Earth Syst. Dynam., 4, 347–357, 2013
www.earth-syst-dynam.net/4/347/2013/
doi:10.5194/esd-4-347-2013


Earth System Dynamics
Open Access

# Critical impacts of global warming on land ecosystems

**S. Ostberg**[1], **W. Lucht**[1,2], **S. Schaphoff**[1], **and D. Gerten**[1]

[1]Potsdam Institute for Climate Impact Research, Research Domain 1: Earth System Analysis, Telegraphenberg A62, 14473 Potsdam, Germany
[2]Dept. of Geography, Humboldt-Universität zu Berlin, Berlin, Germany

*Correspondence to:* S. Ostberg (ostberg@pik-potsdam.de)

Received: 3 May 2013 – Published in Earth Syst. Dynam. Discuss.: 16 May 2013
Revised: 10 September 2013 – Accepted: 11 September 2013 – Published: 8 October 2013

**Abstract.** Globally increasing temperatures are likely to have impacts on terrestrial, aquatic and marine ecosystems that are difficult to manage. Quantifying impacts worldwide and systematically as a function of global warming is fundamental to substantiating the discussion on climate mitigation targets and adaptation planning. Here we present a macro-scale analysis of climate change impacts on terrestrial ecosystems based on newly developed sets of climate scenarios featuring a step-wise sampling of global mean temperature increase between 1.5 and 5 K by 2100. These are processed by a biogeochemical model (LPJmL) to derive an aggregated metric of simultaneous biogeochemical and structural shifts in land surface properties which we interpret as a proxy for the risk of shifts and possibly disruptions in ecosystems.

Our results show a substantial risk of climate change to transform terrestrial ecosystems profoundly. Nearly no area of the world is free from such risk, unless strong mitigation limits global warming to around 2 degrees above preindustrial level. Even then, our simulations for most climate models agree that up to one-fifth of the land surface may experience at least moderate ecosystem change, primarily at high latitudes and high altitudes. If countries fulfil their current emissions reduction pledges, resulting in roughly 3.5 K of warming, this area expands to cover half the land surface, including the majority of tropical forests and savannas and the boreal zone. Due to differences in regional patterns of climate change, the area potentially at risk of major ecosystem change considering all climate models is up to 2.5 times as large as for a single model.

## 1 Introduction

One of the most critical consequences of globally increasing temperatures is the potentially unmanageable impact on terrestrial, aquatic and marine ecosystems, as climate is a prime determinant of ecosystem composition and functioning and explains much of their spatial variation (Woodward et al., 2004). In turn, through their material cycles, ecosystems and land surfaces are fundamental to the functioning of the earth as a system of planetary chemical cycles, and they provide a multitude of ecological functions and services that human societies depend upon socially, culturally and economically (Millennium Ecosystem Assessment, 2005). Nonetheless, the potential of climate change to transform landscapes is less frequently addressed as a principal element of "dangerous climate change" than more physical impacts such as sea level rise or direct damages from extreme weather events. This is partially due to the inherent complexity of ecosystems, rendering it difficult to project their macroscopic response to multidimensional climate change systematically. In fact, ecosystems are characterised by numerous internal feedbacks occurring in interlinked, multi-layered networks across various scales (both in space and time). While each layer is able to absorb some degree of change, reaching the limit of its adaptive capacity may trigger destructive cascades in successive hierarchical levels (Holling, 2001). Unfortunately, comprehensive theories and computer models of such complex systems and their dynamics up to the global scale are not available at present. Complicating the matter, there is considerable uncertainty in climate projections, due primarily to climate model-structural and emissions scenario uncertainty (Hawkins and Sutton, 2010).

**Published by Copernicus Publications on behalf of the European Geosciences Union.**

Notwithstanding these methodological challenges, quantifying climate change impacts on ecosystems worldwide and systematically as a function of global warming is critical to substantiating the ongoing international negotiations on climate mitigation targets, as well as planning adaptation to unavoidable change. While the negotiations focus on a target of a maximum warming of 2 K (cf. Cancún Agreements, UNFCCC, 2011), actual commitments by nation states to reduce greenhouse gas emissions currently add up to a warming well above 3 K (Rogelj et al., 2010, 3.3 K according to www.climateactiontracker.org, retrieved 20 August 2013). Given the inconclusive political debates on climate change in many industrialised countries, the robust economic growth in major developing countries, and a non-negligible possibility of high climate sensitivity of the earth system (IPCC, 2007, ch. 8.6), an increase of global mean temperature (GMT) of 5 K above preindustrial by the end of this century is not out of the question (Rogelj et al., 2012). Therefore, assessing and illustrating the incremental impacts of a GMT rise of for example 2, 3.5 or 5 K and the associated uncertainties is of crucial importance.

Here we present a systematic macro-scale analysis of climate change impacts on terrestrial ecosystems and land surface properties as a function of GMT increase, which addresses the methodological challenges raised above. Our quantitative assessment is based on a consistent modelling framework composed of (1) newly developed sets of climate scenarios that sample the range of GMT increase uniformly (between 1.5 and 5 K), which are processed by (2) a state-of-the-art global biogeochemical model simulating climate-dependent vegetation–soil dynamics to derive (3) an aggregated metric of simultaneous biogeochemical and structural shifts in land surface properties. We interpret this metric as a numerical proxy for the risk of shifts and possibly disruptions in fundamental ecosystem properties and underlying finer scale processes in response to climate change. As there is no simple impact equivalent of ecosystem macro-variables as those characterising the global climate (such as GMT increase or globally mixed atmospheric $CO_2$ concentration), the metric is designed to be spatially explicit.

## 2 Quantification of complex ecosystem change

On a fundamental level, ecosystems are characterised by their carbon exchange with the atmosphere and soil and by the water flowing through living tissues (Chapin et al., 2011; Ripl, 2003). These properties, determined by the primary process of photosynthetic conversion of sunlight into biomass, constitute the base of the ecological food chain upon which trophic cascades and complex community structures depend (Mooney et al., 2009). At landscape level, ecosystems can be characterised by the prevailing broad types of vegetation in terms of their functional strategies, their carbon content, and their carbon and water exchange.

We argue that a climate-driven shift in these broad biogeochemical (water, carbon) and structural properties (vegetation type) implies corresponding impacts on the underlying, much more complex ecosystems (Heyder et al., 2011). In other words, changes in vegetation abundance and in the magnitude of exchange fluxes (in absolute terms and relative to each other) are taken to alter more detailed hierarchical structures, such as predator–prey and host–parasite relations (Parmesan, 2006), complementarity and competition regarding resource use (Hooper et al., 2005), or mutual interactions like pollination (Mooney et al., 2009). To quantify these shifts, we combine changes in the magnitude and relative size of biogeochemical fluxes and stocks of the terrestrial vegetation and changes in its functional structure – which, in contrast to the more detailed ecosystem structures, are captured by spatially explicit simulation models – into one macro-level indicator which we treat as a proxy for the risk of ecosystem and landscape change.

This approach has two advantages. (1) Well-developed models of the impacts of climate change on terrestrial carbon and water biogeochemistry and vegetation structure are available in the form of dynamic global vegetation models (DGVMs; Murray et al., 2012). (2) Using a macro-level proxy that can be simulated with a DGVM in conjunction with climate change scenarios circumvents having to describe in-depth climate change impacts on concrete local ecological networks, or synthesising a large number of smaller scale ecological studies into a coherent global picture, both of which are faced with nearly insurmountable methodological difficulties (Parmesan, 2006; Williams and Jackson, 2007).

