify the annually-resolved patch age distribution within secondary-vegetated tiles, in turn affecting biomass accumulation and turnover rates and hence the magnitude of the secondary forest sink. CABLE incorporates a novel approach to constraining modelled GPP to be consistent with the Co-ordination Hypothesis, predicted by evolutionary theory, which suggests that electron transport and Rubisco-limited rates adjust seasonally and across biomes to be co-limiting.
GLOBIO-ES	The GLOBIO-ES model (Alkemade et al., 2014; Schulp et al., 2012) simulate the influence of various anthropogenic drivers on ecosystem functions and services at the global scale in past, present and future environments using model outcomes of the IMAGE model on food production, livestock production, carbon balance, land use, and climate (Stehfest et al., 2014), in combination with data on GDP per capita, protected area maps and infrastructure. For ecosystem services related to water, water flow regimes are derived from the PCR-GLOBWB model, and nutrient loading is derived from the IMAGE framework model Global Nutrient Model (see also section on GLOBIO-Aquatic). The model transfers IMAGE model outcomes into a supply – demand concept of ecosystem services and uses causal relationships between environmental variables and ecosystem functions and services (definitions according the cascade model by Haines-Young and Potschin (2010) based on literature reviews). The model quantifies a range of provisioning services (e.g. crop production, grass and fodder production, wild food, water availability), regulating services (e.g. pest control, pollination, erosion risk reduction, carbon sequestration, food risk reduction, harmful algal blooms), and culture services (e.g. nature based tourism) These relationships describe how ecosystem services respond to changing environments. The improvements made since last published methodology include updated relationships between land use and the presence of pollinators and predators using additional peer review papers.
InVEST	*Nutrient Delivery Ratio* The InVEST nutrient delivery ratio model (Redhead et al., 2018) maps nutrient sources from watersheds and their transport to the stream using digital elevation model, land-use land-cover data, nutrient runoff proxy, watersheds layer, and biophysical table. This spatial information can be used to assess the service of nutrient retention by natural vegetation. The retention service is of particular interest for surface water quality issues and can be valued in economic or social terms (e.g. avoided treatment costs, improved water security through access to clean drinking water). The model uses a mass balance approach, describing the movement of mass of nutrient through space. Unlike more sophisticated nutrient models, the model does not represent the details of the nutrient cycle but rather represents the long-term, steady-state flow of nutrients through empirical relationships. Sources of nutrient across the landscape, also called nutrient loads, are determined based on the LULC map and associated loading rates. In a second step, delivery factors are computed for each pixel based on the properties of pixels belonging to the same flow path (in particular their slope and retention efficiency of the land use). At the watershed/subwatershed outlet, the nutrient export is computed as the sum of the pixel-level contributions. The model outputs total nutrient loads (sources) in the watershed and total nutrient exports from the water shed at the pixel level. Improvements were made to the model to accept load as a raster for certain LULC classes (agriculture)

BES-SIM model	Description
	instead of a table value. This was so we could utilize the fertilizer application rates in the management files for each SSP. The nitrogen retention is connected to people by multiplying the per-hectare export by the rural population density in the watershed as a weighting factor of the degree to which water quality impacts rural people (who are typically more vulnerable to declines in water quality because they have fewer or no water treatment options). The model generates its own watersheds (hydrologically complete watersheds that drain to the sea) and added a pit-filling algorithm for DEMs to allow for global routing. A function is added to allow for "continuous" streams, meaning a single pixel (of resolution 300 m) doesn't have to be classified as entirely stream, but can be a value between 0-1, indicating the proportion of the pixel that the stream occupies. *Costal Vulnerability* The InVEST Coastal Vulnerability model (Arkema et al., 2013; Guannel et al., 2016) produces a qualitative index of coastal exposure to erosion and inundation as well as a map of the location and size of human settlements. The model creates the exposure index and coastal population maps using a spatial representation (raster) of population and spatial representations (shapefiles and rasters) of seven bio-geophysical variables (geomorphology, relief, natural habitats (biotic and abiotic), net sea level change, wind exposure, wave exposure, surge potential depth contour) and outputs point shapefile with fields representing base risk, and risk without habitat. The software model was refactored to optimize runtime and memory usage so it was computationally feasible to model global runs. *Pollination* The InVEST Pollination model (Chaplin-Kramer et al., 2014) maps pollination contribution to nutrition based on pollinator-dependent nutrient production, and the dependence of that production on natural habitat around farmland. This nutrition production provided by wild pollinators is then translated to potential number of people fed based on dietary requirements. Pollination sufficiency is based on the area of pollinator habitat around farmland. Agricultural pixels with >30% natural habitat in the 2 km area surrounding the farm are designated as receiving sufficient pollination for pollinator-dependent yields. Pollination-dependence of crops, crop yields, and crop micronutrient content are combined to calculate pollination-dependent nutrient production. Nutrition provided by wild pollinators on each pixel of agricultural land is then calculated according to pollination habitat sufficiency and the pollination-dependent nutrient yields. The model uses yield maps for 115 crops (raster; Monfreda et al., 2008), nutrient content of 115 crops (table; USDA 2011), pollination dependence of 115 crops (raster; Klein et al., 2007), land use (raster; GLOBIO downscaled from LUH2), dietary requirements (WHO), demographic data (GPW4 Age Dataset – 2018), and outputs pollination sufficiency (proportion of agricultural land in a grid cell receiving pollination services sufficient for attaining full pollination-dependent yields), pollination service - nutrient (production of macro/micronutrient per grid cell), people fed - nutrient (potential number of people whose annual dietary requirements are met by nutrition provided by wild pollination), self-sufficiency – nutrient (proportion of nutrition needs of population in a grid cell met by nutrition provided wild pollination in that grid cell). The approach for pollination-dependent nutrient production outlined in Chaplin-Kramer et al. (2014) was extended to include pollination habitat sufficiency. *Crop Production* The crop-production model is based closely on the InVEST Crop Production model (Mueller et al., 2012) with calculation methods for nutritional content from Johnson et al., 2014, 2016. The model was modified by aggregating 175 crops (raster; Monfreda et al., 2008) to the 5 crop-types in LUH2: C3 annual, C3 perennial, C4 annual, C4 perennial and N-fixing crops. Each crop type in the LUH2 states data was resampled (bilinear) to a 5 arc-minute grid-cell to match yield data. Caloric production per hectare on each current and future landscape for each crop type is calculated by aggregating yield data and multiplying it by the proportional extent of the 5 arc-minute grid-cell in each crop-type. To identify crop-type yield for cropland expansion that occurred outside of existing cropland extent (and therefore did not have observed yields available), we used the yield-gap method in (Mueller et al., 2012) to identify the 50^{th}-percentile yield for the grid-cell based on its climate bin (defined with growing-degree days and precipitation). The indicator we report does not include increases in per-area crop yield (e.g. from technological change) and instead isolates simply the increase in food security/food production from changes in cropland extent under the different scenarios. Yield was expressed in terms of caloric content based on

