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Innovations and limits in methods of forecasting global environmental change

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Abstract

Environmental science has developed a diverse set of theories, analytical tools and models to understand and predict ecological responses to human impacts. We review recent innovations in the family of methods used to forecast global environmental change, and offer constructive critiques of five common approaches: phenomenological projections, storyline scenarios, integrated assessment models, decomposition-identity approaches, and global climate simulations. Overall, there is a lack of coherent, empirically based validation for many methods and their assumptions, and only partial incorporation of underlying uncertainties in both parameter estimates and interrelationships of model components. The greatest improvements in global environmental forecasting will likely come from a more systemic approach to quantifying the aggregate socio-economic drivers of the agents of change, along with better integration of multi-disciplinary approaches.

Zusammenfassung

Die Umweltwissenschaft hat vielfältige Theorien, analytische Methoden und Modelle entwickelt, um ökologische Reaktionen auf anthropogene Einflüsse zu verstehen und vorherzusagen. Wir untersuchen hier jüngste Innovationen aus der Familie der Methoden zur Vorhersage von globalen Umweltveränderungen und unterbreiten konstruktive Kritik zu fünf

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verbreiteten Forschungsansätzen: phänomenologische Projektion, "storyline"-Szenarien, integrierte Schätzmodelle, Ansätze zur Zerlegungsidentität, und Simulationen des globalen Klimas. Insgesamt herrscht ein Mangel an kohärenter Empirie-gestützter Validierung bei vielen Methoden und ihren Annahmen. Und die zugrunde liegenden Unsicherheiten, was sowohl. Parameterschätzung als auch Beziehungen zwischen den Modellkomponenten angeht, werden nur teilweise eingearbeitet. Die größten Verbesserungen für globale Umweltvorhersagen werden wahrscheinlich mit einem mehr systemischen Ansatz zur Quantifizierung der aggregierten sozio-ökonomischen Treiber der bestimmenden Kräfte des Wandels erreicht werden, in Verbindung mit einer engeren Integration von multi-disziplinären Forschungsansätzen.

Keywords: Projection; Scenario; Integrated assessment; Decomposition; Multi-criteria decision making analysis; Climate models; Decoupling

Introduction

How might the activities of human civilization drive changes in the Earth system during the 21st century and beyond? Projections of future environmental states are inherently constrained by imperfect knowledge and systemic uncertainties in the drivers of change (Clark et al., 2001). As the famous aphorism goes, all models are wrong, but some are useful (Box, 1979). Forecasts of environmental change are useful in helping planners trade off the consequences of, and opportunities offered by, alternative future scenarios (Loftus, Cohen, Long, & Jenkins, 2015). Forecasts offer decision makers a way to anticipate the response of complex systems to chronic stressors or disturbance, and can permit the evaluation of realistic development pathways to improve conservation benefit (Ausubel, 2000; Leadley, Pereira, & Alkemade, 2010; Sala et al., 2000). There are many uses for scenarios: here we focus primarily on their application to conservation management, ecology, and their relation to other planning outcomes such economic development. In this context, the development of 'what if?' scenarios can aid in identifying critical 'pressure points' and flexible 'levers' for policy, thereby expanding the design space and opportunities for global conservation while balancing the concessions between the drive towards equitable human prosperity and the vital need to conserve as much of our rich natural history and biodiversity as possible.

Forecasting should be based on a robust causal framework. One useful heuristic for conceptualising the linkages between human activities and environmental transformation is the driver-pressure-state-impact-response (DPSIR) framework (Omann, Stocker, & Jäger, 2009). Drivers, including population, consumption, and technology, determine the aggregate amount of 'pressures' (although such a structure lacks explicit consideration of the role of governance and other aspects of institutional behaviour that influence the drivers in this framework). Pressures are defined as physical interventions in the environment, and include, for example, land-use change (due to expanding areas of cropland, pasture, biofuels, plantation forests, and built-up land), emissions of greenhouse gases, water extraction, and pollution of air and water (Foley et al., 2005; MEA, 2005; Rands et al., 2010). These pressures alter the state of environmental variables (like the distribution of habitats, or the concentration of greenhouse gases in the atmosphere), with attendant impacts on biodiversity (species and populations), in the form of changing abundance, altered geographical distributions, and extinctions (Brook, Sodhi, & Bradshaw, 2008). Responses are the actions taken by humans to address these problems.

Forecasting possible future pathways of biodiversity change (impacts) requires understanding – and modelling – each prior step in this causal chain. Conservation science has developed and validated a rich set of theories and methods to understand and predict the impacts of various human pressures, including population viability analyses, species-area relationships and coupled niche-population models (Brook et al., 2000; Ibáñez et al., 2006; Botkin et al., 2007; Lacy et al., 2013). Conservation science has, however, made less progress on modelling the connections between drivers and pressures. By contrast, in the physical sciences, computer simulations of the Earth System are now routinely used to project emissions of greenhouse gases, the resultant climate change, and its associated risks and impacts (Hansen et al., 2007; Lenton et al., 2008; Fordham, Wigley, & Brook, 2012). And in the socio-economic realm, integrated assessment models are used to summarize diverse inputs on complex problems such as multi-regional energy projections (Ostrom, 2009; Golub et al., 2012).

Despite the progress outlined above, there remains considerable work to do in developing the theoretical and applied tools needed to project and optimize human development pathways to minimize biodiversity loss from climate change, land-use change, and other pressures. Local interventions like protected areas and payments for ecosystem services can safeguard some of the most valuable elements of biodiversity and ecosystem integrity (Mace, Norris, & Fitter, 2012). Yet they do little to mitigate the overall level of human pressures, since this is governed primarily by changing patterns of consumption (e.g., demand for material resources) and implementation of new technology (e.g., affecting environmental impacts per unit of production) (Ausubel, 2000; Andam, Ferraro, Pfaff, Sanchez-Azofeifa, & Robalino, 2008; Butchart et al., 2010; Clark, Boakes, McGowan, Mace, & Fuller, 2013). If the hypothesis that technology is a driver (rather than simply a consequence) of social/governance pressures holds true, then the success of biodiversity

Table 1. Summary of some key strengths and weaknesses of widely used large-scale approaches to forecasting global environmental change.