### 2.1 Computation of the change metric

The generic change metric $\Gamma$ developed by Heyder et al. (2011) is used to quantify overall biogeochemical and structural change and the implied risk of transitions in underlying ecosystem features. It calculates the difference between an ecosystem state under climate change and the current state. Ecosystem states are characterised as vectors in a multi-dimensional state space, with each dimension representing a specific exchange flux, stock or process variable. The distance between two state vectors represents the change an ecosystem is simulated to experience in terms of its biogeochemical properties. A larger distance implies a higher risk for underlying ecosystems to change, undergo restructuring, or collapse on short timescales. Ecosystem states for both the reference period (1980–2009) and the future (2086–2115) are characterised by the variables specified in Table 1. $\Gamma$ is formulated to evaluate five dimensions of change:

$$\Gamma = \left\{\Delta V + c\,S(c,\sigma_{\mathrm{c}}) + g\,S\left(g,\sigma_{\mathrm{g}}\right) + b\,S(b,\sigma_{\mathrm{b}})\right\}/4, \quad (1)$$

where $\Delta V$ characterises changes in vegetation structure, $c$ is the local change component, $g$ is the global importance component, $b$ is the ecosystem balance component and $S(x,\sigma_x)$ is a change to variability ratio.

**Table 1.** LPJmL model outputs (aggregated to 30 yr averages) used to compute present and future ecosystem states and the $\Gamma$ metric.

| | |
|---|---|
| Carbon exchange fluxes | Net primary production (NPP), heterotrophic respiration (rH), fire carbon emissions |
| Carbon stocks | Carbon contained in vegetation and soils |
| Water exchange fluxes | Transpiration (representing productive water use), soil evaporation and interception from vegetation canopies (representing unproductive water use), runoff |
| Additional parameters describing system-internal processes | Fire frequency, soil water content of the topmost layer (50 cm) |
| Vegetation structure | Composition of PFTs |

Changes of vegetation structure in terms of major functional types representing different ecological strategies (woody vs. herbaceous, broadleaved vs. needleleaved, evergreen vs. deciduous) are quantified using a slightly modified version of the $\Delta V$ metric developed by Sykes et al. (1999) (see Supplement for details). $c$ and $g$ are calculated as the length of the difference vector between state vectors characterised by all variables from Table 1 except vegetation structure. Local change $c$ quantifies changes in biogeochemical state relative to previously prevailing conditions at each location to quantify the magnitude of local ecosystem alterations. All state parameters are normalised to their grid cell-specific mean value during the reference period. Global importance $g$ quantifies changes in the same parameters in absolute terms, i.e. their contribution to global-scale biogeochemistry. To achieve this, all state parameters are normalised to their global mean value during the reference period. $g$ takes into account that even moderate (relative) changes on the local scale may significantly feed back to larger scales (global carbon cycle, atmospheric circulation patterns, downstream water availability), possibly affecting ecosystems in other regions. Ecosystem balance $b$ quantifies changes in the magnitude of stocks and fluxes relative to each other. It is computed as the angle between state vectors (using local normalisation of all parameters). Such shifts in the balance of biogeochemical properties indicate changes in the contributing dynamic processes and hence ecological functioning. Change to variability ratios $S$ are computed for $c$, $g$ and $b$. They relate changes in ecosystem state $x$ to present-day variability $\sigma_x$ and reflect the expectation that ecosystems are adapted to the range of previously encountered year-to-year variations. Since changes in vegetation structure usually take place on far longer timescales, no such ratio is computed for $\Delta V$. All terms in Eq. 1 are scaled between 0 (no change) and 1 (very strong change) and combined into the full metric $\Gamma$ based on the assumption that simultaneous changes in several of the dimensions imply a higher risk of ecosystem destabilisation than changes in just one. See Heyder et al. (2011) for the specific scaling rules for each term.

### 2.2 Biosphere model

We use the well-established LPJmL DGVM (Lund-Potsdam-Jena model with managed land) to calculate the biogeochemical and vegetation–structural process dynamics required to quantify $\Gamma$. LPJmL simulates key physiological and ecological processes for 9 plant functional types (PFTs) representing natural ecosystems at biome level (Sitch et al., 2003). Climate-dependent carbon and water cycles are directly coupled through photosynthesis based on a modified Farquhar approach (Farquhar et al., 1980; Collatz et al., 1992). Carbon taken up from the atmosphere is allocated to different vegetation carbon pools and subsequently converted to litter, forming soil carbon pools that decompose at various rates. PFTs coexisting within a grid cell compete for space, light and water, with establishment depending on climatic suitability and density of existing vegetation, mortality rates depending on growth efficiency, plant density and climatic stress, and fire disturbance depending on climate, fuel availability and PFT-specific fire resistance. The model is forced by monthly fields of temperature, precipitation and cloud cover, yearly values of atmospheric $CO_2$ concentration, and information on soil properties. All processes are calculated at a daily time step on a spatial grid of 0.5° longitude by 0.5° latitude resolution, with monthly climate data disaggregated as described in Gerten et al. (2004). Human land cover/land use changes and their potential effects are neglected here, but areas under cultivation (shown in Fig. S1 in the Supplement) are excluded when computing the absolute area affected (see “Model settings and simulation protocol” in the Supplement for more details).

### 2.3 Interpretation of the change metric

In order to provide a better understanding of what a certain value of $\Gamma$ signifies, we calculate the metric for the difference between present-day biomes, i.e. substituting space for time (Blois et al., 2013). Potential natural vegetation during the reference period is categorised into 16 different biome classes based on the simulated composition of PFTs (see Fig. S3a in the Supplement for the biome map and Fig. S4 in the Supplement for the classification scheme), and $\Gamma$ is computed as the difference between average biome states (rather than between a future and the present state of a grid cell). The difference between present biomes typically adopts values of $\Gamma > 0.3$, corresponding to fundamentally different underlying ecological systems (Fig. S2 in the Supplement). For example, an average evergreen tropical rainforest differs from a tropical seasonal forest by a $\Gamma$ value of 0.31; a shift to an average savanna gives 0.51, and a shift to a C4 grassland 0.86. A shift from a boreal evergreen to a boreal deciduous forest amounts to $\approx 0.21$, to a temperate coniferous forest 0.37 and to a tundra 0.66. Only shifts between similar but still distinct biome types, such as a temperate mixed forest transforming into a temperate broadleaved or temperate coniferous forest, have smaller $\Gamma$ values. Overall, $\Gamma < 0.1$ implies that despite biogeochemical shifts possibly affecting community composition, biomes remain roughly the same in terms of their defining characteristics. Values of $\Gamma$ between 0.1 and 0.3 signal a change that produces a different but related biome. In this study, we consider such changes to reflect risk of "moderate" climate change impacts on ecosystems. Values of $\Gamma > 0.3$ are considered a risk of "major" change. Figure S2 in the Supplement compares biome averages. Since biomes aggregate an often continuous spectrum of actual vegetation composition into discrete categories, ecosystems may change their biome at lower $\Gamma$ values than those in Fig. S2 in the Supplement. Also, biomes can be rather broad categories. For example, the term savanna is used loosely in the literature to refer to very different ecological communities, covering a wide range of tree canopy cover anywhere between 5 and 80 % (Anderson et al., 1999). Owing to this high variability within biomes, our definition of what constitutes major change does not necessarily call for a change in biome class. Large shifts in biogeochemical functioning within a biome also qualify.

