Vienna Yearbook of Population Research 2024 (Vol. 22), pp. 1–29
https://doi.org/10.1553/p-n5en-z38a

RESEARCH ARTICLE

Projecting environmental impacts with varying population, affluence and technology using IPAT – Climate change and land use scenarios

Emma Engström[1,2] and **Martin Kolk**[1,3]

ABSTRACT We theoretically explore the interrelations between population (*P*), affluence (*A*) and technology (*T*) for various environmental impacts (*I*) using IPAT-type modelling. To illustrate the differences across environmental dimensions, climate and land use impacts are modelled. We use middle-of-the-road projections for population and per capita income and different forecasting methods for technology, including extrapolations of historical trends, models based on stochastic IPAT (STIRPAT) and predictions in the literature. The different approaches are compared within the IPAT framework. We also explore the consequences of alternative trajectories for *P*, *A* and *T*, and we discuss the implications of these trajectories for reaching global goals based on our modelling. The findings are analysed in light of three theories in environmental sociology, each of which places a different emphasis on the different components of IPAT. We argue that the large amount of technological mitigation assumed in many forecasts makes affluence and population relatively irrelevant for climate change. However, we also consider it likely that both factors will be determinants of land use impact in the 21st century.

KEYWORDS IPAT • Environmental Kuznets curve (EKC) • Green growth • Human ecology • STIRPAT model • Land use impact

Introduction

For more than half a century, the environmental sciences have highlighted how increasing consumption contributes to environmental problems. In an influential school of thought, such impacts have been conceptualised as the product of the number of people (*P*), per capita affluence (*A*) and a conversion factor (*T*), which translates consumption into environmental impacts (*I*). Ehrlich and Holdren (1971) and Commoner (1971) introduced the IPAT identity to illustrate this point. This conceptualisation has been prominent in both theoretical work and empirical studies on the sources of the world's growing environmental problems. Today, researchers across the globe share a consensus that the world is facing imminent and consequential threats to human and planetary welfare due to climate change

✉ Emma Engström, emma.engstrom@iffs.se
1 Institute for Futures Studies, Stockholm, Sweden
2 Department of Urban Planning and Environment, KTH Royal Institute of Technology, Stockholm, Sweden
3 Stockholm University Demography Unit, Department of Sociology, Stockholm University, Stockholm, Sweden

(IPCC, 2022; Rockström et al., 2009), and that humanity's tendency to appropriate ever larger areas of the earth's surface has urgent environmental implications (Dasgupta, 2021). However, as we show in this study, the extent to which affluence and population can be seen as sources and potential domains for the mitigation of these challenges remains deeply contentious.

We adopt a theoretical method in which we use IPAT-type modelling to examine how IPAT-based reasoning gives different answers depending on the environmental issue that is being addressed. Instead of using IPAT to explain why any *one* part of the identity can be seen as a *universal* tool for understanding all kinds of environmental challenges (which is how IPAT-related arguments have often been used in the past), we show that IPAT is perhaps equally or more useful for understanding how *different* environmental dimensions relate to various parts of the identity. Furthermore, we point out the usefulness of converting various environmental impact models – such as forecasts by the Intergovernmental Panel on Climate Change (IPCC) – into the IPAT framework to illustrate their different implications. We look at a variety of aspects, such as time scales and possibilities for technological solutions, as well as the elasticity of impacts with respect to population and consumption. Using this approach, we show why the relevance of population and affluence may vary for different types of challenges.

We create IPAT-type models for climate and land use impacts using mainstream population and income projections with a set of assumptions about how the *T* factor is calculated. We then model alternative population, affluence and technology trajectories, and discuss their implications for finding sustainable solutions in the future. These environmental dimensions represent two of the most critical challenges facing humanity in the 21st century. They both point to the ways in which human actions risk destabilising the earth system according to the planetary boundaries framework (Rockström et al., 2009; Steffen et al., 2015). Land use is also closely linked to another critical planetary boundary, biosphere integrity, because a large share of biodiversity loss is attributable to habitat destruction through the conversion of forests into farmland (Dasgupta, 2021).

For many environmental problems, the historical empirical evidence of a strongly positive correlation between environmental impacts and both population and affluence is relatively robust. Over the last decade, some scientists have stressed the contributions of population to many contemporary environmental challenges (Bongaarts and O'Neill, 2018; Lidicker, 2020), while others have focused primarily on the contributions of consumption, and have thus downplayed the role of population (Wiedmann et al., 2020). Over the years, the IPAT framework has been used to draw attention to the implications of increasing economic and population growth for different kinds of environmental challenges. Early research on IPAT-type relationships generally proposed either population policies (smaller *P*) or reduced economic growth and consumption (smaller *A*) as possible solutions. Ehrlich and Holdren's (1971) original work focused on addressing future environmental challenges by limiting population growth. In contrast, more recent research has primarily focused on technological solutions to environmental problems, while arguing that efforts to mitigate these problems through reductions in affluence or population are infeasible or indefensible.