BES-SIM model	Description
	aggregated-versions of the food balance sheets of the Food and Agriculture Organization of the United Nations FAOSTAT database.
GLOSP	GLOSP (Guerra et al., 2016) is a 2D soil erosion model based on the Universal Soil Loss Equation, using climate, land use, vegetation cover, topography, and soil data to estimate global and local soil erosion and protection indicators. Protected soil (Ps) is defined as the amount of soil that is prevented from being eroded (water erosion) by the mitigating effect of available vegetation. Ps is calculated from the difference between soil erosion (Se) and potential soil erosion (Pse) [Ps = Pse-Se]. Pse is calculated by the integration of the joint effect of slope length, rainfall erosivity, and soil erodibility. Se is calculated by multiplying Pse by the fractional vegetation cover ($0 \leq$ Fcover ≤ 1). Here soil protection is given by the value of fractional vegetation cover calculated as a function of land use, altitude, precipitation, and soil properties. Global fractional vegetation cover is originally calculated based on a multiple endmembers method described in Filiponi et al. (accepted). This is then resampled to 0.25 degree. To obtain a long temporal distribution of this variable (1900-2099), a spatial explicit polynomial regression function is implemented to calculate monthly Fcover values as a function of land use, altitude, precipitation, and soil properties. For future conditions, vegetation values are calculated based on SSP~RCP correspondences. An assumption is made to the historical projections that the physical processes remain the same through time.

Table S3: Definition of metrics in ecosystem functions and services models in BES-SIM.

Types of services	NCP	Metric	Models	Units	Definitions and formula
Material	Energy	Bioenergy-crop Production	LPJ-GUESS	PgC/yr, $kgC/m^2/yr$	First generation biofuel crop production (carbon removed during harvest)
Material	Food and feed	Crop Yields	LPJ-GUESS	PgC/yr, $kgC/m^2/yr$	Harvested carbon in croplands that are used for food production (excluding pastures)
Material	Food and feed	Crop and Pasture Yield	CABLE	PgC/yr, $kgC/m^2/yr$	Above ground carbon removed from cropland and pastures as a result of harvest and grazing
Material	Food and feed	Crop Production	GLOBIO-ES	10^9KCal	The total crop production derived by applying crop productivity of the IMAGE model on the LUH2 crop area estimates, and is derived from the total human demand (including for livestock); production of various crop categories, including wheat, rice, maize, tubers, pulses etc. using estimates of average caloric content the production was translated into Kcal produced.
Material	Food and feed	Grass Production	GLOBIO-ES	Gcal	Grass and fodder production derived by applying grass productivity from the IMAGE model on the LUH2 grassland area estimates; production derived from the total demand of livestock production; largely from pastures and rangelands.
Material	Food and feed	Production of C3Nfx, C3Ann, C3Per, C4Ann, C4Per	InVEST	kcal	Caloric production on the current landscape for each crop type – crop yields based on Monfreda et al. (2008); kcals calculated based on FAO food-balance sheets (FAO 2017)
Material	Materials, companionship and labor	Wood Harvest	LPJ-GUESS, CABLE	KgC, PgC/yr, $kgC/m^2/yr$	Wood carbon removed from natural vegetation (driven by wood harvest fraction from LUH2)
Regulating	Pollination and dispersal of seeds and other propagules	Pollination: fraction of cropland potentially pollinated, relative to all available cropland	GLOBIO-ES	Proportion	Pollination by natural pollinators assumed to be more effective in cropland situated near natural land; pollination efficiency related to distance from natural elements, based on literature review. A consequence is that pollination increases with the fraction of nature in a cell. We use the relationship between pollination efficiency and the fraction of natural area within a cell 0.5 by 0.5 degrees (Schulp et al., 2012). If NatPerc > 20 and NatPerc < 60, then pollination efficiency = 0.25 * NatPerc + 85, else pollination efficiency = 100 Sum: Total cropland potentially pollinated
Regulating	Pollination and dispersal of seeds and other propagules	Pollination: proportion of agricultural lands whose pollination needs are met	InVEST	Proportion	The model maps pollination contribution to nutrition based on proportion of crop production that is dependent on pollination, and proportion of that production whose pollination needs are met by natural habitat around farmland.

Types of services	NCP	Metric	Models	Units	Definitions and formula
Regulating	Regulation of climate	Total Carbon	LPJ-GUESS, LPJ, CABLE	PgC, kgC/m^2	Sum of vegetation, litter and soil carbon stocks; total carbon pool in the ecosystem, including carbon in stems, branches, leaves, roots, soil and litter
Regulating	Regulation of climate	Total Carbon	GLOBIO-ES	MgC	Total carbon pool in the ecosystem, including carbon in stems, branches, leaves, roots, soil and litter, derived from the IMAGE model (using LPJmL)
Regulating	Regulation of climate	Vegetation Carbon	LPJ-GUESS, LPJ, CABLE	PgC, kg/m^2, PgC, kgC/m^2	Carbon stocks in living wood, roots and leaves
Regulating	Regulation of freshwater quantity, location and timing	Monthly Runoff	LPJ-GUESS, LPJ, CABLE	Pg/s, kg/m^2s, Pg/month, kg/m^2 month, Pg/s, kg/m^2/s	Sum of drainage, surface and base waterflow Maximum monthly runoff - monthly combined surface and subsurface runoff summed
Regulating	Regulation of freshwater quantity, location and timing	Total Runoff	CABLE	km^3/yr, mm/yr	Total surface and subsurface runoff summed over the year
Regulating	Regulation of freshwater quantity, location and timing	Water Scarcity Index	GLOBIO-ES		Ratio demand / availability of renewable water, monthly-weighted (0-1) (Wada and Bierkens, 2014)
Regulating	Regulation of freshwater and coastal water quality	Nitrogen Leaching	LPJ-GUESS	PgN/s, kgN/m^2s	Nitrogen lost from the grid-cell, after subtracting an estimate for gaseous N losses
Regulating	Regulation of freshwater and coastal water quality	Nitrogen in Water	GLOBIO-ES	mgN/l	Total N concentration in the water, i.e. emissions divided by water discharge. The emissions are the sum of urban and diffuse sources, accumulated over the upstream catchment of a cell. The retention in the water network is accounted for Nitrogen concentration in water [mgN/l] per cell, means and quartiles per region.
Regulating	Regulation of freshwater and coastal water quality	Phosphorous in Water	GLOBIO-ES	mgN/l	Total P concentration in the water, i.e. emissions divided by water discharge. The emissions are the sum of urban and diffuse sources, accumulated over the upstream catchment of a cell. The retention in the water network is accounted for Phosphorus concentration in water [mgP/l] per cell, means and quartiles per region.