## 3 Climate uncertainty

Previous studies encountered several problems hampering a systematic quantification of climate change impacts for different GMT levels. (1) Considerable differences are found in the magnitude and spatial pattern of projected climatic changes from different atmosphere–ocean general circulation models (AOGCMs) for a given future time period or GMT increase. This is particularly true for changes in precipitation patterns, with AOGCM differences not just in the magnitude, but even in the sign of change for a number of regions (IPCC, 2007, ch. 11). Internal variability within different realisations of the same AOGCM is another source of uncertainty that has been estimated to account for at least half of the inter-model spread in projected climate trends during 2005–2060 (Deser et al., 2010). This necessitates the use of inputs from multiple AOGCMs and possibly multiple realisations per climate model in impact studies and to treat the differences as uncertainty. (2) Available climate scenarios do not sample the range of future GMT increase uniformly. For a given emissions scenario, the temperature reached by the end of this century differs between climate models due to differences in their climate sensitivity (IPCC, 2007, ch. 8.6). Combined with the limited number of emissions scenarios processed by AOGCMs and available in the CMIP3 archive[1] (Meehl et al., 2007), this introduces significant inconsistencies when attempting to compare multi-AOGCM impacts for different levels of GMT increase, because some future GMT ranges are reached by more (and different) climate models than others, or they are reached at different points in time.

We address these challenges with a new dataset of temperature-stratified climate scenarios. The "PanClim" climate dataset described in Heinke et al. (2012) is created from existing AOGCM runs available in the CMIP3 archive, but processed to reach specific GMT levels around the year 2100. The scenarios are created using a pattern-scaling approach (Huntingford and Cox, 2000) and are based on two pillars: (1) temporal trajectories of GMT increase and (2) spatial patterns relating local AOGCM-specific climate change to GMT change. To cover emissions scenario uncertainty – ranging from ambitious mitigation to current commitment and continued emissions growth throughout the 21st century – trajectories of emissions and resulting GMT increases above preindustrial level are computed by the fast, reduced-complexity carbon cycle–climate model MAGICC6 that has been shown to emulate closely the full range of $C^4$MIP carbon cycle models[2] and CMIP3 AOGCMs (Meinshausen et al., 2011). These warming trajectories are physically and systemically plausible, with carbon cycle parameters adjusted to reproduce the Bern carbon cycle model and model parameters chosen to reproduce the median responses of the CMIP3 AOGCM ensemble, with a climate sensitivity of 3.0 K (Heinke et al., 2012).

The selected emissions trajectories result in global warming of 1.5, 2, 2.5, 3, 3.5, 4, 4.5 and 5 K during the 30 yr mean around the year 2100 (2086–2115). To incorporate climate pattern uncertainty explicitly, these 8 GMT trajectories are combined with the spatial characteristics of 19 CMIP3 AOGCMs. For each AOGCM, existing runs for at least two emissions scenarios (including multiple realisations where available) are used to extract a scaling pattern per month and climate variable. These patterns describe AOGCM-specific local changes in temperature, precipitation and cloud cover as a function of GMT change.

The combination of scaling patterns for each AOGCM and climate variable with GMT trajectories for the 8 warming scenarios results in 152 transient time series of climate anomalies for the scenario period 2010 to 2115. Climate anomalies are then applied to a reference climate constructed from observed historical climate data (see below), which adds mean climatology and information on interannual variability. The process of anomaly application to the reference climate includes a bias correction, adjusting anomalies for regional biases found in the AOGCM data. The resulting climate scenarios allow for a smooth transition from historical data to future projections and therefore transient impact model runs across the whole 20th and 21st century. For a full documentation of the methodology, see Heinke et al. (2012). A flow chart illustrating the data processing steps is supplied as Fig. S5 in the Supplement.

[1] World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset

[2] $C^4$MIP, Coupled Climate Carbon Cycle Model Intercomparison Project

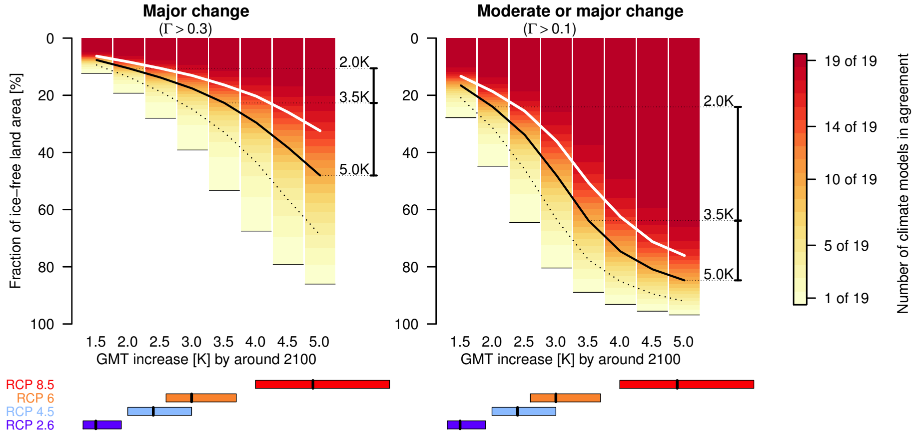


**Fig. 1.** Global land-surface area at risk of major ($\Gamma > 0.3$, left panel) or at least moderate ($\Gamma > 0.1$, right panel) ecosystem change by around 2100. Black and white lines denote confidence based on AOGCM agreement: solid white, high; solid black, medium; dotted black, low confidence. Range bars to the right of each panel illustrate the difference in affected area (with medium confidence) between 2, 3.5 and 5 K of warming. Coloured boxes below the main figure compare results to the 66 % range of warming expected from four Representative Concentration Pathways (RCPs) after Table 2 in Rogelj et al. (2012).

For the historical simulation period, the CRU TS 3.1[3] climatology (Harris et al., 2013) is used for temperature and cloud cover; and the GPCC[4] Full Data Reanalysis version 5 data for precipitation (Rudolf et al., 2010), extended to cover the full CRU grid. The number of wet days per month, used to distribute monthly sums, is created synthetically using the CRU approach (New et al., 2000) in order for the wet-day frequency to be consistent with GPCC precipitation. Historical climate data span from 1901 to 2009 and are followed seamlessly by climate scenario data. The resulting 152 climate scenarios (8 warming levels $\times$ 19 AOGCMs) provide a thorough and systematic sampling of the space of potential future GMT increase, retaining the key spatial properties of available AOGCMs while removing regionally distinct model-inherent biases. They provide a considerable step forward compared to up to 58 partially inconsistent scenarios used in previous DGVM-based, multi-climate-model, global ecosystem impact assessments (Heyder et al., 2011; Scholze et al., 2006).

$\Gamma$ values are computed for impact simulations under each of the 152 climate scenarios separately. A grid cell is considered "at risk" if at least one out of 19 AOGCMs demonstrates moderate or major ecosystem change at the respective GMT level. We determine the confidence in the projected severity of change based on the number of AOGCMs in agreement, using IPCC guidelines on uncertainty: about 2 out of 10 chance (4/19 AOGCMs), low confidence; about 5 out of 10 chance (10/19 AOGCMs), medium confidence; and about 8 out of 10 chance (16/19 AOGCMs), high confidence (IPCC, 2007, ch. 1.6). However, we acknowledge that the 19 AOGCMs used in our study do not allow a full probabilistic assessment of the risks to ecosystems.