Method	Strengths	Weaknesses	Examples
Phenomenological models	Simple to parameterise and validate (at a high level); Suitable for top-down analysis of global or regional data; Easy to interpret	Many embedded (opaque) assumptions; No explicit modelling of processes; Composite parameters are impossible to disaggregate	Species area relationship; Environmental Kuznets Curve
Storyline scenarios	Intuitive to communicate; Maps readily to 'pathway' frameworks and socio-economic narratives; Captures 'snapshots' of continuous axes of discrimination (e.g., global vs regional, technological vs social)	Underestimate range of plausible future outcomes; Constrains thinking about alternative scenarios that cannot be accommodated across selected axes; Programmed with a fixed bundle of parameters	Special Report on Emissions Scenarios; Millennium Ecosystem Assessment
Integrated assessment models	Based on well-verified economic methods for assimilating local to regional data; Aggregates results to produce 'bottom up' analysis of change; Relatively blind to disciplinary borders; Can lead to probabilistic assessments	Different storylines often borrow from same underlying models of drivers; Complex and heavily assumption driven; Difficult to determine sensitivities, especially in relationship to the constraints imposed by strong assumptions	MiniCAM; MERGE; IGSM
Decomposition and identity approaches	Permits use of simple, bottom-up decompositions of aggregate drivers; Based on well-grounded methods developed in industrial ecology; Makes assumptions and exogenous inputs highly transparent; Contribution of each factor can be broken into fine-grained factors	Rudimentary approaches have limited utility in forecasting; High-level aggregated parameters are often assumed rather than data-driven; Typically ignores problems of model selection/choice and stopping rules for 'sufficient' disaggregation are not clear	ImPACT; STIRPAT
Global climate (and ecosystem) models	Coupled (interlinked) system model of geo-physical and some biophysical processes; Captures interaction across multiple atmospheric and oceanic strata; Allow for forecasting using future forcing scenarios that are derived from other modelling methods; Explicitly incorporates feedbacks	Spatial grid-resolution makes simulation of fine-scale processes difficult; Simplified parameterisation of poorly measured processes (e.g. clouds); Assumes hierarchical scaling of local-scale processes to biomes and biosphere (GEM)	HadCM3; CCSM; MAGICC; Madingley Model (GEM)

conservation in the 21st century will depend, to a large extent, on how effectively society can decouple environmental impacts from economic growth and rising human prosperity (Grubler, Nakicenovic, & Victor, 1999; UNEP, 2011; Blomqvist, Nordhaus, & Shellenberger, 2015). A failure to achieve this will likely result in an accelerated rate of species extinctions and severe damage to climate and ecosystems – leading to degradation in human health and irreversible loss of natural history (Laurance, 2001; Pereira et al., 2010).

Forecasting can play an important role in tackling these problems (some key methods discussed in this paper are outlined in Table 1). To map out future options for managing the planetary environment, it is necessary to incorporate the large uncertainties across both the human dimensions of global change (e.g., technological development, population and demographics, and wealth) (Fig. 1), as well as inherent variability and uncertainty in geophysical and biological processes and feedbacks. The portfolio of past successes and failures in environmental stewardship provides important insights on what *has been achievable*; when integrated with well-structured and parameterised systems models, we then have the critical tools for telling us what *might be possible*. Here we explore some of the challenges to projecting change in global-change science.

Phenomenological ('top-down') approaches

Phenomenological models are based on observed relationships between socio-economic and environmental variables (e.g., curves fitted to empirical trend data). These have been used widely across all major impacts of global change, including deforestation, agriculture and pollution (Stern, Common, & Barbier, 1996; Sala et al., 2000; Tilman et al., 2001; Loh et al., 2005; Ewers, Scharlemann, Balmford, & Green, 2009; Defries, Rudel, Uriarte, & Hansen, 2010).

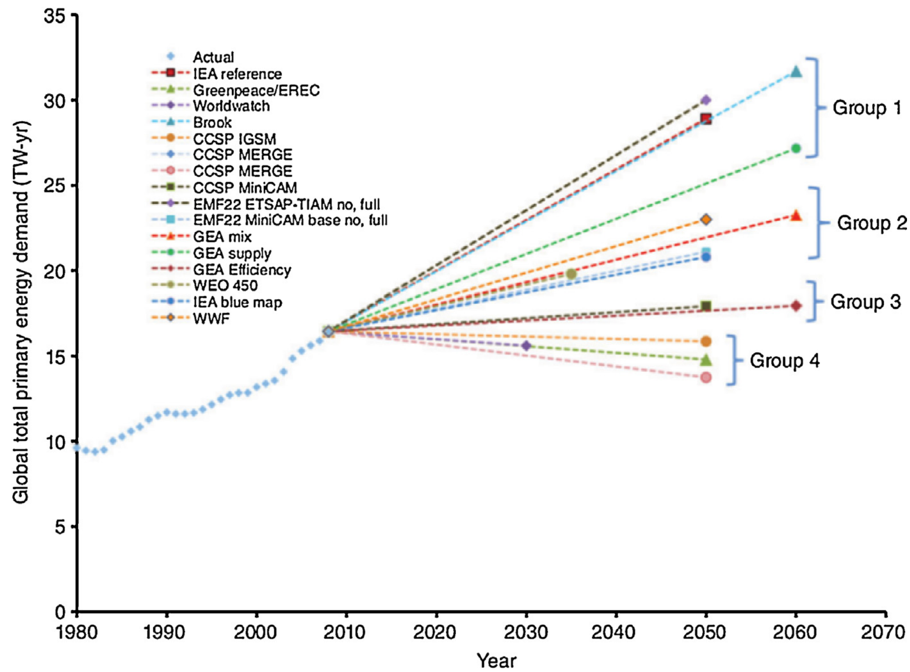

Fig. 1. Projected global energy demand trajectories for the 21st century, drawn from a wide range of storyline scenarios. Two notable points are that the results group into clusters (based on similar assumptions), but also that a wide range of possible futures can be imagined by groups working with different methodologies and goals. A major challenge of projecting change, beyond data and limitations, is coping with inherent uncertainties about future drivers of socio-economic decision-making.
Source: Loftus et al. (2015)

For instance, Wright and Muller-Landau (2006) found a strong correlation between rural population density and remaining forest cover across tropical countries and, based on United Nations projections of urbanization and declining rural populations, projected a reduction in pressure on tropical forests in this century. DeFries et al. (2010), using a similar methodology, came to the opposite conclusion, finding that urbanization was the socio-economic factor most strongly correlated with forest loss. Tilman et al. (2001) used a phenomenological approach to forecast impacts of nitrogen use in agriculture, by extrapolating from historical relationships between nitrogen use, global population, gross domestic product (GDP) and time – estimating that nitrogen use will increase by a factor of 2.7 between 2000 and 2050. The same methodology also underpins a large body of work on the so-called ‘Environmental Kuznets Curve’, based on the proposition that once countries reach a certain income level, environmental impacts peak and then decline (Carson, 2009; Jordan, 2010). The method used to investigate this question generally involves looking for cross-country statistical relationships between income (represented by GDP) and environmental indicators such as pollution levels or forest loss. Results from these studies are mixed, and often conflicting (Dasgupta, Laplante, Wang, & Wheeler, 2002; Stern, 2004).