https://doi.org/10.1553/p-n5en-z38a

While both climate change and land systems change are urgent issues, they have different underlying causes and implications. This suggests that IPAT-based projections of these two challenges will look very different. In terms of drivers, a notable difference between them is that the main sources of land use change have been agriculture and forestry, whereas climate change can be attributed to four other sectors as well (energy systems, industry, buildings and transport) (IPCC, 2022). Moreover, how researchers judge the feasibility of decoupling environmental impacts from consumption differs depending on whether they are discussing climate or land use. To address climate change, many countries have issued zero emissions pledges, and mainstream models typically include the assumption that near zero emissions will be reached at the global level at some point in this century (IPCC, 2022). Even though historical trends are often not compatible with decoupling environmental impacts from population growth and increasing affluence (Haberl et al., 2020), many researchers see the IPCC's scenarios as feasible, albeit challenging to reach. In contrast, land use challenges have been much less explored. In the available literature, researchers have identified substantial challenges in reversing the increasing impact of human land use (Bimonte and Stabile, 2017; Pontarollo and Serpieri, 2020). Thus, our cases serve as illustrations of scenarios in which the possibilities for decoupling consumption from environmental impacts differ.

Through this article, we aim to provide a better theoretical understanding of how the effects of population, affluence and technological mitigation could be substantively different across various forms of environmental stress. Using an IPAT-based approach, we hope to give a better theoretical and conceptual illustration of how and why population and affluence will vary in significance depending on the context. We believe that this analysis can, for example, help to clarify why population policies have often been shown to be of limited relevance when it comes to climate change (e.g., Budolfson and Spears, 2021), but might still be important for addressing other environmental issues. The rest of this article is structured as follows. We present background and theory in relation to the IPAT equation. The methodology we use, together with the underlying models and empirical inputs, are then presented. Next, the results of the modelling are reported. This is followed by a discussion of the results. Finally, we offer a concluding commentary about the implications of the results.

Theoretical and empirical background

A large body of literature has connected economic growth and population growth to environmental impacts in different ways. In this section, we discuss some of the most influential concepts and theoretical perspectives in this research.

Economic growth and environmental impacts

A common finding in empirical studies of environmental impacts across countries is that they are tightly linked to economic consumption. Richer countries consume more, and therefore have a larger impact than poorer countries (York et al., 2004).

https://doi.org/10.1553/p-n5en-z38a

Moreover, contemporary societies have a larger impact than they did historically when they had lower incomes. Most research also suggests that while environmental consequences tend to increase with income, the relationship between environmental impacts and economic consumption is less than linear (Haberl et al., 2020; Vadén et al., 2020; York et al., 2003b).

Several theoretical concepts have been introduced to relate economic growth to environmental impacts. One such model is the *environmental Kuznets curve* (EKC), which was first presented by Grossman and Krueger (1991) to describe a societal evolution in which the relationship between environmental impacts and affluence has an inverse U shape. It stipulates that the levels of environmental degradation are lowest in the societies that are the least and the most affluent. It is named in analogy to the Kuznets (1955) curve, which linked income inequality to economic growth. Relatedly, *green growth*, or the green economy, is a concept introduced by Pearce et al. (1989) to describe a case in which increased affluence is not related to increased environmental consumption. Among the explanations for the EKC and green growth are growth in the scale of the economy; changes in the composition of the economy, i.e., structural shifts from an agrarian to an industrial to an information-intensive service-based economy; as well as the adoption of novel environmentally-friendly production techniques, policies or investments (Antweiler et al., 2001; Coxhead, 2003; Panayotou, 1993; Shafik and Bandyopadhyay, 1992; Stern, 2004). In their background study for the World Development Report 1992, Shafik and Bandyopadhyay (1992) found strong support for the EKC (also discussed in Shafik (1994)). A number of subsequent studies have provided empirical support for the EKC in different contexts (Cole, 2003; Grossman and Krueger, 1995; Lean and Smyth, 2010), as reviewed in Tan et al. (2014). For example, in a study of five Association of Southeast Asian Nations (ASEAN) countries from 1980 to 2006, Lean and Smyth (2010) found that long-run estimates supported the EKC. However, as highlighted by Stern (2004), the EKC may not apply to all types of environmental impacts.

Researchers have made a distinction between a weak and a strong version of green growth or decoupling (Haberl et al., 2020). In the weak format, this notion simply means that as societies get richer, the relative environmental impact of increased affluence declines. Hence, the environmental impact increases less proportional to the rise in affluence. The stronger version implies that in richer societies, the absolute environmental impact is smaller. This can be conceptualised as a situation in which the elasticity between affluence and the environmental impact transforms fundamentally, not only from having a value between zero and one, but to having a negative value at some (high) level of affluence. The weak case can be described as *relative* decoupling, while the strong case can be seen as *absolute* decoupling. While there is considerable evidence of relative decoupling across many environmental dimensions, there is far less evidence of absolute, sector-wide decoupling at the global level. Likewise, the EKC is supported for specific forms of environmental stress in certain regional contexts (Haberl et al., 2020).

In particular, few or no studies have found evidence of absolute decoupling at the global level for either climate change or land use impact, although there are examples at the national level, especially in the former case (Vadén et al., 2020). For example, a recent study based on data from the 1960s to 2015 in the Nordic countries reported that an EKC was

https://doi.org/10.1553/p-n5en-z38a

observed for per capita carbon dioxide (CO_2) emissions in Denmark, Finland, Iceland and Sweden (but not in Norway) (Urban and Nordensvärd, 2018). A literature review of research in 27 advanced economies reported that the majority (41 of 55) of the examined studies found support for the EKC hypothesis and for the absolute decoupling of CO_2 emissions and gross domestic product (GDP) at the national level (Al-Mulali and Ozturk, 2016).