[3]Climatic Research Unit's time-series data available from British Atmospheric Data Centre (BADC), http://badc.nerc.ac.uk/data/cru/

[4]Global Precipitation Climatology Centre operated by Deutscher Wetterdienst, http://gpcc.dwd.de

## 4 Results: major and moderate ecosystem changes as a function of global warming

Our simulations show that the extent of global land area affected by either moderate or major ecosystem change is substantial and increases strongly with global warming. Assuming business-as-usual emissions leading to a GMT increase of 4–5 K above preindustrial by 2100, more than two-thirds of the global ice-free land surface not currently used for agriculture is at risk of major ecosystem change ($\Gamma > 0.3$, 68 % at 4 K warming and up to 86 % at 5 K, left panel in Fig. 1). The uncertainty caused by differences in spatial patterns between climate models is large, however. For a global warming of 4 K, there is less than low confidence (less than 4 out of 19 AOGCMs in agreement) on 24 % of the land area, low to medium confidence on 23 % and high confidence (at least 16 of 19 models) on 20 % of the land area (dotted black and solid white lines in Fig. 1). At 5 K, the affected areas are 17, 36 and 32 % of the land area with less than low, low to medium and high confidence, respectively.

Figure 2 shows the regions affected by either major or moderate change, with colours indicating the degree of model agreement. Already for a warming of 2 K above preindustrial – the target agreed upon in the Cancún accords following the UNFCCC's objective to prevent dangerous interference with the climate system (UNFCCC, 1992) – major ecosystem shifts are projected under a majority of the AOGCM simulations for the temperature-sensitive high

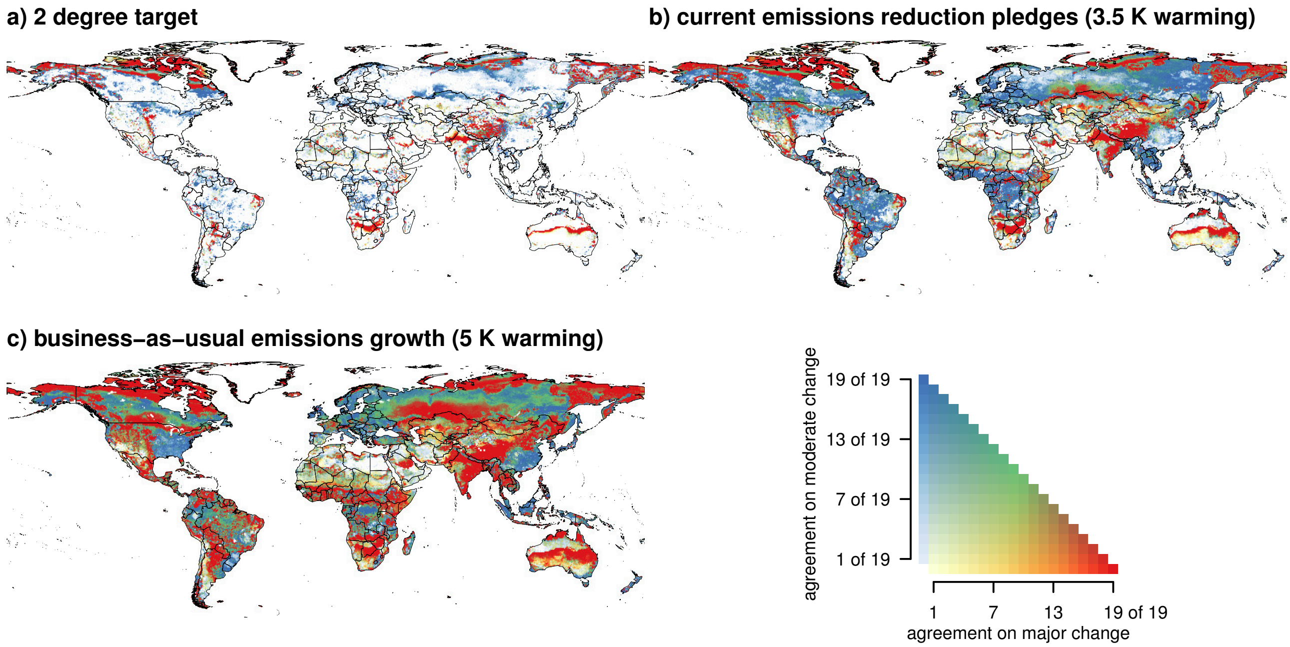


**Fig. 2.** Regional patterns of simulated ecosystem change by 2100 and their confidence, for different climate policies leading to a GMT increase of 2, 3.5 and 5 K above preindustrial, respectively. Colours indicate the number of simulations agreeing on either major ($\Gamma > 0.3$) or moderate ecosystem change ($0.1 < \Gamma < 0.3$) in each grid cell.

northern latitudes and some high-altitude regions (Figs. 2a and 3a). These changes are associated primarily with migrations of the tree line and increased vegetation productivity, both of which have already been observed to some extent in recent decades (Lloyd, 2005; Walker et al., 2012). Significantly larger areas, equalling 23 % of the global land area with at least medium confidence (Fig. 1), would be affected by major change at a global warming of 3.5 K – i.e. if countries restricted their greenhouse gas emissions according to their current pledges. In a 5 K world, vast areas on each continent and most biomes are likely to be affected in a major way (Figs. 2c and 3a). They expand into the Sahel region and eastern Africa, cover large portions of southern Africa, most of the Australian interior, the eastern flanks of the Andes and the Brazilian northeast, areas of the central US, the temperate-to-boreal ecotone in North America, most of India and the northern part of Southeast Asia, the Tibetan Plateau and extensive areas of the boreal-steppe ecotone in the Asian continental interiors of Mongolia, Kazakhstan, southern Russia and northern China, as well as all of the circumpolar region presently covered by tundra. Many of these large-scale patterns are already partly realised at 3.5 K of warming, such as along the southern edge of the boreal zone, the forest transition zone in tropical Africa, East India, and the Chaco region in South America (Fig. 2b).

In addition to areas affected by major change, there are regions for which our simulations project moderate ecosystem changes ($0.1 < \Gamma < 0.3$). Moderate change as defined here may still correspond for example to a tropical seasonal forest changing into a densely wooded savanna or may signal significant changes of tree composition in temperate forests (Fig. S2 in the Supplement). Taking these into account, the total global area at risk more than doubles in the low emissions scenarios; for example, 45 % of the land area is at risk of at least moderate change compared to 19 % at risk of major change in the 2 K scenarios (Fig. 1). The area for which we project moderate ecosystem change is largest at 4 K and actually decreases in the higher warming scenarios as more and more regions go from moderate to major change. As a result, the increment between GMT steps of the total area at risk – i.e. affected by either moderate or major change under at least one AOGCM – tapers off beyond 3–3.5 K warming. On the other hand, confidence, based on AOGCM agreement, that ecosystems will be subjected to either moderate or major change continues to grow (Fig. 1, right panel). The remaining model disagreement is located primarily in some deserts and grasslands – the only biomes that still have non-negligible parts where under no AOGCM moderate or major change is projected at 5 K global warming (16 % of deserts, 7 % of warm grasslands, 5 % of temperate grasslands, Fig. S6 in the Supplement). Moderate changes are projected predominantly for the forest biomes. Changes in the tundra and in savannas tend to be major, with smaller surrounding areas experiencing moderate change. This is reflected in the shape of the curves in Fig. 3, which are markedly different in panels a and b for forests but have quite similar shapes for the other biomes.