Phenomenological studies like the above have been useful in bringing attention to socio-economic and technological drivers of environmental change, and attempting to assess which factors are most influential. Yet, this approach, for a number of reasons, is strongly limited in its application to forecasting. This is because it cannot illuminate the mechanisms whereby socio-economic or technological factors drive environmental change. Its results can therefore be misleading, especially when extrapolated beyond the historical range of data. For instance, neither Wright and Muller-Landau (2006) nor DeFries et al. (2010) look at the set of interlinked changes in consumption, production, and trade patterns that are associated with urbanization. Thus, while urbanization may be correlated with forest loss, phenomenological studies do not show whether it is causally related, or in which ways. Geist and Lambin (2002) concluded that these top-down approaches to studying drivers of deforestation have failed to reveal “any distinct patterns” and thus left the broader question “largely unanswered” – a conclusion echoed also by DeFries et al. (2010). Similarly, the Tilman et al. (2001) extrapolation of global nitrogen use fails to account for regional patterns in nitrogen use, which tend to follow an inverse U-shaped trend as countries first adopt synthetic fertilisers and then improve the precision by which it is applied (Zhang et al., 2015). Combining regional trends thus likely yields a plateauing and even declining trend in nitrogen pollution from agriculture over this century, rather than a three-fold increase.

Studies in the Environmental Kuznets Curve tradition allude to the mechanisms underpinning improvements in environmental quality in qualitative terms, but do not analyse them directly. Thus the method does not differentiate between technological improvements *per se*, and displacement of environmentally harmful activities abroad (Ansuategi & Perrings, 2000). It also overlooks the often significant differences in environmental pressures between countries at similar income levels, which seem to have resulted from path-dependent economic and technological choices rather than differences in economic growth.

'Storyline' scenarios

Storyline scenarios have been used extensively by the Intergovernmental Panel on Climate Change in their five Assessment Reports, and underpinned the 'Scenarios' volume of the 2005 Millennium Ecosystem Assessment (MA; MEA, 2005), the Global Biodiversity Outlook (CBD, 2013), and many other assessments and horizon scans. Indeed, this approach has become the main analytical lens through which the future of global biodiversity and ecosystems has been perceived and interpreted.

Storyline scenarios start with a narrative that defines a hypothetical pathway for population growth and economic development, as well as technological and institutional change. In the case of the MA, the scenarios are framed along two axes: degree of globalisation and proactive versus reactive policies – yielding four different storylines (MEA, 2005). These assumptions then serve as input to complex cross-disciplinary simulations – in most cases a form of 'bottom-up' economic analysis called integrated assessment modelling (IAM, see next section) – which can be used to project (i) the magnitude of pressures like land-use change or pollution, and (ii) resultant changes in biodiversity and ecosystem integrity.

Storyline approaches, although intellectually appealing and easy to communicate, almost certainly underestimate the range of plausible future outcomes (Leadley et al., 2010) and typically say little about the feasibility of implementation (Loftus et al., 2015). For example, projections for increases in global agricultural area fall within a relatively narrow 11% range for all millennium ecosystem assessment scenarios. This seems to be due to compensatory mechanisms whereby inputs that lead to increased land use (e.g., vastly expanded use of crops for bioenergy) are combined in the same scenario with other parameters that reduce land use (e.g., reduced meat consumption and higher agricultural yields). Similarities across 'different' storyline scenarios are exacerbated further by use of the same IAMs for estimating drivers and biodiversity responses (Tallis & Kareiva, 2006). Furthermore, a well-established psychological effect exists whereby a high level of detail, such as exists for any of the MA storylines, leads to a high level of perceived likelihood of the scenario coming true (Morgan & Keith, 2008). Thus, contrary to the stated objective of typical storyline scenarios, this method might often lead to constrained thinking around different options and pathways. Perhaps most critically, the fact that storyline scenarios come as a fixed bundle of parameters also makes it nearly impossible to gauge the effects or sensitivity of the environmental outcomes to individual policy options, such as organic versus conventional farming, or wind power versus biomass.

Integrated assessment models

Integrated Assessment Models are closely linked to storylines in that they often base their projections on assumptions about drivers like population, GDP, and technology derived from storylines. IAMs leverage well-verified economic approaches such as computable general equilibrium models to assimilate data on how individual economies might respond to changes in policy, technology, or cross-border factors (Fig. 2), and then aggregate these results to produce plausible bottom-up scenarios of change (Garnaut, 2008; Valin et al., 2013). This is typically achieved using recursive-dynamic approaches, based on mechanistic relationships, which are solved sequentially. These models can also be used for probabilistic assessments of policy, especially in situations where uncertainty is accepted to be high (such as for evaluating interventions to mitigate climate change; Mastrandrea & Schneider, 2004). The philosophy of IAMs is relatively blind to disciplinary borders and typically involves inputs from a diversity of specialized experts. Widely used examples in the climate-energy policy realm include MiniCAM, MERGE and IGSM (Clarke et al., 2007).

Although IAM results provide cohesive information that can assist policy makers in developing more transparent approaches to scenario analysis, they have the disadvantage of being (by definition) quite complex, heavily assumption driven, and rather opaque (van der Sluijs, 2002; Pielke, Wigley, & Green, 2008). For instance, modelling the stabilization pathways for greenhouse-gas emissions involves three broad items: a reduction in end-use demand (efficiency and conservation), an increase in carbon-free energy to replace fossil fuels (e.g., renewables and nuclear), and some switch-over of fossil fuels to carbon capture and storage (CCS) (Hoffert et al., 2002). On this basis, the IAMs attempt to resolve cost-optimized scenarios that meet defined emissions targets, usually in decadal bands through to mid- or end-of century (Clarke et al., 2007; Wise et al., 2009).