Studies of the relationship between land use and affluence are rarer and tend to have a narrower scope. In this literature, the evidence presented often does *not* support the EKC. For example, Pontarollo and Serpieri (2020) studied residential built-up land in 42 Romanian counties from 2000 to 2014, and found an inverted EKC. These results are in line with an earlier study relating land consumption to per capita GDP in 20 Italian regions over the 1980–2010 period (Bimonte and Stabile, 2017), which reported an N-shaped curve with increasing impacts for very high levels of affluence.

As we will illustrate later in our IPAT models, some climate forecasting approaches imply absolute decoupling, while many other climate change and land use scenarios instead point to relative, but not absolute, decoupling.

Population growth and the environment

Efforts to link population, land use, productivity and wages go back to classical economic writings by legendary economists and demographers such as Malthus (1798). During the 1960s and 1970s, when human population growth reached its historical maximum (Lam, 2011), there was increasing concern that population was a major cause of environmental problems. The theoretical perspectives we apply in this article, primarily the IPAT equation, originate from this period. Many of the worst predictions from this time did not come true (Lam, 2011), although subsequent research has confirmed a link between population size and environmental impacts (York et al., 2003a).

Recent empirical and theoretical studies on the association between population growth and environmental impacts at the national, regional and global levels have generally found that the relationships are close to *one* (Rosa et al., 2004; York et al., 2003b); that is, everything else being equal, most environmental impacts are directly proportional to population size. It is important to note, however, that these calculations generally account for the effect of population *net* of the level of affluence, which means that an individual in a high-income society still contributes more to environmental problems than an individual in a low-income society. The evidence for relationships that diverge distinctly from one is rather limited (Rosa et al., 2004), even though elasticities can be theoretically expected to vary. Elasticities above one could apply if new, low-quality land is needed for a given unit of consumption after a certain amount of high-quality land has been used. Lower elasticities might be valid if higher population densities lead to more efficient societal organisation. Researchers have also argued that there is a danger in estimating population elasticities from longitudinal data because such coefficients may partly reflect omitted variable bias, and have instead suggested using population as a scaling factor (O’Neill et al., 2012). In line with most previous research, we find elasticities of population very close to one.

https://doi.org/10.1553/p-n5en-z38a

Social theories on population, affluence and environmental impacts

York et al. (2003a) related IPAT to three different social theories that address how consumption and population contribute to environmental challenges. First, the *human ecology*, or neo-Malthusian view, focuses on population growth as a key driver of anthropogenic environmental impacts. According to this perspective, environmental conditions determine human development, and in an IPAT model, this means there is a positive, linear relationship between population and the total environmental impact. This is close to how the IPAT was originally introduced by Ehrlich and Holdren (1971).

Second, *modernisation*, or environmental economics from a neo-classical perspective, asserts that environmental challenges can be addressed through existing social, political and economic institutions (York et al., 2003a). Accordingly, this view argues that current levels of economic growth, capitalism and globalisation can be maintained without fundamentally harming the planet. Hence, this theory posits a relationship between environmental quality and economic development that reflects the green growth model or the EKC. This implies that the IPAT models would generate values of I that are curvilinear with income; that is, above a certain level of income, I decreases even though A increases. While such relationships have been shown to hold for some pollutants, for instance for air pollution in the form of sulphur dioxide (Grossman and Krueger, 1991), there is less evidence of sector-wide decoupling, as discussed above.

Third, the *political economy* perspective holds that economic production is the most important factor in this relationship (York et al., 2003a). This position maintains that neither technological development nor political reforms will suffice to adequately mitigate environmental impacts. As producers develop technologies and other methods to reduce labour costs, they will increase their use of shared ecological resources, which means that environmental externalities are inevitable. Economic elites will not internalise the costs voluntarily, and they will use their political power to challenge any reforms that fundamentally change this system, as described further by York et al. (2003a). This perspective maintains that even technologies that reduce ecological damage will, in the end, increase it, because higher profits will be used to escalate growth (and will thus aggravate the effects of economic production). Hence, according to this view, the only solution is an end to economic growth. Thus, this position is consistent with the degrowth perspective and with calls for a fundamental restructuring of society. In the IPAT models, this means that for the total environmental impact (I) to decrease, affluence (A) must decrease as well.

IPAT and STIRPAT frameworks

In the early 1970s, Ehrlich and Holdren (1971) and Commoner (1971) introduced the IPAT equation to elucidate the relationship between population, affluence and environmental impacts (Chertow, 2000):

$$I = PAT \tag{1}$$

where I is total environmental impact, P is population, A is affluence and T is impact per unit of economic activity. While this equation has been challenged as a simplification because of

https://doi.org/10.1553/p-n5en-z38a

interactions and dependencies between affluence, population and technology, it formalises essential components of the relationship between these factors. Nevertheless, any interpretations derived from IPAT will have to relate to interaction effects. Chertow (2000) provided a discussion of the strengths and weaknesses of various versions of IPAT in the literature. A further development of IPAT with respect to carbon emissions was proposed by Kaya and Yokobori (1997), in which energy use per unit of consumption and the carbon intensity of energy consumption were distinguished.