Types of services	NCP	Metric	Models	Units	Definitions and formula
Regulating	Regulation of freshwater and coastal water quality	Nitrogen Export	InVEST	Tons N/year	The model maps nutrient sources from watersheds and their transport to the stream. This spatial information can be used to assess the service of nutrient retention by natural vegetation. The retention service is of particular interest for surface water quality issues and can be valued in economic or social terms (e.g. avoided treatment costs, improved water security through access to clean drinking water).
Regulating	Regulation of freshwater and coastal water quality	Nitrogen Export*Capita	InVEST	Tons N*people /year	Nitrogen export times rural population, as an indication of where people are most vulnerable to changes in drinking water quality, because rural communities typically have fewer water treatment options or use well-water that may show similar patterns of nitrate leaching.
Regulating	Formation, protection and decontamination of soils and sediments	Erosion Protection: fraction with low risk relative to the area that needs protection	GLOBIO-ES	index (0-100)	Erosion risk calculation for pasture, rangeland, cropland and urban from the USLE as implemented in the IMAGE model. Based on soil characteristics (e.g. texture, depths and slope), climate characteristics (e.g. precipitation) and land-use sensitivity. The risk is calculated as a relative figure between 0 and 100, from high to low risk. Sum: total area with low risk (ER > 80)
Regulating	Formation, protection and decontamination of soils and sediments	Soil Protection	GLOSP	%	The amount of vegetation cover (in %cover) across all pixels within a specific subset (e.g., global, region 'x'). For each observed year, these values vary between 0 and 1 and for the change index negative values represent the rate of decrease in relation to a reference year.
Regulating	Regulation of hazards and extreme events	Flood Risk: number of people exposed to river flood risk	GLOBIO-ES	people affected	The number of people exposed to river flood risk calculated based on the frequency of daily river discharge exceeding the river's capacity, the potentially inundated area and the population density in that area. 'Normal' predictable yearly flooding is left out. Sum = number of people affected, per region
Regulating	Regulation of hazards and extreme events	Coastal Vulnerability Index	InVEST	unitless score from 1 (min) to 5 (max)	Geophysical and natural habitat characteristics of coastlines are used to compare relative exposure to erosion and flooding in severe weather across space and different scenarios (Arkema et al., 2013).
Regulating	Regulation of hazards and extreme events	Coastal Vulnerability *Capita	InVEST	unitless score*people	Total exposure risk times population within 2km of shore. When overlaid with data on coastal population density, the model's outputs can be used to identify where humans face higher risks of damage from storm waves and surge.

Types of services	NCP	Metric	Models	Units	Definitions and formula
Regulating	Regulation of detrimental organisms and biological processes	Pest Control: fraction of cropland potentially protected, relative to all available cropland	GLOBIO-ES	km^2	Cropland area that is potentially covered by sufficient pest predators. Pest control by natural predators is assumed to be more effective in cropland situated near natural land. The pest control efficiency is related to distance from natural elements, relation is based on literature review. A consequence is that pollination increases with the fraction of nature in a cell. We use the relationship between pollination efficiency and the fraction of natural area within a cell 0.5 by 0.5 degrees (Schulp et al., 2012). If NatPerc < 35, then pest control = 0.48 * NatPerc + 12,75, else pest control = 0.67 * NatPerc + 7.25 Sum: Total cropland potentially covered by natural predators

References

Alkemade, R., van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M. and ten Brink, B.: GLOBIO3: A Framework to Investigate Options for Reducing Global Terrestrial Biodiversity Loss, Ecosystems, 12(3), 374–390, doi:10.1007/s10021-009-9229-5, 2009.

Alkemade, R., Burkhard, B., Crossman, N. D., Nedkov, S. and Petz, K.: Quantifying ecosystem services and indicators for science, policy and practice, Ecol. Indic., 37, 161–162, doi:10.1016/j.ecolind.2013.11.014, 2014.

Allen, L. H., De Benoist, B., Dary, O., Hurrell, R.: World Health Organization: Guidelines on food fortification with micronutrients, 2006.

Allnutt, T. F., Ferrier, S., Manion, G., Powell, G. V. N., Ricketts, T. H., Fisher, B. L., Harper, G. J., Irwin, M. E., Kremen, C., Labat, J.-N., Lees, D. C., Pearce, T. A. and Rakotondrainibe, F.: A method for quantifying biodiversity loss and its application to a 50-year record of deforestation across Madagascar: Extinction estimates in Madagascar from deforestation, Conserv. Lett., 1(4), 173–181, doi:10.1111/j.1755-263X.2008.00027.x, 2008.

Arkema, K. K., Guannel, G., Verutes, G., Wood, S. A., Guerry, A., Ruckelshaus, M., Kareiva, P., Lacayo, M. and Silver, J. M.: Coastal habitats shield people and property from sea-level rise and storms, Nat. Clim. Change, 3(10), 913–918, doi:10.1038/nclimate1944, 2013.

Bateman, B. L., Murphy, H. T., Reside, A. E., Mokany, K., VanDerWal, J. and Thuiller, W. (Eds.): Appropriateness of full-, partial- and no-dispersal scenarios in climate change impact modelling, Divers. Distrib., 19(10), 1224–1234, doi:10.1111/ddi.12107, 2013.

Benítez-López, A., Alkemade, R., Schipper, A. M., Ingram, D. J., Verweij, P. A., Eikelboom, J. A. J. and Huijbregts, M. A. J.: The impact of hunting on tropical mammal and bird populations, Science, 356(6334), 180–183, doi:10.1126/science.aaj1891, 2017.