The principal challenge in projecting something like greenhouse gas emissions using IAMs is to realistically characterize both socio-political choices (e.g. when and at what level a carbon price or low-carbon-energy production credit is implemented, community antagonism against widespread use of nuclear fission or building of wind farms) and the scientific-economic evolution of, and deployment rates for, the underlying technologies themselves (e.g., engineering efficiencies of energy conversion, dispatchability of the resource for load balancing, or cost-reduction curves for grid-scale renewables with integrated storage) (Utgikar & Scott, 2006; Lenzen et al., 2013). This is important, because these uncertainties and assumptions are not only difficult to constrain *a priori*, they also cascade into a wide range of possible climate-forcing scenarios (which are fed into global

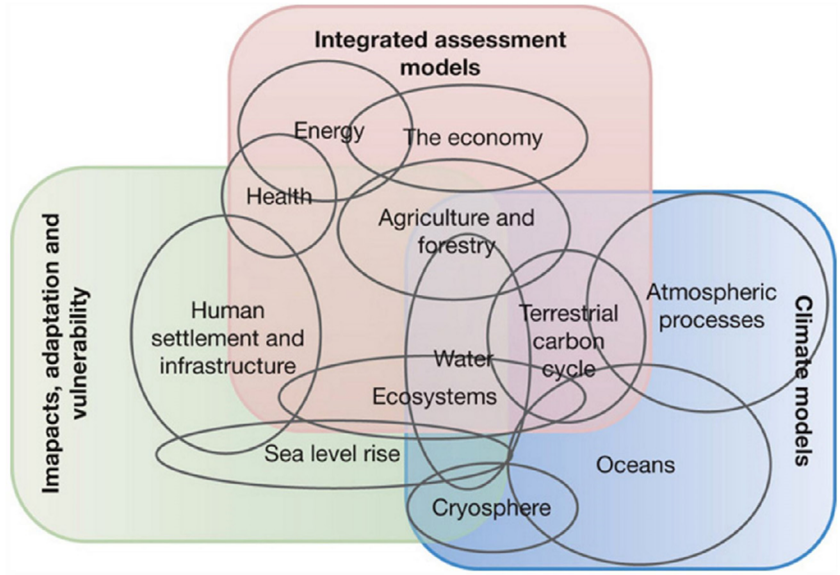

Fig. 2. Example of the multi-sectorial components of integrated assessment models, and how they link to assessments of environmental impacts and climate forecasts.
Source: Moss et al. (2010)

climate models; GCMs) (Wigley et al., 2009). As a consequence, methods that build upon the intrinsic uncertainties in the GCMs typically result in (necessarily) wide bounds of probability for projections of habitat change and species distributions when forecasting biodiversity responses, thus appropriately reflecting our high degree of uncertainty about many future ecological outcomes (Botkin et al., 2007; Fordham, Wigley, & Brook, 2011).

Decomposition and identity approaches

The alternative to the phenomenological and storyline approaches is to apply a suite of relatively simple, bottom-up decompositions of human drivers into a set of multiplicative factors, using a set of methods associated with ecological economics and industrial ecology (Duchin & Lange, 1995; Thomas et al., 2003; Wiedmann, 2009; Steinberger, Krausmann, & Eisenmenger, 2010). This approach seeks to make all assumptions and exogenous inputs into the models transparent. Drawing on the classical IPAT formula (impact = population × affluence × technology) (Ehrlich & Holdren, 1971; Chertow, 2001), Waggoner and Ausubel (2002) developed a mathematical identity, ImPACT (with C being consumer use per GDP), wherein environmental impacts are the product of population, income, intensity of use (material throughput per unit of income), and intensity of impact (environmental impact per unit material throughput). This type of ‘decomposition’ (i.e., breakdown of general models into more fined-grained factors) (Ang, 2004) has been applied extensively to the study of energy and greenhouse-gas emissions, under the umbrella of the Kaya Identity, where total emissions are a product of population, income, energy intensity (energy use per unit income), and emissions intensity (emissions per unit energy) (Hamilton & Turton, 2002; Rosa & Dietz, 2012). The framework and precise factors used are flexible, provided they form an identity; for instance transport-sector emissions can be decomposed into passenger-km, transport modes, carbon and energy intensity, and fuel mix (Stern, 1997).

The idea behind this approach to projecting change is that demand forecasts for key economic goods, as outlined above, should be combined with a rigorous analysis of technological trajectories and options to estimate aggregate environmental impacts. The benefit of the decomposition-identity approach is that the contribution of each factor to the aggregate change in impacts can be determined readily, with general models broken down into increasingly fined-grained factors, thereby allowing direct investigation of the sensitivity of outcomes to different policy levers. The method has also served to highlight how a combination of declining intensity of use (dematerialization) and intensity of impact (i.e., increasing technical efficiency) can offset some or all of the pressure from growing population and economic activity, thereby decoupling environmental impacts like land use and water consumption from economic growth (Voet, Oers, & Nikolic, 2005; Ausubel & Waggoner, 2008; Ausubel, Wernick, & Waggoner, 2012).

However, as York, Rosa, & Dietz (2003) have pointed out, rudimentary mathematical identities like ImPACT, while useful accounting tools, have limited utility in forecasting. Although it encourages mechanistic ‘bottom-up’ approaches to forecasting, the aggregated parameters have to be assumed, rather than being data-driven; interactions between factors are not accounted for, and growth functions are typically assumed to be exponential. Moreover, this method has primarily been applied to very high levels of aggregation, often global, thereby omitting many lower-scale patterns and dynamics. The STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) method is a step forward, because it allows for data-driven fitting of coefficients and sensitivity evaluation (Liddle & Lung, 2010). However, it does not offer a fully adequate and comprehensive method, since, for instance, it ignores model selection and does not make use of prior information. For more accurate forecasting, the technology factor must be disaggregated into distinct processes or transformations, each with their own theoretical limits, learning curves, and variation across systems and countries. Technological change has a second component in addition to incremental improvement: understanding the benefits and limits of *substitution*, whereby one technology replaces another (Grubler et al., 1999; Chang & Baek, 2010; Mace, 2012).

Global climate and general ecosystem models

Predicting future impacts of climate change on biodiversity illustrates the many challenges involved in forecasting the interlinked components of the causal chain, from drivers like consumption and technology, to pressures (greenhouse gas emissions), to changes in the state of the global climate system, and finally to impacts on biodiversity. Indeed, in seeking to bracket the range of plausible anthropogenically forced scenarios, climate modellers typically employ a combination of mechanistic and scenario-based approaches to projecting change (Moss et al., 2010) (Fig. 1). They assess the skill of global climate models (GCMs) based on validation against historical data (Fordham, Akçakaya, Araújo, Keith, & Brook, 2013). The linking of GCM outputs to forecasts of biodiversity response necessitates estimates of both mean trends in climatic variables like temperature and precipitation, and also a characterization of their variability, extremes, and key uncertainties in the underpinning models (Botkin et al., 2007; Brook et al., 2009).