As IPAT implies by design that the different factors contribute equally to environmental impacts, it does not allow for hypothesis testing of their respective contributions. To address this limitation, Dietz and Rosa (1997) developed a stochastic form of IPAT, Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT). This model does not presume a priori functional relationships between P, A and T; instead, it considers that these associations can be estimated from data, following:

$$I = aP^b A^c T^d e \tag{2}$$

where a scales the model, b, c and d denote coefficients of P, A and T, respectively; and e is a random error term. The coefficients are similar to elasticities in economics, as they reflect the degree to which a percentage change in the explanatory variable generates a percentage change in impact. York et al. (2003b) introduced the notion of *ecological elasticity* as the responsiveness of an environmental effect to a change in any of the driving forces, specifically population elasticity of impact, b, and affluence elasticity of impact, c, in eq. 2.

STIRPAT implies that if the elasticity is null, the impacts are not affected by changes in population or affluence. If it is one, then there is a proportional relationship between factors; that is, a 1% change in population ($b = 1$) or income ($c = 1$) results in a 1% change in the impact, while higher values imply that the impacts grow faster than the driving factor (York et al., 2003a). For climate, this could apply if higher incomes increase the demand for products with a higher carbon impact, such as airfare. For land use, it may be valid if higher incomes lead to more demand for products and services that increase deforestation. Values above zero and below one indicate inelastic relationships, with impacts that are less reactive. This may happen if higher incomes increase the demand for products with lower environmental impacts, such as services. Values of b and c below zero mean that environmental impacts decrease when population and affluence increase. This would imply that increasing population and income levels enable disruptive innovations that fundamentally alter the way humans impact the environment. In IPAT, the coefficients and the error term equal unity.

STIRPAT has been applied to quantify the relationship between environmental impacts, population and affluence in a wide range of contexts (Dietz and Rosa, 1997; Rosa et al., 2004; Shi, 2003; York et al., 2003a). In addition to such historical assessments, STIRPAT-type models have been used for projections. For example, Liddle (2011) projected carbon emissions from transport and residential electricity in different countries in the Organisation for Economic Co-operation and Development (OECD) from 2010 to 2050. Several related studies have addressed China's carbon emissions in the coming century

https://doi.org/10.1553/p-n5en-z38a

(Fan and Lu, 2022; Li et al., 2016). Li et al. (2016) predicted China's GHG emissions from 2015 to 2035, with parameters derived from a STIRPAT-based analysis of data from 1998 to 2014. They made projections based on three emissions scenarios, with variations in population, affluence, carbon emission intensity, urbanisation, energy consumption structure and economic structure (Li et al., 2016).

However, it could be argued that STIRPAT is too simplistic to model the relationship between greenhouse gas emissions and *P*, *A* and *T*, as it excludes well-documented and complex relationships between, for example, energy use and carbon emissions (Kaya and Yokobori, 1997), or models incorporating energy prices (Liddle and Huntington, 2020). The current study builds on these studies, although it evaluates two ecological challenges and three forecasting approaches. An advantage of STIRPAT is that we can use it *across* environmental dimensions.

Methods and empirical inputs

With IPAT as the theoretical foundation, we develop broad, quantitative projections of climate impact and land use impact between 2020 and 2100. Specifically, we evaluate normalised trajectories of impact, I/I_0, population, P/P_0, affluence, A/A_0 and technological development, T/T_0, where subscripts with 0 represent the values of *I*, *P*, *A* and *T*, respectively, in our base year (2020). For population and affluence, we rely on generic, commonly cited middle-of-the-road forecasts in the literature. Regarding *P*, we use the United Nations (UN, 2022) World Population Prospects (WPP) Medium variant. This is the main forecast of the UN's Population division, and it is based on qualitative expert-based assessments of likely future population trajectories on a country-by-country basis. For *A*, we use the global GDP predicted in the IPCC's middle-of-the-road scenario: the Shared Socioeconomic Pathway 2 (SSP2) (Dellink et al., 2017; Fricko et al., 2017; Riahi et al., 2017). We obtain these data from the SSP Public Database, which is hosted by the International Institute for Applied Systems Analysis (IIASA, 2023).

The last part of IPAT, *T*, is inherently difficult to measure and predict. It relates to a multitude of processes, such as the demand and consumption of various products and services, the adoption of environmental policies (public and organisational), and the development of technologies that allow actors to produce a given amount of outcome with less impact. We therefore use a *set* of model families that can be seen as different methods for projecting *T,* which represent three distinct conceptual approaches to prediction. The first approach is centred around a linear projection of *T* that is based on historical trends. This approach sees IPAT as an identity (York et al., 2003b), whereby observations of *I, P* and *A* at different points in time can used to solve for *T,* and temporal improvements in *T* can be calculated given the assumption of constant annual change. The second approach applies the STIRPAT model (Dietz and Rosa, 1997), and it implies that projections of *T* vary explicitly with projections of *P* and *A*. The third approach is based on elaborate forecasts in the literature, specifically on the SSP2 middle-of-the-road scenario (Fricko et al., 2017; IPCC, 2022; Popp et al., 2017; Riahi et al., 2017). These three approaches are summarised in Table 1, and will be described in the following subsections.

https://doi.org/10.1553/p-n5en-z38a

Table 1 Three different approaches to developing trajectories for *T* between 2020 and 2100 (all of them use the same predictions for *P* and *A*)

Approach	Explanation
(1) Extrapolation of historical trends	Seeing IPAT as an identity (York et al., 2003b), we extrapolate historical trends in which values of *T* at different points in time are calculated based on observations of *I, A* and *P*. Annual historical changes in *T* are then calculated by assuming constant temporal developments, and these values are then assumed in predictions. Thus, projections of *T* do not depend on *P* and *A*.
(2) STIRPAT-derived projections	We apply STIRPAT (Dietz and Rosa, 1997), with elasticities inferred from the literature. Here, projections of *T* depend explicitly on *P* and *A*.
(3) Forecasts in previous research	We infer *T* from projections for *P* and *A* and trajectories of *I* from published forecasts that directly model environmental impacts until 2100 (Fricko et al., 2017; IPCC, 2022; Popp et al., 2017; Riahi et al., 2017).