Bijl, D. L., Bogaart, P. W., Kram, T., de Vries, B. J. M. and van Vuuren, D. P.: Long-term water demand for electricity, industry and households, Environ. Sci. Policy, 55, 75–86, doi:10.1016/j.envsci.2015.09.005, 2016.

Blois, J. L., Williams, J. W., Fitzpatrick, M. C., Jackson, S. T. and Ferrier, S.: Space can substitute for time in predicting climate-change effects on biodiversity, Proc. Natl. Acad. Sci., 110(23), 9374–9379, doi:10.1073/pnas.1220228110, 2013.

Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., Haberl, H., Creutzig, F. and Seto, K. C.: Future urban land expansion and implications for global croplands, Proc. Natl. Acad. Sci., 114(34), 8939–8944, doi:10.1073/pnas.1606036114, 2017.

Brinsmead, T.S., Smith, K., Hatfield-Dodds, S., Adams, P., Baynes, T., Ferrier, S., Harwood, T., Hayward, J.A., Lennox, J., Marcos Martinez, R., Nolan, M., Qiu, J.: A novel integrated assessment framework for exploring possible futures for Australia: the GNOME.3 suite for the Australian National Outlook, in MODSIM2017 (eds), Syme, G., Hatton MacDonald, D., Fulton, B. and Piantadosi, J., 22nd International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, pp. 1440-1446, 2017.

British Nutrition Foundation: Nutrition requirements, https://www.nutrition.org.uk/attachments/article/234/Nutrition%20Requirements_Revised%20Oct%202016.pdf, last access: January 2018.

Brown, J. H., Gillooly, J. F., Allen, A. P., Savage, V. M. and West, G. B.: TOWARD A METABOLIC THEORY OF ECOLOGY, Ecology, 85(7), 1771–1789, doi:10.1890/03-9000, 2004.

Bryan, B. A., Nolan, M., Harwood, T. D., Connor, J. D., Navarro-Garcia, J., King, D., Summers, D. M., Newth, D., Cai, Y., Grigg, N., Harman, I., Crossman, N. D., Grundy, M. J., Finnigan, J. J., Ferrier, S., Williams, K. J., Wilson, K. A., Law, E. A. and Hatfield-Dodds, S.: Supply of carbon sequestration and biodiversity services from Australia's agricultural land under global change, Glob. Environ. Change, 28, 166–181, doi:10.1016/j.gloenvcha.2014.06.013, 2014.

Busch, J. and Ferretti-Gallon, K.: What Drives Deforestation and What Stops It? A Meta-Analysis, Rev. Environ. Econ. Policy, 11(1), 3–23, doi:10.1093/reep/rew013, 2017.

Chaplin-Kramer, R., Dombeck, E., Gerber, J., Knuth, K. A., Mueller, N. D., Mueller, M., Ziv, G. and Klein, A.-M.: Global malnutrition overlaps with pollinator-dependent micronutrient production, Proc. R. Soc. B Biol. Sci., 281(1794), 20141799–20141799, doi:10.1098/rspb.2014.1799, 2014.

Chaudhary, A., Verones, F., de Baan, L. and Hellweg, S.: Quantifying Land Use Impacts on Biodiversity: Combining Species–Area Models and Vulnerability Indicators, Environ. Sci. Technol., 49(16), 9987–9995, doi:10.1021/acs.est.5b02507, 2015.

Denno, R.F., Lewis, D.: Predator-prey interactions: in, The Princeton guide to ecology, Levin, SA, Carpenter, S.R., Godfray, H.C.J., Kinzig, A.P., Loreau, M., et al., Princeton, NJ: Princeton University Press, pp. 202–212, 2012.

Deutsch, C. A., Tewksbury, J. J., Huey, R. B., Sheldon, K. S., Ghalambor, C. K., Haak, D. C. and Martin, P. R.: Impacts of climate warming on terrestrial ectotherms across latitude, Proc. Natl. Acad. Sci., 105(18), 6668–6672, doi:10.1073/pnas.0709472105, 2008.

Döll, P. and Lehner, B.: Validation of a new global 30-min drainage direction map, J. Hydrol., 258(1–4), 214–231, doi:10.1016/S0022-1694(01)00565-0, 2002.

Fekete, B. M., Wisser, D., Kroeze, C., Mayorga, E., Bouwman, L., Wollheim, W. M. and Vörösmarty, C.: Millennium Ecosystem Assessment scenario drivers (1970-2050): Climate and hydrological alterations: GLOBAL NEWS HYDROLOGY, Glob. Biogeochem. Cycles, 24(4), n/a-n/a, doi:10.1029/2009GB003593, 2010.

Ferrier, S., Harwood, T.D., Williams, K.J.: Assessing refugial potential using compositional-turnover modelling, Pages 51-76, in: Climate change refugia for terrestrial biodiversity: defining areas that promote species persistence and ecosystem resilience in the face of global climate change, National Climate Change Adaptation Research Facility, Gold Coast, 2013.

Ferrier, S., Powell, G. V. N., Richardson, K. S., Manion, G., Overton, J. M., Allnutt, T. F., Cameron, S. E., Mantle, K., Burgess, N. D., Faith, D. P., Lamoreux, J. F., Kier, G., Hijmans, R. J., Funk, V. A., Cassis, G. A., Fisher, B. L., Flemons, P., Lees, D., Lovett, J. C. and Van Rompaey, R. S. A. R.: Mapping More of Terrestrial Biodiversity for Global Conservation Assessment, BioScience, 54(12), 1101, doi:10.1641/0006-3568(2004)054[1101:MMOTBF]2.0.CO;2, 2004.

Ferrier, S., Manion, G., Elith, J. and Richardson, K.: Using generalized dissimilarity modelling to analyse and predict patterns of beta diversity in regional biodiversity assessment, Divers. Distrib., 13(3), 252–264, doi:10.1111/j.1472-4642.2007.00341.x, 2007.

Filipponi F., Valentini E., Xuan A., Guerra C.A., Wolf F., Andrzejak M., Taramelli A.: Global MODIS Fraction of green vegetation Cover for monitoring vegetation abrupt and gradual changes, Remote Sensing. [accepted]

Fitzpatrick, M. C., Sanders, N. J., Ferrier, S., Longino, J. T., Weiser, M. D. and Dunn, R.: Forecasting the future of biodiversity: a test of single- and multi-species models for ants in North America, Ecography, 34(5), 836–847, doi:10.1111/j.1600-0587.2011.06653.x, 2011.

Frischknecht R., Jolliet O. (eds): Global Guidance for Life Cycle Impact Assessment Indicators, vol 1, United Nations Environment Programme, 2016.