One of the challenges in projecting climate change lies in the structural adequacy and spatial resolution of the atmosphere-ocean global circulation models that underpin the simulations (Wigley & Raper, 2001). This stems from modellers' incomplete understanding (and weak parameterization) of crucial mechanisms such as heat transport in the ocean, cloud formation, and boundary-layer formulations (IPCC, 2013). Another source of ambiguity is in how well-known geophysical processes and less-certain amplifying or diminishing feedbacks should be best represented and integrated, which results in a band of nearly irreducible uncertainty in the equilibrium climate sensitivity of different GCMs (Hansen et al., 2007). A reassuring result of the last few decades of work in this area has been steady improvements in both the short-term forecasting (used for weather predictions) and longer-term hindcasting ability of GCMs, thanks to greatly increased spatial resolution and inclusion of increasingly complex features (e.g., layered-ocean modelling, carbon-cycle processes, and explicit incorporation of dynamic vegetation and ice-sheet models) (Reichler & Kim, 2008). These enhancements have been made possible by the exponential recent growth in computer power, and should continue for many years.

Even accepting that current GCMs will remain an imperfect simplification of the highly complex Earth system for years to come, we can still make progress in the challenge of more objectively representing future change. A well-regarded method is to accept that there are a range of potentially valid ways of simulating these complex systems and so treat the diversity of approaches tried by different climate-modelling communities as an advantage, by pooling their probabilistic GCM results in an 'ensemble' forecast (Tebaldi & Knutti, 2007). This combining of multi-model output can include the assignment of differential weightings to alternative models on the basis of, say, their 'skill' score with respect to their ability to simulate past climates (Gleckler, Taylor, & Doutriaux, 2008). Besides global metrics, this skill ranking can also be disaggregated at regional scales and separately for different outputs (e.g., some models seem to be better at reconstructing changes in temperate, whereas others are superior at reconstructing past interannual variability in precipitation (Scherrer, 2011), even though their temperature forecasts may be sub-par). Recent advances in user-friendly emulation software (e.g. MAGICC/SCENGEN and GridMapper) have more readily opened the application of the climate-ensembling approach to ecologically focused end-users (Fordham et al., 2012) (Fig. 3). Another simpler but related approach relies on projecting change using both the best-performing and the most extreme models (for a given output), to attempt to encompass the full range of possible futures using selected inter-model comparisons.

An additional component of uncertainty in climate models is in characterizing the likely future pathways of climate forcing factors, which includes long-lived greenhouse gases such as carbon dioxide and methane, aerosol loads, the capacity of the oceans, vegetation and soil to continue to act as a net carbon sink, as well as the dynamics of natural variability in ocean circulation, volcanoes, and solar output (Wigley et al., 2009). This can be done by assuming little or no long-term trend in volcanic or solar forcing, treating observed regional fluctuations such as El Niño Southern Oscillation (ENSO) as canonical or emergent properties, and exploring the climatic implications (over the next few centuries, and for the stabilized equilibrium condition) of a range of different 'storylines' of future global energy and emissions profiles (from business-as-usual to explicit mitigation policies). Forecasts then can be expressed either via socio-economic pathways using IAMs (Nakicenovic & Swart, 2000) or selected from a large suite of possible scenarios on the basis of their resultant radiative forcing potential (e.g. the 'representative

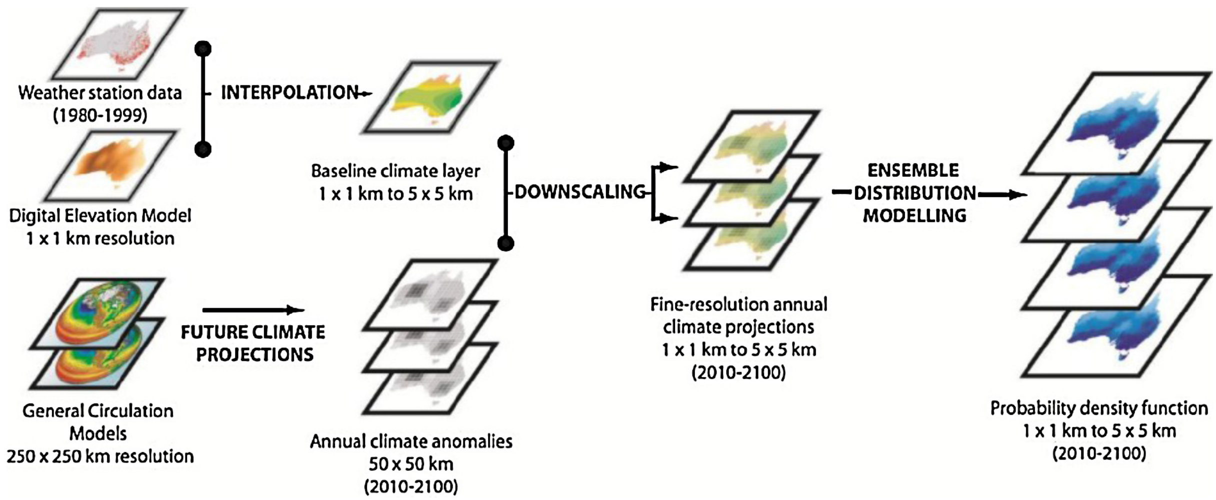

Fig. 3. Schematic depiction of ensemble forecasting of climate change, whereby high-resolution baseline climate grids from station data are linked to global climate models with good regional skill, to produce downscaled probabilistic multi-model predictions.
Source: Modified from Fordham et al. (2011)

concentration pathways' of the Intergovernmental Fifth Assessment Report; IPCC, 2013).

It is obvious from the above discussion that the development of general circulation models for climate simulation has advanced considerably over the last few decades, and these arguably offer salutary lessons for the design of analogous system-level biodiversity-response models. For instance, one promising recent approach is the 'general ecosystem model' (GEM), developed in a collaboration between the United Nations Environment Program, World Conservation Monitoring Centre, and Microsoft Research. The ambitious goal of this global simulation model is to capture the fundamental ecological processes that affect all life on Earth as a 'virtual biosphere' using an interactive mathematical simulation (called the Madingley Model: madingleymodel.org). The code has been released as open source, and is undergoing testing, validation and ongoing community development (Harfoot et al., 2014). An ongoing challenge for such GEMs will be solving the challenges of integrating human decision-making processes and including institutional complexities into the underpinning regional- and global-level processes (Rounsevell et al., 2013; Geographical Sciences Committee, 2014).