Approach 1: Extrapolation of historical trends

Our first approach to predicting *T* is grounded in the assumption that future technological developments in the form of annually reduced environmental impacts per unit of production will follow historical trends. It postulates that changes in *T* in the past have been independent of changes in *P* and *A*, and that annual improvements in *T* will be constant throughout the 21st century at a rate that reflects average historical rates. In this approach, projections of *T* are *independent* of changes in *A* and *P* (although the annual rate of change in *T* is derived from historical records of *I, P* and *A*).

For climate impact data, we use records for global GDP (International Monetary Fund [IMF], 2022) and emissions from all greenhouse gases (GHG) in units of gigatons (Gton) of CO_2-equivalents (CO_2e) (Climate Watch, 2022) (Table 2). This implies an average decline in emissions of 3.00% per year between 1990 and 2019, and we set the annual *T* reduction ahead to this rate. Note that this assumption is consistent with estimates in the literature. For example, the International Energy Agency (IEA, 2022) reported that the emissions

Table 2 Global historical GDP and GHG (calculated as CO_2e), measured in 1990 and 2019 (these data are used to generate the models that reflect an extrapolation of historical trends: Approach 1)

Dimension	IPAT entry	1990	2019	Comment
Climate impact [Gton CO_2e]	*I*	32.52	49.76	Historical GHG calculated as CO_2-equivalents (Climate Watch, 2022).
GDP [billion (bn) US$ 2022 prices]	*P*×*A*	23,663	87,654	World Economic Outlook Database October 2022, global GDP (IMF, 2022).
Carbon intensity [Gton CO_2e per bn US$]	*T*	1.37	0.57	An average decrease of 3.00% per year.

Table 3 Global GDP and the area of arable land used for crop production in the 1960s and 2000s (these data provide the foundation for models that extrapolate historical trends: Approach 1)

Dimension	IPAT entry	1961/ 1963	2005/ 2007	Comment
Crop land use [million (mn) ha]	I	1,372	1,592	Arable land used for crop production in hectares (Alexandratos and Bruinsma, 2012).
GDP [constant 2015 bn US$]	$P \times A$	11,918 (1962)	59,025 (2006)	National accounts data obtained from the World Bank (2023).
Crop land use per unit of total production [mn ha per bn US$]	T	0.115	0.027	This results in an average annualised T decrease of 3.2% per year.

intensity of GDP declined by approximately 3% per year in the US and the EU between 2010 and 2021, and that it was reduced by 40% in China between 2000 and 2021 (IEA, 2022), which also corresponds to approximately 3% annually.

For land use impacts, we account for estimates by the Food and Agriculture Organization (FAO) regarding the amount of arable land used for crop production in 1961/1963 (1,372 million hectares (mn ha)), and in 2005/2007 (1,592 mn ha) with data from Alexandratos and Bruinsma (2012). Based on global GDP data obtained from the World Bank (2023), this implies an average decrease in land use per level of affluence of 3.2% per year (Table 3), which is the rate we assume in our land use models in Approach 1. This rate is relatively consistent with previous findings. For example, Lamb et al. (2021) reported that the land needed per unit of agricultural and forestry production declined by an average of 2.7% annually between 2010 and 2017.

In this approach, the calculation of the total land use impact is based on historic levels of population growth and affluence. Thus, an important assumption when fitting the impact to an IPAT framework and setting $T = I/(A \times P)$ is that the total environmental impact is a function of consumption in the past. This approach assumes that changes in GDP per capita have driven land use change historically, which is appropriate if human land use is proportional to economic activity. However, if humanity is instead viewed from a more ecological perspective in which all humans are assumed to have similar caloric needs, land use needs will tend to be very similar across all levels of affluence. The reality is most likely somewhere in between, and will vary for different types of land use. Another association between land use and affluence is reflected in the STIRPAT-based projections, which are presented below.