Food and Agriculture Organization of the United Nations: Food balance sheets, Rome, http://www.fao.org/economic/ess/fbs/en, 2017.

Food and Agriculture Organization of the United Nations: Global Forest Resources Assessment 2000, Rome, FAO Forestry Department, 2000.

Gray, C. L., Hill, S. L. L., Newbold, T., Hudson, L. N., Börger, L., Contu, S., Hoskins, A. J., Ferrier, S., Purvis, A. and Scharlemann, J. P. W.: Local biodiversity is higher inside than outside terrestrial protected areas worldwide, Nat. Commun., 7, 12306, doi:10.1038/ncomms12306, 2016.

Guannel, G., Arkema, K., Ruggiero, P., Verutes, G. and Bianchi, C. N. (Eds.): The Power of Three: Coral Reefs, Seagrasses and Mangroves Protect Coastal Regions and Increase Their Resilience, PLOS ONE, 11(7), e0158094, doi:10.1371/journal.pone.0158094, 2016.

Guerra, C. A., Maes, J., Geijzendorffer, I. and Metzger, M. J.: An assessment of soil erosion prevention by vegetation in Mediterranean Europe: Current trends of ecosystem service provision, Ecol. Indic., 60, 213–222, doi:10.1016/j.ecolind.2015.06.043, 2016.

Haberl, H., Erb, K. H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W. and Fischer-Kowalski, M.: Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems, Proc. Natl. Acad. Sci., 104(31), 12942–12947, doi:10.1073/pnas.0704243104, 2007.

Haines-Young, R., Potschin, M.: The links between biodiversity, ecosystem services and human well-being, Ch 7: in, Ecosystem Ecology: A New Synthesis (eds.), Raffaelli, D., Frid, C., BES Ecological Reviews Series, CUP, Cambridge, in press, 2010.

Harfoot, M. B. J., Newbold, T., Tittensor, D. P., Emmott, S., Hutton, J., Lyutsarev, V., Smith, M. J., Scharlemann, J. P. W., Purves, D. W., Loreau, M. (Eds.): Emergent Global Patterns of Ecosystem Structure and Function from a Mechanistic General Ecosystem Model, PLoS Biol., 12(4), e1001841, doi:10.1371/journal.pbio.1001841, 2014.

Hasegawa, T., Fujimori, S., Ito, A., Takahashi, K. and Masui, T.: Global land-use allocation model linked to an integrated assessment model, Sci. Total Environ., 580, 787–796, doi:10.1016/j.scitotenv.2016.12.025, 2017.

Hatfield-Dodds, S., Schandl, H., Adams, P. D., Baynes, T. M., Brinsmead, T. S., Bryan, B. A., Chiew, F. H. S., Graham, P. W., Grundy, M., Harwood, T., McCallum, R., McCrea, R., McKellar, L. E., Newth, D., Nolan, M., Prosser, I. and Wonhas, A.: Australia is 'free to choose' economic growth and falling environmental pressures, Nature, 527(7576), 49–53, doi:10.1038/nature16065, 2015.

Haverd, V., Smith, B., Nieradzik, L., Briggs, P. R., Woodgate, W., Trudinger, C. M. and Canadell, J. G.: A new version of the CABLE land surface model (Subversion revision r4546), incorporating land use and land cover change, woody vegetation demography and a novel optimisation-based approach to plant coordination of electron transport and carboxylation capacity-limited photosynthesis, Geosci. Model Dev. Discuss., 1–33, doi:10.5194/gmd-2017-265, 2017.

Hengl, T., de Jesus, J. M., MacMillan, R. A., Batjes, N. H., Heuvelink, G. B. M., Ribeiro, E., Samuel-Rosa, A., Kempen, B., Leenaars, J. G. B., Walsh, M. G., Gonzalez, M. R. and Bond-Lamberty, B. (Eds.): SoilGrids1km — Global Soil Information Based on Automated Mapping, PLoS ONE, 9(8), e105992, doi:10.1371/journal.pone.0105992, 2014.

Hoskins, A. J., Bush, A., Gilmore, J., Harwood, T., Hudson, L. N., Ware, C., Williams, K. J. and Ferrier, S.: Downscaling land-use data to provide global 30″ estimates of five land-use classes, Ecol. Evol., 6(9), 3040–3055, doi:10.1002/ece3.2104, 2016.

Hoskins, A.J., Harwood, T.D., Ware, C., Williams, K.J., Perry, J.J., Ota, N., Croft, J.R., Yeates, D.K., Jetz, W., Golebiewski, M., Purvis, A., Ferrier, S., 2018. Supporting global biodiversity assessment through high-resolution macroecological modelling: Methodological underpinnings of the BILBI framework. BioRxiv http://biorxiv.org/cgi/content/short/309377v1. [in prep.]

Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., De Palma, A., Phillips, H. R. P., Senior, R. A., Bennett, D. J., Booth, H., Choimes, A., Correia, D. L. P., Day, J., Echeverría-Londoño, S., Garon, M., Harrison, M. L. K., Ingram, D. J., Jung, M., Kemp, V., Kirkpatrick, L., Martin, C. D., Pan, Y., White, H. J., Aben, J., Abrahamczyk, S., Adum, G. B., Aguilar-Barquero, V., Aizen, M. A., Ancrenaz, M., Arbeláez-Cortés, E., Armbrecht, I., Azhar, B., Azpiroz, A. B., Baeten, L., Báldi, A., Banks, J. E., Barlow, J., Batáry, P., Bates, A. J., Bayne, E. M., Beja, P., Berg, Å., Berry, N. J., Bicknell, J. E., Bihn, J. H., Böhning-Gaese, K., Boekhout, T., Boutin, C., Bouyer, J., Brearley, F. Q., Brito, I., Brunet, J., Buczkowski, G., Buscardo, E., Cabra-García, J., Calviño-Cancela, M., Cameron, S. A., Cancello, E. M., Carrijo, T. F., Carvalho, A. L., Castro, H., Castro-Luna, A. A., Cerda, R., Cerezo, A., Chauvat, M., Clarke, F. M., Cleary, D. F. R., Connop, S. P., D'Aniello, B., da Silva, P. G., Darvill, B., Dauber, J., Dejean, A., Diekötter, T., Dominguez-Haydar, Y., Dormann, C. F., Dumont, B., Dures, S. G., Dynesius, M., Edenius, L., Elek, Z., Entling, M. H., Farwig, N., Fayle, T. M., Felicioli, A., Felton, A. M., Ficetola, G. F., Filgueiras, B. K. C., Fonte, S. J., Fraser, L. H., Fukuda, D., Furlani, D., Ganzhorn, J. U., Garden, J. G., Gheler-Costa, C., Giordani, P., Giordano, S., Gottschalk, M. S., Goulson, D., et al.: The PREDICTS database: a global database of how local terrestrial biodiversity responds to human impacts, Ecol. Evol., 4(24), 4701–4735, doi:10.1002/ece3.1303, 2014.

Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., et al.: Dataset: The 2016 release of the PREDICTS database, http://dx.doi.org/10.5519/0066354, 2016.

Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., De Palma, A., Phillips, H. R. P., Alhusseini, T. I., Bedford, F. E., Bennett, D. J., Booth, H., Burton, V. J., Chng, C. W. T., Choimes, A., Correia, D. L. P., Day, J., Echeverría-Londoño, S., Emerson, S. R., Gao, D., Garon, M., Harrison, M. L. K., Ingram, D. J., Jung, M., Kemp, V., Kirkpatrick, L., Martin, C. D., Pan, Y., Pask-Hale, G. D., Pynegar, E. L., Robinson, A. N., Sanchez-Ortiz, K., Senior, R. A., Simmons, B. I., White, H. J., Zhang, H., Aben, J., Abrahamczyk, S., Adum, G. B., Aguilar-Barquero, V., Aizen, M. A., Albertos, B., Alcala, E. L., del Mar Alguacil, M., Alignier, A., Ancrenaz, M., Andersen, A. N., Arbeláez-Cortés, E., Armbrecht, I., Arroyo-Rodríguez, V., Aumann, T., Axmacher, J. C., Azhar, B., Azpiroz, A. B., Baeten, L., Bakayoko, A., Báldi, A., Banks, J. E., Baral, S. K., Barlow, J., Barratt, B. I. P., Barrico, L., Bartolommei, P., Barton, D. M., Basset, Y., Batáry, P., Bates, A. J., Baur, B., Bayne, E. M., Beja, P., Benedick, S., Berg, Å., Bernard, H., Berry, N. J., Bhatt, D., Bicknell, J. E., Bihn, J. H., Blake, R. J., Bobo, K. S., Bóçon, R., Boekhout, T., Böhning-Gaese, K., Bonham, K. J., Borges, P. A. V., Borges, S. H., Boutin, C., Bouyer, J., Bragagnolo, C., Brandt, J. S., Brearley, F. Q., Brito, I., Bros, V., Brunet, J., Buczkowski, G., Buddle, C. M., Bugter, R., Buscardo, E., Buse, J., Cabra-García, J., Cáceres, N. C., et al.: The database of the PREDICTS (Projecting Responses of Ecological Diversity In Changing Terrestrial Systems) project, Ecol. Evol., 7(1), 145–188, doi:10.1002/ece3.2579, 2017.

Hurtt, G. C., Chini, L. P., Frolking, S., Betts, R. A., Feddema, J., Fischer, G., Fisk, J. P., Hibbard, K., Houghton, R. A., Janetos, A., Jones, C. D., Kindermann, G., Kinoshita, T., Klein Goldewijk, K., Riahi, K., Shevliakova, E., Smith, S., Stehfest, E., Thomson, A., Thornton, P., van Vuuren, D. P. and Wang, Y. P.: Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands, Clim. Change, 109(1–2), 117–161, doi:10.1007/s10584-011-0153-2, 2011.

Hurtt, G., Chini, L., Sahajpal, R., Frolking, S., Calvin, K., Fujimori, S., Klein Goldewijk, K., Hasegawa, T., Havlik, P., Lawrence, D., Lawrence, P., Popp, A., Stehfest, E., van Vuuren, D., and Zhang, X.: Harmonization of global land-use change and management for the period 850–2100. [submitted]

Janse, J. H., Bakkenes, M. & Meijer, J.: Globio-Aquatic, Technical model description v. 1.3: PBL publication 2829, The Hague, PBL Netherlands Environmental Assessment Agency, 2016.

Janse, J. H., Kuiper, J. J., Weijters, M. J., Westerbeek, E. P., Jeuken, M. H. J. L., Bakkenes, M., Alkemade, R., Mooij, W. M. and Verhoeven, J. T. A.: GLOBIO-Aquatic, a global model of human impact on the biodiversity of inland aquatic ecosystems, Environ. Sci. Policy, 48, 99–114, doi:10.1016/j.envsci.2014.12.007, 2015.

Jetz, W., Wilcove, D. S., Dobson, A. P. and Mace, G. M. (Eds.): Projected Impacts of Climate and Land-Use Change on the Global Diversity of Birds, PLoS Biol., 5(6), e157, doi:10.1371/journal.pbio.0050157, 2007.

Johnson, J. A., Runge, C. F., Senauer, B., Foley, J. and Polasky, S.: Global agriculture and carbon trade-offs, Proc. Natl. Acad. Sci., 111(34), 12342–12347, doi:10.1073/pnas.1412835111, 2014.

Johnson, J. A., Runge, C. F., Senauer, B. and Polasky, S.: Global Food Demand and Carbon-Preserving Cropland Expansion under Varying Levels of Intensification, Land Econ., 92(4), 579–592, doi:10.3368/le.92.4.579, 2016.

Jones, B. and O'Neill, B. C.: Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways, Environ. Res. Lett., 11(8), 084003, doi:10.1088/1748-9326/11/8/084003, 2016.

Klein, A.-M., Vaissiere, B. E., Cane, J. H., Steffan-Dewenter, I., Cunningham, S. A., Kremen, C. and Tscharntke, T.: Importance of pollinators in changing landscapes for world crops, Proc. R. Soc. B Biol. Sci., 274(1608), 303–313, doi:10.1098/rspb.2006.3721, 2007.

Klein Goldewijk, K., Beusen, A., Doelman, J. and Stehfest, E.: New anthropogenic land use estimates for the Holocene; HYDE 3.2, Earth Syst. Sci. Data Discuss., 1–40, doi:10.5194/essd-2016-58, 2016.

Kourzeneva, E.: External data for lake parameterization in Numerical Weather Prediction and climate modelling, Boreal Environment Research, 15: 165-177, 2010.