Conclusions

A range of useful methods has been developed to project global change. Yet, as reviewed above, there are clearly limitations with all of these lines of attack. Perhaps most pressingly, global-change science still lacks a coherent, empirically based, statistically robust, and transparent methodology to understand and forecast human drivers of land-use change (and associated impacts) and in turn connect this to biodiversity responses at regional to global scales. This constrains our understanding of both the long-term prospects of biodiversity change and of what interventions might be most effective. At higher levels of aggregation, patterns in consumption and use of technology over time and between countries and regions constitute perhaps the most readily identifiable and consistent bases for projecting change.

To increase confidence in our representations of the future, we must seek broad expert elicitation (for proper representation of different disciplinary perspectives) and ensure that models (and assumptions) are validated against robust historical data on key uncertainties, such as rates of technology uptake and barriers to deployment. Confidence in the likelihood of scenarios can be enhanced by analysis of the short-term impact of already announced government policy targets (assuming they are implemented in full, e.g., IEA, 2010) or by reference to the envisaged goals from organizations or businesses with a strong track record at delivery (Chang & Baek, 2010; Smil, 2010; Nicholson, Biegler, & Brook, 2011). Quantitative tools like multi-criteria decision-making analysis, decomposition and input-output models (Rose & Casler, 1996; Hong, Bradshaw, & Brook, 2013) offer a particularly useful pathway for ensuring high levels of robustness and openness in such validation. Models should also be tested repeatedly against real-world data on patterns and trends – just like hypotheses – to learn from their failures as much as their successes (Brook, Burgman, Akcakaya, O'grady, & Frankham, 2002; Grimm et al., 2005). Crucially, the modelling of aggregate drivers provides boundary conditions for more local contexts, which are often more complex, and so can complement and support studies and methodologies at lower spatial scales. To further improve our forecasting, mechanistic approaches based on robust data – on demographics, incomes, industrial sectors, per-capita consumption of key resources, trade, land use, technical efficiencies of production methods, pollution, and so on – will need to come from many sources: global to national reporting inventories, remote sensing, and biological surveys, among others. These sources should be set up in a way that is readily interrogated with relational databasing.

A transformation is underway in research on global-change science, driven by ready access to 'big data' from observational and experimental networks, ongoing growth in computational power, and complementary advances in statistical and optimisation methodologies. What is critically needed to complement these developments are validated, mechanistic models of the drivers of global change, integrated with approaches that are flexible enough to capture key uncertainties and complex interrelationships, but simple and transparent enough to be applied efficiently for optimising decision-making and testing the sensitivity of assumptions.

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References

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 16089–16094.

Ang, B. W. (2004). Decomposition analysis for policymaking in energy. *Energy Policy*, *32*, 1131–1139.

Ansuategi, A., & Perrings, C. (2000). Transboundary externalities in the environmental transition hypothesis. *Environmental and Resource Economics*, *17*, 353–373.

Ausubel, J. H. (2000). The great reversal: nature's chance to restore land and sea. *Technology in Society*, *22*, 289–301.

Ausubel, J. H., & Waggoner, P. E. (2008). Dematerialization: Variety, caution, and persistence. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 12774–12779.

Ausubel, J. H., Wernick, I. K., & Waggoner, P. E. (2012). Peak farmland and the prospect for land sparing. *Population and Development Review*, *38*, 221–242.

Blomqvist, L., Nordhaus, T., & Shellenberger, M. (2015). *Nature unbound: Decoupling for conservation*. Oakland, CA: Breakthrough Institute.

Botkin, D. B., Saxe, H., Araujo, M. B., Betts, R., Bradshaw, R. H. W., Cedhagen, T., et al. (2007). Forecasting the effects of global warming on biodiversity. *BioScience*, *57*, 227–236.

Box, G. E. (1979). Robustness in the strategy of scientific model building. In *Robustness in statistics*. pp. 201–236. Academic Press.

Brook, B. W., Akcakaya, H. R., Keith, D. A., Mace, G. M., Pearson, R. G., & Araujo, M. B. (2009). Integrating bioclimate with population models to improve forecasts of species extinctions under climate change. *Biology Letters*, *5*, 723–725.

Brook, B. W., Burgman, M. A., Akcakaya, H. R., O'grady, J. J., & Frankham, R. (2002). Critiques of PVA ask the wrong questions: throwing the heuristic baby out with the numerical bath water. *Conservation Biology*, *16*, 262–263.

Brook, B. W., O'Grady, J. J., Chapman, A. P., Burgman, M. A., Akçakaya, H. R., & Frankham, R. (2000). Predictive accuracy of population viability analysis in conservation biology. *Nature*, *404*, 385–387.

Brook, B. W., Sodhi, N. S., & Bradshaw, C. J. A. (2008). Synergies among extinction drivers under global change. *Trends in Ecology & Evolution*, *23*, 453–460.

Butchart, S. H. M., Walpole, M., Collen, B., van Strien, A., Scharlemann, J. P. W., Almond, R. E. A., et al. (2010). Global biodiversity: Indicators of recent declines. *Science*, *328*, 1164–1168.

Carson, R. T. (2009). The Environmental Kuznets Curve: Seeking empirical regularity and theoretical structure. *Review of Environmental Economics and Policy*, *4*, 3–23.

CBD. (2013). *Convention on biological diversity: Global biodiversity outlook 3*.. http://www.cbd.int/gbo3/

Chang, Y. S., & Baek, S. J. (2010). Limit to improvement: Myth or reality? Empirical analysis of historical improvement on three technologies influential in the evolution of civilization. *Technological Forecasting and Social Change*, *77*, 712–729.

Chertow, M. R. (2001). The IPAT equation and its variants and environmental impact. *Journal of Industrial Ecology*, *4*, 13–29.

Clark, J. S., Carpenter, S. R., Barber, M., Collins, S., Dobson, A., Foley, J. A., et al. (2001). Ecological forecasts: an emerging imperative. *Science*, *293*, 657–660.