Approach 2: STIRPAT-derived projections

In the second approach, we use projections of technological development grounded in the STIRPAT framework (eq. 2). This implies that we assume that T varies explicitly with population and affluence levels. We use elasticities in STIRPAT that have been estimated under the assumption that the error term, e in eq. 2, and its coefficient, d, are included in T.

https://doi.org/10.1553/p-n5en-z38a

This is consistent with the early STIRPAT literature, which assumed that it is not possible to operationalise T (Dietz et al., 2007; Dietz and Rosa, 1994, 1997; Rosa et al., 2004). However, note that more recent studies have argued that there *are* means to measure T, and a variety of factors have been proposed to reflect it. For example, McGee et al. (2015) found that impervious surface area (denoted terrestrial technology) is correlated with carbon outputs, arguing that it should be a measure of T in STIRPAT. Other factors that have been accounted for in the STIRPAT literature include urbanisation, financial development and trade openness, as well as renewable and non-renewable energy consumption (Jia et al., 2009; Usman et al., 2022). Nevertheless, as there is still a lack of consensus regarding how T should be operationalised, we opt for the standard method of keeping T in the error term. Specifically, we make projections of the total environmental impact based on the projections for population and affluence detailed above using literature estimates of elasticities (b and c in eq. 2). Then, we calculate T by the IPAT identity, according to:

$$T = \frac{I}{AP} = \{eq.\ 2 \text{ with } e \text{ comprising } T \text{ and } d\} = \frac{aP^bA^ce}{AP} = aP^{b-1}A^{c-1}e \qquad (3)$$

When we examine changes over time, we then get:

$$\frac{T}{T_0} = \{eq.\ 3\} = \frac{aP^{b-1}A^{c-1}e}{aP_0^{b-1}A_0^{c-1}e} = \left(\frac{P}{P_0}\right)^{b-1}\left(\frac{A}{A_0}\right)^{c-1} \qquad (4)$$

If population and affluence increase monotonically, T/T_0 slopes downward for elasticities below one ($b < 1$ and $c < 1$). For higher elasticities ($b > 1$ and $c > 1$), T/T_0 instead increases over time. However, if b and c diverge, with one but not the other above unity, then T depends on the relative difference between P and A.

The elasticities for P and A in our projections are grounded in a review of previously estimated STIRPAT models. For climate impact, we use elasticities obtained from two literature reviews of CO_2 and GHG emissions (Liddle, 2015; Pottier, 2022). (This definition of climate impact varies slightly from the one that we use in Approach 1, which is based on CO_2e, as this method assumes that the general trends are consistent across these different definitions of climate impact.)

Regarding elasticities with respect to population, we use the median of the cross-national, inter-temporal STIRPAT studies listed in Liddle (2015). In this data set, we exclude short-run data when long-run data are available, and we use disaggregated estimates (per income level) rather than overall estimates when both forms of data have been published, implying $N = 29$ data points. Concerning elasticities with respect to affluence, we additionally consider the review by Pottier (2022), who presented income elasticities of GHG or CO_2 emissions from various countries and time periods. We assume the upper bound in cases in which no other data were listed by Pottier (2022), generating 36 data points. We then use the median of the entries in Liddle (2015) and Pottier (2022) (Table 4).

For land use impact, we assume the elasticities of population and affluence published by Rosa et al. (2004), in which STIRPATs were estimated using data from 142 countries (Table 5). As proxies for land use, we use the results for arable land and grazing in Rosa et al. (2004), ultimately using the mean of the two analyses. Because we depend on this

https://doi.org/10.1553/p-n5en-z38a

Table 4 Elasticities of population and affluence with respect to climate impact in the two literature reviews that we consider; we use the median values in our models (Approach 2)

Climate impact elasticity	Median	Range	*N* data points	Reference
Population, b in eq. 2	1.12	0.26–2.75	29 studies	Liddle (2015)
Affluence, c in eq. 2	0.58	0.31–1.04 in Pottier (2022) and 0.15–2.5 in Liddle (2015)	36 + 27 studies	Pottier (2022), Liddle (2015)

Table 5 Elasticities of population and affluence with respect to land use that we use in our models (Approach 2)

Land use impact elasticity	Mean	Range	*N* data points	Reference
Population, b in eq. 2	0.99	0.94 (Grazing)–1.04 (Arable land)	142 countries	Rosa et al. (2004)
Affluence, c in eq. 2	0.50	0.36 (Arable land)–0.64 (Grazing)	142 countries	Rosa et al. (2004)

single study to model land use impact, the elasticities that we use are less reliable than those we use to model climate impact, which reflect the results of two comprehensive literature reviews. This imbalance is undesirable but unavoidable, because the literature on STIRPAT has mainly focused on climate impact (e.g., Wang et al., 2011 and Xiong et al., 2019). Studies with land use as the dependent variable are still scarce, even though there are alternative approaches, such as those that focus on the ecological footprint, a general measure that aggregates over many types of environmental stress (Dietz et al., 2007; Jia et al., 2009; Usman et al., 2022).

Note that the empirical literature suggests that the impact elasticities of population are near unity for both climate impact (Table 4) and land use impact (Table 5). However, elasticities of income are generally below one, which signals relatively inelastic relationships in which environmental effects increase at a slower rate than GDP. The median elasticity of income for climate impact, 0.58 (Table 4), is only slightly larger than the elasticity for land use impact, 0.50 (Table 5). Moreover, b for climate impact is above unity (1.12) while c is not (0.58), which implies that T depends on the relative difference between changes in P and A. However, for land use, elasticities of both population and income are less than unity, which means that increases in P and A result in declining T over time.

Approach 3: Forecasts in previous research

Lastly, we consider forecasts in the literature regarding impact I, and we examine how they relate to T in the IPAT framework (Approach 3). For climate, we apply the IPCC's (2022) most recent models, which use a scenario matrix architecture in which socio-economic patterns are reflected in five key SSPs. In these models, various climate mitigation strategies are represented by five distinct levels of radiative forcing (Fujimori et al., 2018), which reflect concentrations of GHG and other factors of climate warming in 2100, in units of watts per square meter (Supplementary material, Figure S.1, available at https://doi.org/10.1553/p-n5en-z38a). These levels reflect five distinct Representative Concentration Pathways (RCPs), which account for different behavioural trends and efforts to curb emissions relating to, for example, energy generation, novel technologies and transportation.