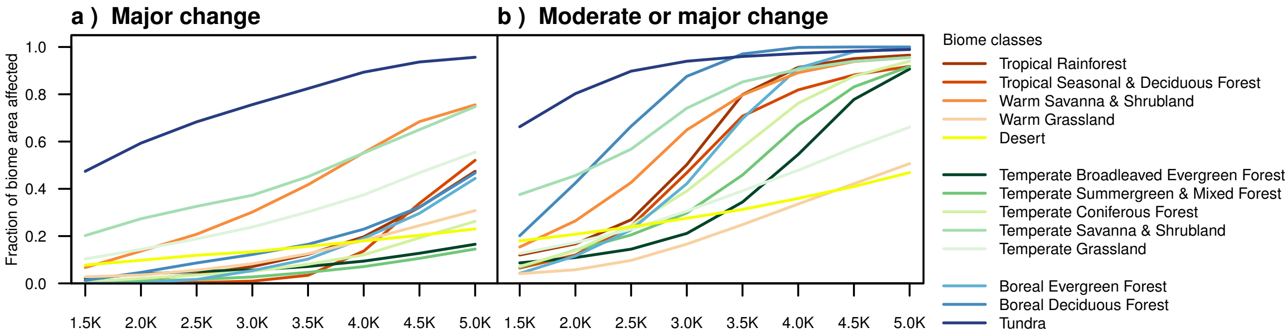


**Fig. 3.** Biome area affected by **(a)** major ($\Gamma > 0.3$) or **(b)** at least moderate ($\Gamma > 0.1$) ecosystem change by around 2100 with at least medium confidence ($\geq$ 10/19 AOGCMs in agreement). For other levels of confidence, see Fig. S6 in the Supplement.

## 4.1 Dimensions of ecosystem change

By using the $\Gamma$ metric as a proxy our analysis specifically focuses on the overall magnitude of change instead of the individual processes driving that change, which differ between regions and sometimes even between AOGCMs for the same region. Still, it is possible to derive some generalisations as to which dimensions of change covered by $\Gamma$ dominate in different biomes. For Figs. 4 and S7 in the Supplement, we separate the full metric into the local change, global importance, ecosystem balance and vegetation structure component. $c$, $g$ and $b$ are scaled with their respective change to variability ratio $S$. In addition, we compute biogeochemical change separately for the carbon stocks, carbon exchange fluxes and water exchange fluxes subsets of parameters in Table 1. Figure 4 presents results for the four largest present-day biomes (except deserts), while Fig. S7 in the Supplement includes all biomes.

Tundra regions are projected to experience the strongest relative changes in biogeochemistry (local change component), moving from a value of 0.65 at 2 K to 0.95 at 5 K of global warming – note that local temperature increases in these regions are much higher than the global average. These shifts in biogeochemistry are accompanied by large shifts in vegetation structure (0.4 at 2 K, almost 0.7 at 5 K). The complete restructuring of tundra ecosystems is also represented in strong changes of the ecosystem balance component, the highest of any biome. Changes in warm savannas are of similar overall magnitude as changes in the tundra, starting out slightly lower in the low warming scenarios and ending slightly higher in the high warming scenarios (Fig. S7 in the Supplement). The higher total $\Gamma$ values are primarily due to a higher global importance of savannas (0.3 versus 0.8 at 5 K). In general, changes in tropical forests and savannas have the highest global importance of all biomes, once global warming exceeds 2 K. This means that they have more impact on global biogeochemistry than changes in other biomes that may be stronger on the local level.

Our results show very little change in vegetation structure for all tropical and temperate forest biomes, with slightly higher values in boreal deciduous forests (Fig. S7 in the Supplement). More importantly, what little changes are found are independent of the level of GMT increase and stay fairly constant between 1.5 and 5 K warming. All other biomes show a clear trend of increasing $\Delta V$ with increasing global warming. Boreal evergreen forests differ from the other forest biomes in that projections show increasing areas of forest decline in the boreal-steppe ecotone as well as an invasion of temperate broadleaved trees with increasing warming. Temperate grasslands are characterised by a temperature-driven shift from temperate (C3) to tropical (C4) grasses along their warm edge. Due to better water use efficiency of C4 photosynthesis, this shift has strong implications on biogeochemistry. There is desertification in some grassland areas, although spatial patterns vary between climate models. Looking at the different stocks and fluxes describing biogeochemical states the general pattern is as follows: change in carbon stocks is usually more substantial than change in carbon fluxes in the low warming scenarios. Higher warming tends to lead to stronger increase of carbon flux changes while carbon stocks have a higher tendency to saturate. Projected changes in water exchange fluxes are considerably weaker than changes in carbon stocks and fluxes across all biomes. While of smaller magnitude from a biogeochemical standpoint, changes in freshwater availability have considerable effects on chronic supply-side water scarcity, as demonstrated by Gerten et al. (2013) for the “PanClim” set of climate scenarios.

## 4.2 Climate pattern uncertainty

Comparing changes in impact simulations under individual AOGCMs reveals the importance of using a large ensemble of climate models. Affected areas at a specific GMT level vary between AOGCM projections. In addition – because affected areas in different AOGCMs may lie in different regions (see Fig. S8 in the Supplement for maps of $\Gamma$ values from individual model runs) – the total area at risk across all