Clark, N. E., Boakes, E. H., McGowan, P. J. K., Mace, G. M., & Fuller, R. A. (2013). Protected areas in South Asia have not prevented habitat loss: A study using historical models of land-use change. *PLoS ONE*, *8*, e65298.

Clarke, L., Edmonds, J., Jacoby, J., Pitcher, H., Reilly, J., Richels, R., et al. (2007). *CCSP scenarios of greenhouse gas emissions and atmospheric concentrations*. Washington, DC: Department of Energy, Office of Biological & Environmental Research.

Dasgupta, S., Laplante, B., Wang, H., & Wheeler, D. (2002). Confronting the environmental Kuznets curve. *Journal of Economic Perspectives*, *16*, 147–168.

DeFries, R. S., Rudel, T., Uriarte, M., & Hansen, M. (2010). Deforestation driven by urban population growth and agricultural trade in the twenty-first century. *Nature Geoscience*, *3*, 178–181.

Duchin, F., & Lange, G.-M. (1995). *The future of the environment: ecological economics & technological change*. pp. 222.

Ehrlich, P. R., & Holdren, J. P. (1971). Impacts of population growth. *Science*, *171*, 1212–1217.

Ewers, R. M., Scharlemann, J. P. W., Balmford, A., & Green, R. E. (2009). Do increases in agricultural yield spare land for nature? *Global Change Biology*, *15*, 1716–1726.

Foley, J. A., DeFries, R. S., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science*, *309*, 570–574.

Fordham, D. A., Akçakaya, H. R., Araújo, M. B., Keith, D. A., & Brook, B. W. (2013). Tools for integrating range change, extinction risk and climate change information into conservation management. *Ecography*, *36*, 956–964.

Fordham, D. A., Wigley, T. M. L., & Brook, B. W. (2011). Multi-model climate projections for biodiversity risk assessments. *Ecological Applications*, *21*, 3317–3331.

Fordham, D. A., Wigley, T. M. L., & Brook, B. W. (2012). Strengthening forecasts of climate change impacts with multi-model ensemble averaged projections using MAGICC/SCENGEN 5.3. *Ecography*, *35*, 4–8.

Garnaut, R. (2008). *The Garnaut climate change review*. Cambridge University Press: Melbourne.

Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience*, *52*, 143–150.

Geographical Sciences Committee. (2014). *Advancing land change modeling: Opportunities and research requirements*. National Academies Press.

Gleckler, P. J., Taylor, K. E., & Doutriaux, C. (2008). Performance metrics for climate models. *Journal of Geophysical Research*, *113*, D06104.

Golub, A. a., Henderson, B. B., Hertel, T. W., Gerber, P. J., Rose, S. K., & Sohngen, B. (2012). Global climate policy impacts on livestock, land use, livelihoods, and food security. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 20894–20899.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., et al. (2005). Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *Science*, *310*, 987–991.

Grubler, A., Nakicenovic, N., & Victor, D. G. (1999). Modeling technological change: Implications for the global environment. *Annual Review of Energy and the Environment*, *24*, 545–569.

Hamilton, C., & Turton, H. (2002). Determinants of emissions growth in OECD countries. *Energy Policy*, *30*, 63–71.

Hansen, J., Sato, M., Kharecha, P., Russell, G., Lea, D. W., & Siddall, M. (2007). Climate change and trace gases. *Philosophical Transactions of the Royal Society of London. Series A, Mathematical Physical and Engineering Sciences*, *365*, 1925–1954.

Harfoot, M. B., Newbold, T., Tittensor, D. P., Emmott, S., Hutton, J., Lyutsarev, V., et al. (2014). Emergent global patterns of ecosystem structure and function from a mechanistic general ecosystem model. *PLoS Biology*, *12*, e1001841.

Hoffert, M. I., Caldeira, K., Benford, G., Criswell, D. R., Green, C., Herzog, H., et al. (2002). Advanced technology paths to global climate stability: Energy for a greenhouse planet. *Science*, *298*, 981–987.

Hong, S., Bradshaw, C. J. A., & Brook, B. W. (2013). Evaluating options for the future energy mix of Japan after the Fukushima nuclear crisis. *Energy Policy*, *56*, 418–424.

Ibáñez, I., Clark, J. S., Dietze, M. C., Feeley, K., Hersh, M., LaDeau, S., et al. (2006). Predicting biodiversity change: outside the climate envelope, beyond the species-area curve. *Ecology*, *87*, 1896–1906.

IEA. (2010). *World Energy Outlook 2010*.. http://www.worldenergyoutlook.org/

IPCC. (2013). *Intergovernmental panel on climate change – Fifth assessment report (AR5)*. Geneva, Switzerland: IPCC. http://www.ipcc.ch

Jordan, B. R. (2010). *The environmental Kuznets curve: Preliminary meta-analysis of published studies, 1995–2010*.

Lacy, R. C., Miller, P. S., Nyhus, P. J., Pollak, J. P., Raboy, B. E., & Zeigler, S. L. (2013). Metamodels for transdisciplinary analysis of wildlife population dynamics. *PLoS ONE*, *8*, e84211.

Laurance, W. F. (2001). Future shock: Forecasting a grim fate for the Earth. *Trends in Ecology & Evolution*, *16*, 531–533.

Leadley, P., Pereira, H., & Alkemade, R. (2010). *Biodiversity scenarios: Projections of 21st century change in biodiversity and associated ecosystem services*. Montreal: Secretariat of the Convention on Biological Diversity.

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., et al. (2008). Tipping elements in the Earth's climate system. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 1786–1793.

Lenzen, M., Dey, C., Foran, B., Widmer-Cooper, A., Ohlemüller, R., Williams, M., et al. (2013). Modelling interactions between economic activity, greenhouse gas emissions, biodiversity and agricultural production. *Environmental Modeling & Assessment*, *18*, 377–416.

Liddle, B., & Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Population and Environment*, *31*, 317–343.

Loftus, P. J., Cohen, A. M., Long, J. C. S., & Jenkins, J. D. (2015). A critical review of global decarbonization scenarios: what do they tell us about feasibility? *Wiley Interdisciplinary Reviews: Climate Change*, *6*, 93–112.

Loh, J., Green, R. E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V., et al. (2005). The Living Planet Index: using species population time series to track trends in biodiversity. *Philosophical Transactions of the Royal Society of London. Series B, Biological sciences*, *360*, 289–295.

Mace, G. M. (2012). The limits to sustainability science: ecological constraints or endless innovation? *PLoS Biology*, *10*, e1001343.