Specifically, our IPAT model for climate change is based on the IPCC's (2022) middle-of-the-road projection SSP2 with RCP 4.5, which was developed by IIASA (Fricko et al., 2017; Riahi et al., 2017). The SSP2 assumes the continuation of current social and economic trends and moderate mitigation efforts. We operationalise climate impact as GHG emissions in terms of unharmonised emissions of Kyoto gases in units of megatons of CO_2e per year, with data sets obtained from the SSP Public Database (IIASA, 2023). Note that this conceptualisation varies slightly from the one we use in Approach 1, which is based on *all* GHGs in units of CO_2e, and in Approach 2, which reflects CO_2 and GHG emissions. Thus, it is an assumption in our models that patterns over time are consistent across these three specifications. To obtain a trajectory for *T,* we divide the projection of climate emissions with trajectories for population and per capita GDP in SSP2.

For land use, we also account for forecasts in the IPPC's middle-of-the-road scenario SSP2, which assume that current trajectories in the land sector will continue, with medium levels of regulation and technological change and material-intensive consumption, as well as an increase in animal calorie share and ongoing tropical deforestation (Popp et al., 2017). These forecasts assume that the total cropland in 2005 was 1.5 bn ha, and that the use of cropland will increase by 231 mn ha in the period from 2005 to 2100 due to increased demand for food and feed (Popp et al., 2017). We account for this development in relation to the projection of GDP in the SSP2 (Dellink et al., 2017) to calculate the annual decrease in T (Table 6). The approach thus assumes that T responds to the inverse of $P \times A$ ahead.

Calculated this way, the annual reduction of T is very dramatic, because land use has been relatively unchanged over the last decades, while affluence and population have grown considerably. This approach thus assumes that the levels of agricultural intensification,

Table 6 Global historical data (2005) and projections (2100) in terms of the area of arable land forecasted to be used, and the value of T implied by these numbers (Approach 3)

Dimension	IPAT entry	2005	2100	Comment
Cropland use [bn ha]	I	1.5	1.731	SSP2 land use forecast for cropland in hectares, as detailed in Popp et al. (2017).
GDP [bn US$2005]	$P \times A$	56,380	537,272	The 2005 GDP record was obtained from the SSP Public Database, hosted by IIASA (2023), and the 2100 forecast was from the SSP2 (Dellink et al., 2017).
Cropland use per unit of total production	T	0.027	0.0032	This generates an average T decrease of 2.2% per year.

mechanisation, capital investment and nutritional inputs to the land that have taken place since the 1960s (i.e., the Green Revolution) will continue over the 21st century (Evenson and Gollin, 2003). For low-income countries, this reflects the adoption of agricultural intensification practices that have mainly been applied in more affluent countries. For high-income countries, it implies the continuation of agricultural intensification at the same spectacular rate as in the last half-century (Evenson and Gollin, 2003).

Note that it is a major simplification in our models that we do not consider that A, P and T are endogenously related to each other. This approach diverges from historical trends and forecasts in which these endogenous relationships were accounted for either explicitly, as in the IPCC's models, or indirectly, through various known and unknown causal links reflected in historical records. Thus, our IPAT-type extensions are based on strong assumptions that likely do not hold regarding the independence of and the temporal invariance in the relationships we have studied. Therefore, our approach contrasts with those of prominent researchers who have theorised that P and T are interdependent (Boserup, 1965). However, we believe that our approach is still conceptually helpful because it uses IPAT as a theoretical tool to explore how different methods used to predict environmental impacts relate to one another.

Robustness assessments with varying *P*, *A* and *T* trajectories

We also examine to what extent changes in different parameters affect I in the different models. Examining changes in P speaks directly to theories linking environmental effects to population, such as the human ecology view. We model population using four diverging trajectories, whereby our standard middle-of-the-road trajectory is the medium scenario in the WPP (2022). We first change the medium scenario with 10% in 2100 and assume a linear change up to that point. We also use the projections for low and constant fertility in the WPP (2022). The low scenario represents rapid fertility decline in Asia and Sub-Saharan Africa, while the (arguably quite unlikely) scenario of constant fertility characterises population trajectories with the fertility levels of 2022 extrapolated into the future. In practice, population policies aimed at reducing fertility could provide non-coercive support for family planning or less government support for childrearing, while scenarios aimed at promoting fertility could instead involve increased socialisation of childrearing (Kolk, 2021).

For variations in affluence, which are directly related to degrowth from a theoretical perspective, we similarly model per capita GDP based on a 10% increase and a 10% decrease compared to the 2100 level in our standard scenario. Examining the effect on I of such a reduction in income can be seen as an assessment of degrowth as a strategy to address environmental challenges. It is therefore associated with the political economy viewpoint.