Lamarque, J.-F., Kyle, G. P., Meinshausen, M., Riahi, K., Smith, S. J., van Vuuren, D. P., Conley, A. J. and Vitt, F.: Global and regional evolution of short-lived radiatively-active gases and aerosols in the Representative Concentration Pathways, Clim. Change, 109(1–2), 191–212, doi:10.1007/s10584-011-0155-0, 2011.

Lehner, B. and Döll, P.: Development and validation of a global database of lakes, reservoirs and wetlands, J. Hydrol., 296(1–4), 1–22, doi:10.1016/j.jhydrol.2004.03.028, 2004.

Lehner, B., Liermann, C. R., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P., Endejan, M., Frenken, K., Magome, J., Nilsson, C., Robertson, J. C., Rödel, R., Sindorf, N. and Wisser, D.: High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management, Front. Ecol. Environ., 9(9), 494–502, doi:10.1890/100125, 2011.

Lindeskog, M., Arneth, A., Bondeau, A., Waha, K., Seaquist, J., Olin, S. and Smith, B.: Implications of accounting for land use in simulations of ecosystem carbon cycling in Africa, Earth Syst. Dyn., 4(2), 385–407, doi:10.5194/esd-4-385-2013, 2013.

Martins, I. S. and Pereira, H. M.: Improving extinction projections across scales and habitats using the countryside species-area relationship, Sci. Rep., 7(1), doi:10.1038/s41598-017-13059-y, 2017.

Meijer, J. R., Huijbregts, M. A. J., Schotten, K. C. G. J. and Schipper, A. M.: Global patterns of current and future road infrastructure, Environmental Research Letters, 13(6), 064006, doi:10.1088/1748-9326/aabd42, 2018.

Merow, C., Smith, M. J. and Silander, J. A.: A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter, Ecography, 36(10), 1058–1069, doi:10.1111/j.1600-0587.2013.07872.x, 2013.

Midgley, G. F., Hughes, G. O., Thuiller, W. and Rebelo, A. G.: Migration rate limitations on climate change-induced range shifts in Cape Proteaceae, Divers. Htmlent Glyphamp Asciiamp Distrib., 12(5), 555–562, doi:10.1111/j.1366-9516.2006.00273.x, 2006.

Mokany, K., Harwood, T. D., Williams, K. J. and Ferrier, S.: Dynamic macroecology and the future for biodiversity, Glob. Change Biol., 18(10), 3149–3159, doi:10.1111/j.1365-2486.2012.02760.x, 2012.

Monfreda, C., Ramankutty, N. and Foley, J. A.: Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000: GLOBAL CROP AREAS AND YIELDS IN 2000, Glob. Biogeochem. Cycles, 22(1), n/a-n/a, doi:10.1029/2007GB002947, 2008.

Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N. and Foley, J. A.: Closing yield gaps through nutrient and water management, Nature, 490(7419), 254–257, doi:10.1038/nature11420, 2012.

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., Ingram, D. J., Itescu, Y., Kattge, J., Kemp, V., Kirkpatrick, L., Kleyer, M., Correia, D. L. P., Martin, C. D., Meiri, S., Novosolov, M., Pan, Y., Phillips, H. R. P., Purves, D. W., Robinson, A., Simpson, J., Tuck, S. L., Weiher, E., White, H. J., Ewers, R. M., Mace, G. M., Scharlemann, J. P. W. and Purvis, A.: Global effects of land use on local terrestrial biodiversity, Nature, 520(7545), 45–50, doi:10.1038/nature14324, 2015.

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Gray, C. L., Scharlemann, J. P. W., Börger, L., Phillips, H. R. P., Sheil, D., Lysenko, I. and Purvis, A.: Global patterns of terrestrial assemblage turnover within and among land uses, Ecography, 39(12), 1151–1163, doi:10.1111/ecog.01932, 2016a.

Newbold, T., Hudson, L. N., Arnell, A. P., Contu, S., De Palma, A., Ferrier, S., Hill, S. L. L., Hoskins, A. J., Lysenko, I., Phillips, H. R. P., Burton, V. J., Chng, C. W. T., Emerson, S., Gao, D., Pask-Hale, G., Hutton, J., Jung, M., Sanchez-Ortiz, K., Simmons, B. I., Whitmee, S., Zhang, H., Scharlemann, J. P. W. and Purvis, A.: Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment, Science, 353(6296), 288–291, doi:10.1126/science.aaf2201, 2016b.

Ohashi, H., Hasegawa, T., Hirata, A., Fujimori, S., Takahashi, K., Tsuyama, I., Nakao, K., Kominami, Y., Tanaka, N., Hijioka, Y., Matsui, T.: Biodiversity can benefit from long-term climate mitigation regardless of land-based measures. [submitted]

Olin, S., Schurgers, G., Lindeskog, M., Wårlind, D., Smith, B., Bodin, P., Holmér, J. and Arneth, A.: Modelling the response of yields and tissue C : N to changes in atmospheric CO_2 and N management in the main wheat regions of western Europe, Biogeosciences, 12(8), 2489–2515, doi:10.5194/bg-12-2489-2015, 2015.

Pereira, H. M. and Daily, G. C.: Modelling biodiversity dynamics in countryside landscapes, Ecology, 87(8), 1877–1885, doi:10.1890/0012-9658(2006)87[1877:MBDICL]2.0.CO;2, 2006.

Petz, K., Alkemade, R., Bakkenes, M., Schulp, C. J. E., van der Velde, M. and Leemans, R.: Mapping and modelling trade-offs and synergies between grazing intensity and ecosystem services in rangelands using global-scale datasets and models, Glob. Environ. Change, 29, 223–234, doi:10.1016/j.gloenvcha.2014.08.007, 2014.

Phillips, S. J., Anderson, R. P. and Schapire, R. E.: Maximum entropy modeling of species geographic distributions, Ecol. Model., 190(3–4), 231–259, doi:10.1016/j.ecolmodel.2005.03.026, 2006.

Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J. and Ferrier, S.: Sample selection bias and presence-only distribution models: implications for background and pseudo-absence data, Ecol. Appl., 19(1), 181–197, doi:10.1890/07-2153.1, 2009.

Pletcher: Model fitting and hypothesis testing for age-specific mortality data, J. Evol. Biol., 12(3), 430–439, doi:10.1046/j.1420-9101.1999.00058.x, 1999.

Poulter, B., Frank, D. C., Hodson, E. L. and Zimmermann, N. E.: Impacts of land cover and climate data selection on understanding terrestrial carbon dynamics and the CO_2 airborne fraction, Biogeosciences, 8(8), 2027–2036, doi:10.5194/bg-8-2027-2011, 2011.