Mace, G. M., Norris, K., & Fitter, A. H. (2012). Biodiversity and ecosystem services: a multilayered relationship. *Trends in Ecology & Evolution*, *27*, 19–26.

Mastrandrea, M. D., & Schneider, S. H. (2004). Probabilistic integrated assessment of dangerous climate change. *Science*, *304*, 571–575.

MEA. (2005). *Millenium ecosystem assessment: Ecosystems and human well-being: scenarios*. Washington, DC: Island Press.

Morgan, M. G., & Keith, D. W. (2008). Improving the way we think about projecting future energy use and emissions of carbon dioxide. *Climatic Change*, *90*, 189–215.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., et al. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, *463*, 747–756.

Nakicenovic, N., & Swart, R. (Eds.). (2000). *Special report on emissions scenarios*. UK: Cambridge University Press.

Nicholson, M., Biegler, T., & Brook, B. W. (2011). How carbon pricing changes the relative competitiveness of low-carbon baseload generating technologies. *Energy*, *36*, 305–313.

Omann, I., Stocker, A., & Jäger, J. (2009). Climate change as a threat to biodiversity: An application of the DPSIR approach. *Ecological Economics*, *69*, 24–31.

Ostrom, E. (2009). A general framework for analyzing sustainability of social–ecological systems. *Science*, *325*, 419–422.

Pereira, H. M., Leadley, P. W., Proença, V., Alkemade, R., Scharlemann, J. P. W., Fernandez-Manjarrés, J. F., et al. (2010). Scenarios for global biodiversity in the 21st century. *Science*, *330*, 1496–1501.

Pielke, R., Wigley, T., & Green, C. (2008). Dangerous assumptions. *Nature*, *452*, 531–532.

Rands, M. R. W., Adams, W. M., Bennun, L., Butchart, S. H. M., Clements, A., Coomes, D., et al. (2010). Biodiversity conservation: challenges beyond 2010. *Science*, *329*, 1298–1303.

Reichler, T., & Kim, J. (2008). How well do coupled models simulate today's climate? *Bulletin of the American Meteorological Society*, *89*, 303–311.

Rosa, E. A., & Dietz, T. (2012). Human drivers of national greenhouse-gas emissions. *Nature Climate Change*, *2*, 581–586.

Rose, A., & Casler, S. (1996). Input–output structural decomposition analysis: a critical appraisal. *Economic Systems Research*, *8*, 33–62.

Rounsevell, M., Arneth, A., Brown, D., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., et al. (2013). Incorporating human behaviour and decision making processes in land use and climate system models. In *GLP Report*.

Sala, O. E., Chapin, F. S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., et al. (2000). Global biodiversity scenarios for the year 2100. *Science*, *287*, 1770–1774.

Scherrer, S. C. (2011). Present-day interannual variability of surface climate in CMIP3 models and its relation to future warming, I. *International Journal of Climatology*, *31*, 1518–1529.

Smil, V. (2010). *Energy myths and realities: Bringing science to the energy policy debate*. Washington, DC: AEI Press.

Steinberger, J. K., Krausmann, F., & Eisenmenger, N. (2010). Global patterns of materials use: A socioeconomic and geophysical analysis. *Ecological Economics*, *69*, 1148–1158.

Stern, D. (2004). The rise and fall of the environmental Kuznets curve. *World Development*, *32*, 1419–1439.

Stern, D. I., Common, M. S., & Barbier, E. B. (1996). Economic growth and environmental degradation: The environmental Kuznets curve and sustainable development. *World Development*, *24*, 1151–1160.

Stern, P. C. (1997). *Environmentally significant consumption: Research directions*.

Tallis, H. M., & Kareiva, P. (2006). Shaping global environmental decisions using socio-ecological models. *Trends in Ecology & Evolution*, *21*, 562–568.

Tebaldi, C., & Knutti, R. (2007). The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society of London. Series A, Mathematical Physical and Engineering Sciences*, *365*, 2053–2075.

Thomas, V., Theis, T., Lifset, R., Grasso, D., Kim, B., Koshland, C., et al. (2003). Industrial ecology: policy potential and research needs. *Environmental Engineering Science*, 20.

Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., et al. (2001). Forecasting agriculturally driven global environmental change. *Science*, *292*, 281–284.

UNEP. (2011). *Decoupling natural resource use and environmental impacts from economic growth*.. http://www.unep.org/resourcepanel/Publications/Decoupling/tabid/56048

Utgikar, V. P., & Scott, J. P. (2006). Energy forecasting: Predictions, reality and analysis of causes of error. *Energy Policy*, *34*, 3087–3092.

Valin, H., Sands, R. D., van der Mensbrugghe, D., Nelson, G. C., Ahammad, H., Blanc, E., et al. (2013). The future of food demand: understanding differences in global economic models. *Agricultural Economics*, 45.

van der Sluijs, J. P. (2002). A way out of the credibility crisis of models used in integrated environmental assessment. *Futures*, *34*, 133–146.

Voet, E. V. D., Oers, L. V., & Nikolic, I. (2005). Dematerialization: Not just a matter of weight. *Journal of Industrial Ecology*, *8*, 121–137.

Waggoner, P. E., & Ausubel, J. H. (2002). A framework for sustainability science: A renovated IPAT identity. *Proceedings of the National Academy of Sciences of the United States of America*, *99*, 7860–7865.

Wiedmann, T. (2009). A review of recent multi-region input–output models used for consumption-based emission and resource accounting. *Ecological Economics*, *69*, 211–222.

Wigley, T. M. L., Clarke, L. E., Edmonds, J. A., Jacoby, H. D., Paltsev, S., Pitcher, H., et al. (2009). Uncertainties in climate stabilization. *Climatic Change*, *97*, 85–121.

Wigley, T. M. L., & Raper, S. C. B. (2001). Interpretation of high projections for global-mean warming. *Science*, *293*, 451–454.

Wise, M., Calvin, K., Thomson, A., Clarke, L., Bond-Lamberty, B., Sands, R., et al. (2009). Implications of limiting CO_2 concentrations for land use and energy. *Science*, *324*, 1183–1186.

Wright, S., & Muller-Landau, H. (2006). The future of tropical forest species. *Biotropica*, *38*, 287–301.

York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, *46*, 351–365.

Zhang, X., Davidson, E. A., Mauzerall, D. L., Searchinger, T. D., Dumas, P., & Shen, Y. (2015). Managing nitrogen for sustainable development. *Nature*, *528*, 51–59.