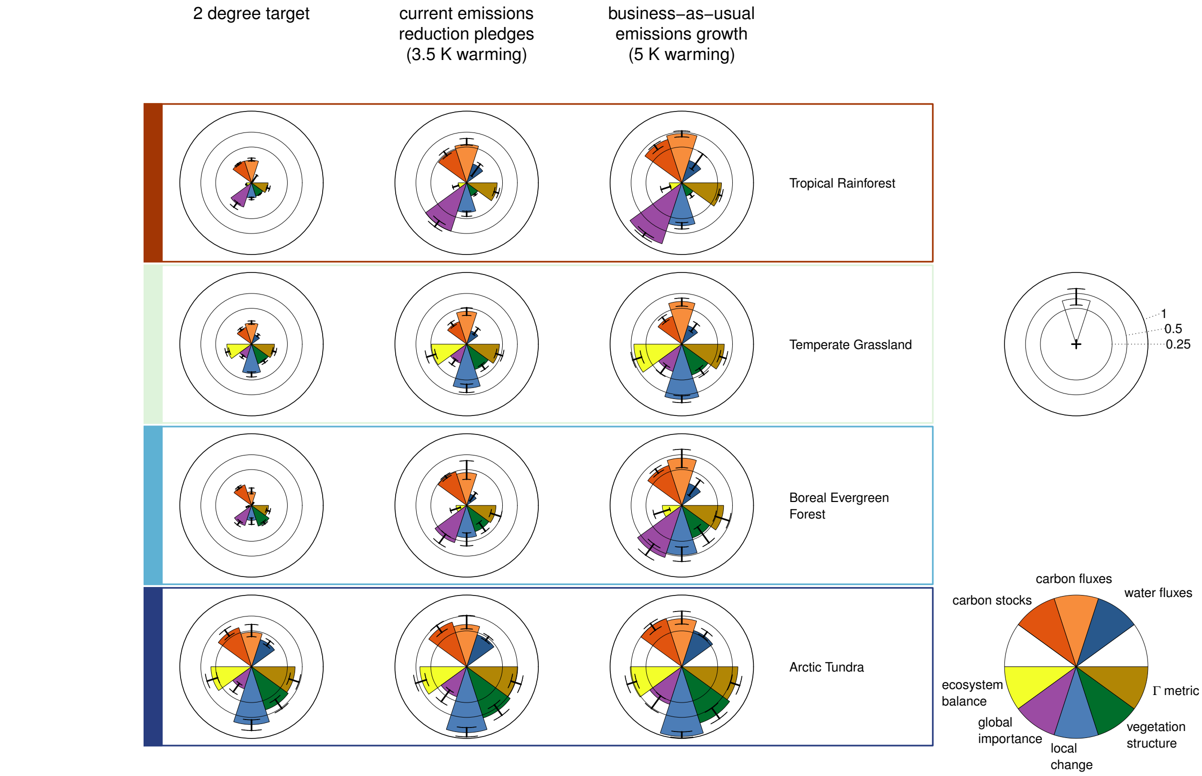


**Fig. 4.** Dimensions of ecosystem change for select biomes. Components of Γ are averaged over all grid cells belonging to the biome during the reference period. Vegetation structure: $\Delta V$; local change: $c \cdot S(c, \sigma_c)$; global importance: $g \cdot S(g, \sigma_g)$; ecosystem balance: $b \cdot S(b, \sigma_b)$. Carbon stocks, fluxes and water fluxes refer to parameter subsets in Table 1. Error bars denote the range across the 19 climate patterns per GMT level. The four largest biomes (except deserts) are presented. For all 16 biome classes, see Fig. S7 in the Supplement.

models is consistently higher than the model with the largest affected area (Fig. 5). For example, the total area where at least 1 AOGCM shows major change is between 33 % (1.5 K warming) and 67 % (3.5 K) higher than the largest area simulated by any individual AOGCM (compare individual circles in Fig. 5 to solid black line). Even at 5 K, using the less strict criterion of $\Gamma > 0.1$ where AOGCM agreement is much higher, the total area taking into account the whole ensemble is at least 10 % higher than for any individual AOGCM. While the total area at risk represents a worst case that is extremely unlikely to come to pass, major or at least moderate changes cannot be precluded in these regions based on the climate scenarios used.

## 5 Discussion and conclusions

This paper shows that there is a substantial risk of climate change to transform the world's terrestrial ecosystems profoundly, as judged by shifts in basic biogeochemical functioning. Nearly no area of the world is free from such risk, unless strong mitigation limits global warming to around 2 K above preindustrial level. Even then, most climate models agree that up to one-fifth of the world's ice-free, non-agricultural land surface is under a risk of at least moderate change.

The results presented here are snapshots of the projected changes at the end of the 21st century. GMT is likely to continue to rise beyond the simulation period, which means that pressure on ecosystems will continue into the 22nd century. Because of time lags in their response, ecosystems may also continue to change if GMT is stabilised by 2100. Adaptation can take place at the scale of years to decades in the case of vegetation decline, but time lags may extend to centuries or even millennia where adaptation entails the migration and regrowth of forests (Leemans and Eickhout, 2004). The different speeds of adaptation processes mean that ecosystem changes projected for the low warming scenarios cannot simply be taken to represent transitional states that happen at an earlier point in time of the higher warming scenarios.

The Γ metric goes beyond commonly used indexes like the Köppen–Geiger climate classification system and the Holdridge life zones system which map the state of land areas (and their biomes) based on climatic indicators. In contrast, Γ particularly measures changes in the biogeochemical as well as structural state of the land surface. This means that our metric can have values even without a change of

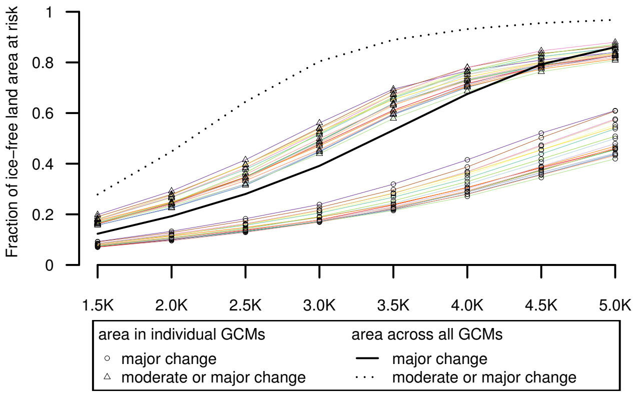


**Fig. 5.** Importance of climate ensemble analysis. Circles and triangles denote the area projected at risk of major or at least moderate change, respectively, by individual AOGCMs. The black solid and dashed lines mark the total area at risk across all AOGCMs. Higher total areas result from regional differences between AOGCMs.

either Köppen or Holdridge class (i.e. without changing to a different climate zone or biome).

Since Γ measures the amount of change regardless of the direction of change (increase or decrease) in the individual parameters describing ecosystem states, a high confidence in projected moderate or major ecosystem change does not necessarily imply agreement on the type of change. For example, a tropical savanna may change into a seasonal forest following reduced water limitation or into a grassland if precipitation is reduced, both of which would be considered major change in this analysis. From the view of the Γ metric, in either case the present ecosystem "as we know it" would be affected in a major way and likely disappear. This focus on the magnitude of change instead of the individual processes driving that change can be considered a disadvantage. On the other hand, the ability to capture many types of changes at once is important in the context of a risk assessment. The metric does not categorise changes as positive or negative, as such evaluations often depend on the perspective taken (Leemans and Eickhout, 2004). Any significant change in the underlying biogeochemistry is considered an ecological adaptation challenge that puts pressure on species and communities either to adapt, migrate or disappear entirely (Mooney et al., 2009). Combining the Γ metric with maps of present-day species endemism richness, Gerten et al. (2013) expand on our analysis of affected areas and attempt to assess climate change risks to biodiversity.

While possibly the most comprehensive sampling of climate uncertainty with respect to projected changes in biogeochemical functioning to date, this study is based on one impact model only. Previous DGVM intercomparison studies found that model results matched quite well for contemporary, observed climatology, but diverged in their response to climate change (Cramer et al., 2001; Sitch et al., 2008). The ongoing Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP, http://www.isi-mip.org) compiled impact simulations from more than 30 impact models within a consistent modelling framework covering the agricultural, biome, health and water sector. The ISI-MIP archive includes simulations from 7 global vegetation models including LPJmL which are analysed with the Γ metric. While using a different model set-up and different climate scenarios, these results provide an indication of the representativeness of LPJmL as used here in comparison to other vegetation models. Overall, LPJmL results are found to fall well within the range of the other biogeochemical models participating in ISI-MIP (Piontek et al., 2013; Warszawski et al., 2013), although analysis suggests that uncertainty from differences in impact models is larger than that caused by climate model differences. However, biome sector results in the ISI-MIP archive are based on climate scenarios from only three AOGCMs. Also, they directly relate ecosystem changes to changes in GMT regardless of emissions scenario and therefore timing, ignoring possible time lag effects. Several of the participating models lack dynamic vegetation, and there are other differences regarding included processes (e.g. fire disturbance, nutrient limitation). While the Γ metric can be computed for different sets of parameters describing ecosystem states, this hampers comparability of results.

Processes determining species composition in ecosystems are highly complex and in many cases poorly understood, especially in connection with novel climates (Williams and Jackson, 2007). While simulated dynamics in LPJmL constitutes best current knowledge, further model development is required to improve the reliability of projected change in vegetation structure (see Supplement for further discussion).