Prober, S. M., Hilbert, D. W., Ferrier, S., Dunlop, M. and Gobbett, D.: Combining community-level spatial modelling and expert knowledge to inform climate adaptation in temperate grassy eucalypt woodlands and related grasslands, Biodivers. Conserv., 21(7), 1627–1650, doi:10.1007/s10531-012-0268-4, 2012.

Prober, S.M., Williams, K.J., Harwood, T.D., Doerr, V.A.J., Jeanneret, T., Manion, G., Ferrier, S.: *Helping biodiversity adapt: Supporting climate-adaptation planning using a community-level modelling approach*, CSIRO Land and Water Flagship, 2015.

Redhead, J. W., May, L., Oliver, T. H., Hamel, P., Sharp, R. and Bullock, J. M.: National scale evaluation of the InVEST nutrient retention model in the United Kingdom, Sci. Total Environ., 610–611, 666–677, doi:10.1016/j.scitotenv.2017.08.092, 2018.

Rondinini, C., Di Marco, M., Chiozza, F., Santulli, G., Baisero, D., Visconti, P., Hoffmann, M., Schipper, J., Stuart, S. N., Tognelli, M. F., Amori, G., Falcucci, A., Maiorano, L. and Boitani, L.: Global habitat suitability models of terrestrial mammals, Philos. Trans. R. Soc. B Biol. Sci., 366(1578), 2633–2641, doi:10.1098/rstb.2011.0113, 2011.

Schipper, A.M., Bakkenes, M., Meijer, J.R., Alkemade, R., Huijbregts, M.J.: The GLOBIO model. A technical description of version 3.5. PBL publication 2369, The Hague, PBL Netherlands Environmental Assessment Agency, 2016.

Scholes, R. J. and Biggs, R.: A biodiversity intactness index, Nature, 434(7029), 45, 2005.

Schulp, C. J. E., Alkemade, R., Klein Goldewijk, K. and Petz, K.: Mapping ecosystem functions and services in Eastern Europe using global-scale data sets, Int. J. Biodivers. Sci. Ecosyst. Serv. Manag., 8(1–2), 156–168, doi:10.1080/21513732.2011.645880, 2012.

Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Kim, C.K., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M. Mandle, L., Hamel, P., Vogl, A.L., Rogers, L., Bierbower, W., Denu, D., and Douglass, J.: InVEST +VERSION+ User's Guide, The Natural Capital Project, Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund, 2018.

Smith, B., Wårlind, D., Arneth, A., Hickler, T., Leadley, P., Siltberg, J. and Zaehle, S.: Implications of incorporating N cycling and N limitations on primary production in an individual-based dynamic vegetation model, Biogeosciences, 11(7), 2027–2054, doi:10.5194/bg-11-2027-2014, 2014.

Smith, M. J., Purves, D. W., Vanderwel, M. C., Lyutsarev, V. and Emmott, S.: The climate dependence of the terrestrial carbon cycle, including parameter and structural uncertainties, Biogeosciences, 10(1), 583–606, doi:10.5194/bg-10-583-2013, 2013.

Stehfest, E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Biemans, H., Bouwman, A., den Elzen, M., Janse, J., Lucas, P., van Minnen, J., Müller, M., Prins, A.: Integrated Assessment of Global Environmental Change with IMAGE 3.0. Model description and policy applications, The Hague: PBL Netherlands Environmental Assessment Agency, 2014.

Temme, A. J. A. M. and Verburg, P. H.: Mapping and modelling of changes in agricultural intensity in Europe, Agric. Ecosyst. Environ., 140(1–2), 46–56, doi:10.1016/j.agee.2010.11.010, 2011.

Thuiller, W.: Patterns and uncertainties of species' range shifts under climate change, Glob. Change Biol., 10(12), 2020–2027, doi:10.1111/j.1365-2486.2004.00859.x, 2004.

Thuiller, W., Lafourcade, B., Engler, R. and Araújo, M. B.: BIOMOD - a platform for ensemble forecasting of species distributions, Ecography, 32(3), 369–373, doi:10.1111/j.1600-0587.2008.05742.x, 2009.

Thuiller, W., Lavergne, S., Roquet, C., Boulangeat, I., Lafourcade, B. and Araujo, M. B.: Consequences of climate change on the tree of life in Europe, Nature, 470(7335), 531–534, doi:10.1038/nature09705, 2011.

Tolman, H.L.: User Manual and System Documentation of WAVEWATCH III version 3.14 Technical Note, US Department of Commerce, National Oceanographic and Atmospheric Administration, National Weather Service, National Centers for Environmental Predictions, 2009.

Visconti, P., Bakkenes, M., Baisero, D., Brooks, T., Butchart, S. H. M., Joppa, L., Alkemade, R., Di Marco, M., Santini, L., Hoffmann, M., Maiorano, L., Pressey, R. L., Arponen, A., Boitani, L., Reside, A. E., van Vuuren, D. P. and Rondinini, C.: Projecting Global Biodiversity Indicators under Future Development Scenarios: Projecting biodiversity indicators, Conserv. Lett., 9(1), 5–13, doi:10.1111/conl.12159, 2016.

Wang, Y. P., Law, R. M. and Pak, B.: A global model of carbon, nitrogen and phosphorus cycles for the terrestrial biosphere, Biogeosciences, 7(7), 2261–2282, doi:10.5194/bg-7-2261-2010, 2010.

Williams, K.J., Prober, S.M., Harwood, T.D., Doerr, V.A.J., Jeanneret, T., Manion, G., Ferrier, S.: *Implications of climate change for biodiversity: A community-level modelling approach.* CSIRO Land and Water Flagship, http://adaptnrm.csiro.au/wp-content/uploads/2014/12/biodiversity-implications-tech-guide.pdf, 2015.

Williams, R. J., Anandanadesan, A., Purves, D. and Bersier, L.-F. (Eds.): The Probabilistic Niche Model Reveals the Niche Structure and Role of Body Size in a Complex Food Web, PLoS ONE, 5(8), e12092, doi:10.1371/journal.pone.0012092, 2010.

Zabel, F., Putzenlechner, B., Mauser, W. and Kropp, J. P. (Eds.): Global Agricultural Land Resources – A High Resolution Suitability Evaluation and Its Perspectives until 2100 under Climate Change Conditions, PLoS ONE, 9(9), e107522, doi:10.1371/journal.pone.0107522, 2014.