Climate change is closely linked to increasing $CO_2$ concentrations in the atmosphere, which have a fertilisation effect on vegetation growth. Both drivers act together to produce the biogeochemical shifts in the biosphere measured by Γ. Compared to just the climate effect, $CO_2$ fertilisation increases the magnitude of change in many regions, while in others it partially counteracts climate-driven changes, resulting in lower Γ values. While there is still some debate about the long-term magnitude of $CO_2$ fertilisation and the potential role of nutrient co-limitations in some biomes (e.g. Hickler et al., 2008), a complete absence of fertilisation effects is not realistic and therefore not investigated here.

In addition to the effects of climate change and $CO_2$ fertilisation, land use change is a concurrent pressure acting upon ecosystems. This is expected to increase, as a rising global population and growing economic wealth will increase demand for food and feed, combined with a potentially substantial future demand for bioenergy production to achieve energy independence and climate mitigation targets (Lotze-Campen et al., 2010; van Vuuren et al., 2010). Ecosystem protection in the 21st century will therefore face both of these interacting pressures, global climate and land use change.

In view of the substantial risks of ecosystem change from global warming found in this study, advancing systematic, comprehensive numerical analysis of terrestrial climate change impacts should be a focus of scientific research in the next years with the aim of reducing the large present uncertainty in the quantification of impacts. This would provide a better foundation for policy processes considering trade-offs with the political, social and economic transformations implied in managing global change. Despite the remaining uncertainties, our findings demonstrate that there is a large difference in the risk of global ecosystem change under business as usual or limited as compared to effective mitigation.

**Supplementary material related to this article is available online at http://www.earth-syst-dynam.net/4/347/2013/esd-4-347-2013-supplement.pdf.**

*Acknowledgements.* This study was supported by GLUES (Global Assessment of Land Use Dynamics, Greenhouse Gas Emissions and Ecosystem Services), a scientific coordination and synthesis project of the German Federal Ministry of Education and Research's (BMBF's) "Sustainable Land Management" programme (Code01LL0901A), and by the EU-FP7 research project ERMITAGE (grant no. 265170).

The "PanClim" climate dataset, the Γ metric results for all our 152 scenarios and the source code for the Γ metric software and related analysis tools are available for download at http://www.panclim.org. LPJmL can be obtained through the LPJ & LPJmL Web Distribution Portal at http://www.pik-potsdam.de/research/projects/lpjweb.

Edited by: M. Huber

## References

Anderson, R. C., Fralish, J. S., and Baskin, J. M.: Introduction, in: Savanna, Barrens, and Rock Outcrop Plant Communities of North America, Cambridge University Press, Cambridge, 1–6, 1999.

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, P. Natl. Acad. Sci. USA, 110, 9374–9379, doi:10.1073/pnas.1220228110, 2013.

Chapin, F. S., Matson, P. A., and Vitousek, P. M.: Principles of Terrestrial Ecosystem Ecology, 2nd Edn., Springer, New York, doi:10.1007/978-1-4419-9504-9, 2011.

Collatz, G., Ribas-Carbo, M., and Berry, J.: Coupled Photosynthesis-Stomatal Conductance Model for Leaves of C4 Plants, Aust. J. Plant Physiol., 19, 519–538, doi:10.1071/PP9920519, 1992.

Cramer, W., Bondeau, A., Woodward, F. I., Prentice, I. C., Betts, R. A., Brovkin, V., Cox, P. M., Fisher, V., Foley, J. A., Friend, A. D., Kucharik, C., Lomas, M. R., Ramankutty, N., Sitch, S., Smith, B., White, A., and Young-Molling, C.: Global response of terrestrial ecosystem structure and function to $CO_2$ and climate change: results from six dynamic global vegetation models, Global Change Biol., 7, 357–373, doi:10.1046/j.1365-2486.2001.00383.x, 2001.

Deser, C., Phillips, A., Bourdette, V., and Teng, H.: Uncertainty in climate change projections: the role of internal variability, Clim. Dynam., 38, 527–546, doi:10.1007/s00382-010-0977-x, 2010.

Farquhar, G. D., Caemmerer, S., and Berry, J. A.: A biochemical model of photosynthetic $CO_2$ assimilation in leaves of C3 species, Planta, 149, 78–90, doi:10.1007/BF00386231, 1980.

Gerten, D., Schaphoff, S., Haberlandt, U., Lucht, W., and Sitch, S.: Terrestrial vegetation and water balance – hydrological evaluation of a dynamic global vegetation model, J. Hydrol., 286, 249–270, doi:10.1016/j.jhydrol.2003.09.029, 2004.

Gerten, D., Lucht, W., Ostberg, S., Heinke, J., Kowarsch, M., Kreft, H., Kundzewicz, Z. W., Rastgooy, J., Warren, R., and Schellnhuber, H. J.: Asynchronous exposure to global warming: freshwater resources and terrestrial ecosystems, Environ. Res. Lett., 8, 034032, doi:10.1088/1748-9326/8/3/034032, 2013.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H.: Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset, Int. J. Climatol., doi:10.1002/joc.3711, online first, 2013.

Hawkins, E. and Sutton, R.: The potential to narrow uncertainty in projections of regional precipitation change, Clim. Dynam., 37, 407–418, doi:10.1007/s00382-010-0810-6, 2010.

Heinke, J., Ostberg, S., Schaphoff, S., Frieler, K., Müller, C., Gerten, D., Meinshausen, M., and Lucht, W.: A new dataset for systematic assessments of climate change impacts as a function of global warming, Geosci. Model Dev. Discuss., 5, 3533–3572, doi:10.5194/gmdd-5-3533-2012, 2012.

Heyder, U., Schaphoff, S., Gerten, D., and Lucht, W.: Risk of severe climate change impact on the terrestrial biosphere, Environ. Res. Lett., 6, 034036, doi:10.1088/1748-9326/6/3/034036, 2011.

Hickler, T., Smith, B., Prentice, I. C., Mjöfors, K., Miller, P., Arneth, A., and Sykes, M. T.: $CO_2$ fertilization in temperate FACE experiments not representative of boreal and tropical forests, Global Change Biol., 14, 1531–1542, doi:10.1111/j.1365-2486.2008.01598.x, 2008.

Holling, C. S.: Understanding the Complexity of Economic, Ecological, and Social Systems, Ecosystems, 4, 390–405, doi:10.1007/s10021-001-0101-5, 2001.

Hooper, D. U., Chapin, F. S., Ewel, J. J., Hector, A., Inchausti, P., Lavorel, S., Lawton, J. H., Lodge, D. M., Loreau, M., Naeem, S., Schmid, B., Setälä, H., Symstad, A. J., Vandermeer, J., and Wardle, D. A.: Effects of Biodiversity on Ecosystem Functioning: A Consensus of Current Knowledge, Ecol. Monogr., 75, 3–35, doi:10.1890/04-0922, 2005.

Huntingford, C. and Cox, P. M.: An analogue model to derive additional climate change scenarios from existing GCM simulations, Clim. Dynam., 16, 575–586, doi:10.1007/s003820000067, 2000.

IPCC: Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK and New York, NY, USA, 2007.

Leemans, R. and Eickhout, B.: Another reason for concern: regional and global impacts on ecosystems for different levels of climate change, Global Environ. Change, 14, 219–228, doi:10.1016/j.gloenvcha.2004.04.009, 2004.

Lloyd, A. H.: Ecological histories from Alaskan tree lines provide insight into future change, Ecology, 86, 1687–1695, doi:10.1890/03-0786, 2005.

Lotze-Campen, H., Popp, A., Beringer, T., Müller, C., Bondeau, A., Rost, S., and Lucht, W.: Scenarios of global bioenergy production: The trade-offs between agricultural expansion, intensification and trade, Ecol. Model., 221, 2188–2196, doi:10.1016/j.ecolmodel.2009.10.002, 2010.

Meehl, G. A., Covey, C., Taylor, K. E., Delworth, T., Stouffer, R. J., Latif, M., McAvaney, B., and Mitchell, J. F. B.: The WCRP CMIP3 Multimodel Dataset: A New Era in Climate Change Research, B. Am. Meteorol. Soc., 88, 1383–1394, doi:10.1175/BAMS-88-9-1383, 2007.

Meinshausen, M., Raper, S. C. B., and Wigley, T. M. L.: Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration, Atmos. Chem. Phys., 11, 1417–1456, doi:10.5194/acp-11-1417-2011, 2011.

Millennium Ecosystem Assessment: Ecosystems and Human Well-being: Synthesis, available at: http://www.millenniumassessment.org/en/Synthesis.html, Island Press, Washington, D.C., 2005.

Mooney, H., Larigauderie, A., Cesario, M., Elmquist, T., Hoegh-Guldberg, O., Lavorel, S., Mace, G. M., Palmer, M., Scholes, R., and Yahara, T.: Biodiversity, climate change, and ecosystem services, Curr. Opin. Environ. Sustain., 1, 46–54, doi:10.1016/j.cosust.2009.07.006, 2009.

Murray, S. J., Watson, I. M., and Prentice, I. C.: The use of dynamic global vegetation models for simulating hydrology and the potential integration of satellite observations, Prog. Phys. Geogr., 37, 63–97, doi:10.1177/0309133312460072, 2012.

New, M., Hulme, M., and Jones, P.: Representing Twentieth-Century Space-Time Climate Variability, Part II: Development of 1901–96 Monthly Grids of Terrestrial Surface Climate, J. Climate, 13, 2217–2238, doi:10.1175/1520-0442(2000)013<2217:RTCSTC>2.0.CO;2, 2000.

Parmesan, C.: Ecological and Evolutionary Responses to Recent Climate Change, Annu. Rev. Ecol. Evol. S., 37, 637–669, doi:10.1146/annurev.ecolsys.37.091305.110100, 2006.

Piontek, F., Müller, C., Pugh, T. A. M., Clark, D., Deryng, D., Elliott, J., Colón-González, F. J., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Goslin, S. N., Hemming, D., Khabarov, N., Kim, H., Lomas, M., Masaki, Y., Mengel, M., Morse, A., Neumann, K., Nishina, K., Ostberg, S., Pavlick, R., Ruane, A. C., Schewe, J., Schmid, E., Stacke, T., Tang, Q., Tessler, Z., Tompkins, A. M., Warszawski, L., Wisser, D., and Schellnhuber, H. J.: Leaving the world as we know it: Hotspots of global climate change impacts, P. Natl. Acad. Sci. USA, in press, 2013.

Ripl, W.: Water: the bloodstream of the biosphere, Philos. T. Roy. Soc. B, 358, 1921–1934, doi:10.1098/rstb.2003.1378, 2003.

Rogelj, J., Nabel, J., Chen, C., Hare, W., Markmann, K., Meinshausen, M., Schaeffer, M., Macey, K., and Höhne, N.: Copenhagen Accord pledges are paltry, Nature, 464, 1126–1128, doi:10.1038/4641126a, 2010.

Rogelj, J., Meinshausen, M., and Knutti, R.: Global warming under old and new scenarios using IPCC climate sensitivity range estimates, Nat. Clim. Change, 2, 248–253, doi:10.1038/nclimate1385, 2012.

Rudolf, B., Becker, A., Schneider, U., Meyer-Christoffer, A., and Ziese, M.: GPCC Status Report December 2010 (New gridded global data by the Global Precipitation Climatology Centre (GPCC)), Tech. Rep., DWD/GPCC, Offenbach/Main, Germany, 2010.

Scholze, M., Knorr, W., Arnell, N. W., and Prentice, I. C.: A climate-change risk analysis for world ecosystems, P. Natl. Acad. Sci. USA, 103, 13116–13120, doi:10.1073/pnas.0601816103, 2006.

Sitch, S., Smith, B., Prentice, I. C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J. O., Levis, S., Lucht, W., Sykes, M. T., Thonicke, K., and Venevsky, S.: Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model, Global Change Biol., 9, 161–185, doi:10.1046/j.1365-2486.2003.00569.x, 2003.

Sitch, S., Huntingford, C., Gedney, N., Levy, P. E., Lomas, M., Piao, S. L., Betts, R., Ciais, P., Cox, P., Friedlingstein, P., Jones, C. D., Prentice, I. C., and Woodward, F. I.: Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs), Global Change Biol., 14, 2015–2039, doi:10.1111/j.1365-2486.2008.01626.x, 2008.

Sykes, M. T., Prentice, I. C., and Laarif, F.: Quantifying the impact of global climate change on potential natural vegetation, Climatic Change, 41, 37–52, doi:10.1023/A:1005435831549, 1999.

UNFCCC: United Nations Framework Convention on Climate Change, http://unfccc.int/key_documents/the_convention/items/2853.php (last access: 15 May 2013), 1992.

UNFCCC – Conference of the Parties (COP): Decision 1/CP.16 The Cancun Agreements: Outcome of the work of the Ad Hoc Working Group on Long-term Cooperative Action under the Convention, available at: http://unfccc.int/resource/docs/2010/cop16/eng/07a01.pdf, last access: 15 May 2013, 2–31, 2011.

van Vuuren, D. P., Isaac, M., den Elzen, M. G., Stehfest, E., and van Vliet, J.: Low Stabilization Scenarios and Implications for Major World Regions from an Integrated Assessment Perspective, Energy J., 31, 165–191, doi:10.5547/ISSN0195-6574-EJ-Vol31-NoSI-7, 2010.

Walker, D. A., Epstein, H. E., Raynolds, M. K., Kuss, P., Kopecky, M. A., Frost, G. V., Daniëls, F. J. A., Leibman, M. O., Moskalenko, N. G., Matyshak, G. V., Khitun, O. V., Khomutov, A. V., Forbes, B. C., Bhatt, U. S., Kade, A. N., Vonlanthen, C. M., and Tichý, L.: Environment, vegetation and greenness (NDVI) along the North America and Eurasia Arctic transects, Environ. Res. Lett., 7, 015504, doi:10.1088/1748-9326/7/1/015504, 2012.

Warszawski, L., Friend, A., Ostberg, S., Frieler, K., Lucht, W., Schaphoff, S., Beerling, D., Cadule, P., Ciais, P., Clark, D. B., Kahana, R., Ito, A., Keribin, R., Kleidon, A., Lomas, M., Nishina, K., Pavlick, R., Rademacher, T. T., Piontek, F., Schewe, J., Serdeczny, O., Buechner, M., and Schellnhuber, H. J.: A multi-model analysis of risk of ecosystem shift under climate change, Environ. Res. Lett., accepted, 2013.

Williams, J. W. and Jackson, S. T.: Novel climates, no-analog communities, and ecological surprises, Front. Ecol. Environ., 5, 475–482, doi:10.1890/070037, 2007.

Woodward, F. I., Lomas, M. R., and Kelly, C. K.: Global climate and the distribution of plant biomes, Philos. T. Roy. Soc. B, 359, 1465–1476, doi:10.1098/rstb.2004.1525, 2004.