We also explore the impact of a range of possibilities regarding technological development. First, we consider variations in T of 10% in the models based on extrapolations of historical data (Approach 1). Second, we consider the first and the third quartile of impact elasticities of population and affluence in the reviewed STIRPAT literature (Approach 2). Third, we consider different radiative forcings in 2100 in the SSP2 (IPCC, 2022) (Approach 3) (Supplementary material, Figure S.1, left panel). These levels imply

https://doi.org/10.1553/p-n5en-z38a

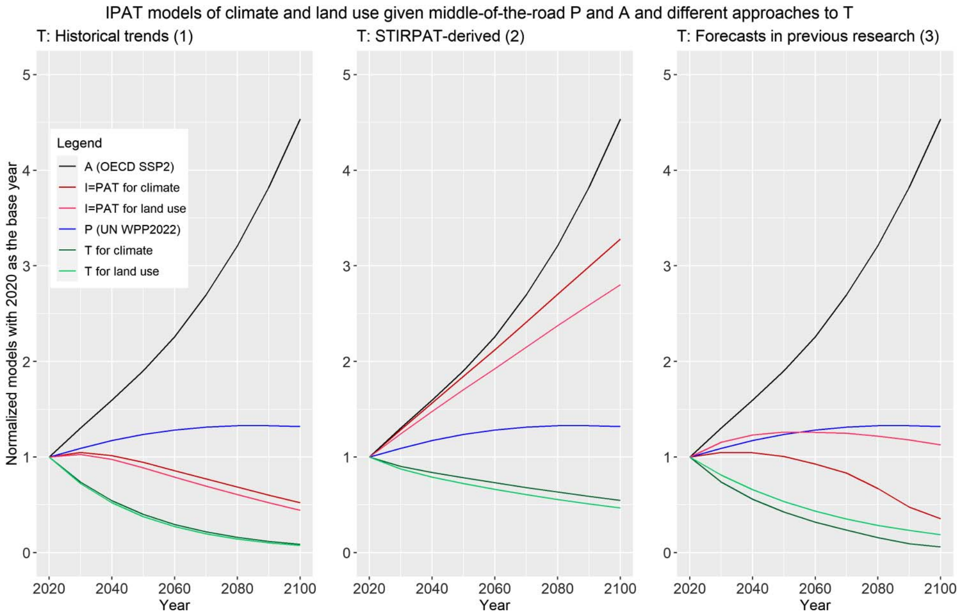
varying *T,* since they assume that the socio-economic patterns (*P* and *A*) are similar while the climate behaviours, policies and technologies (*T*) differ. We therefore obtain different projections for *T* by dividing climate forecasts with population and GDP trajectories in the SSP2 (Supplementary material, Figure S.1, right panel). This assessment relates to the modernisation perspective, as it focuses on effects of developments in *T*. We cannot use the corresponding method for land use because we have found only *one* relevant forecasting scenario in the literature (Approach 3).

Results

Projections for climate and land use

The developed IPAT models for climate and land use impacts are shown in Figure 1. The historical extrapolations (Approach 1) result in climate impacts at the end of the century that

Figure 1 IPAT projections of impact, *I,* for climate impact (red) and land use impact (light red). In all three panels, the same assumptions apply for population (*P*, blue) and affluence (*A*, black), while *T* varies. The left panel shows projections in which *T* for climate impact (green) and land use impact (light green) are based on the extrapolation of historical trends (Approach 1). The central panel is based on STIRPAT estimates of impact elasticities of *P* and *A* (Approach 2). The right panel shows forecasts in the literature in which *T* for climate impact is inferred from the IPCC's SSP2 (RCP 4.5) (Fricko et al., 2017; Riahi et al., 2017) and land use impact is derived from the SSP2 (Popp et al., 2017) (Approach 3).



https://doi.org/10.1553/p-n5en-z38a

are about half of current levels (Figure 1, left panel). This finding is relatively similar to the IPCC's forecasts (Approach 3) (Figure 1, right panel), which imply that the likelihood of peak global warming staying below 2 °C is only 8% (5% to 95% percentile: [2% – 18%]), and that the global mean temperature in 2100 will likely increase to around 2.7 °C (IPCC, 2022). Our model illustrates that even scenarios such as the SSP2 RCP4.5, which is likely to be insufficient to mitigate climate impact, still imply a T that is very close to zero in 2100 ($T = 0.06$) (Table 7). (It echoes the substantial increases in population and affluence that the IPCC expects by then, with levels of P and A that are 1.32 and 4.54 of current readings, respectively.) These scenarios indicate that the IPCC is very optimistic, as even their middle-of-the-road scenario implies that the world will commit to substantial climate mitigation efforts.

The models based on STIRPAT are more alarming (Approach 2) (Figure 1, central panel). The calculated effects in 2100 are closer to catastrophic climate impacts (e.g., SSP5 RCP 8.5), and project a much larger T than in Approach 1 (Table 7). Moreover, in sharp contrast to environmental targets, our land use projections based on STIRPAT (Approach 2) and forecasts in previous research (Approach 3) suggest that environmental impacts will *increase* rather than decrease in 2100. The latter approach indicates that land use impact will increase to 1.13 of current levels in 2100, despite estimates that T will decrease to about one-fifth of today's levels (Table 7). This is an example of weak decoupling, since A is expected to rise considerably by then. The lack of evidence of strong decoupling is disconcerting, considering that many environmental studies argue that current levels of human impact on land systems and biodiversity are already unsustainable (Steffen et al., 2015; Dasgupta, 2021).

The left panel in Figure 1 depicts the land use impact if historical trends continue and T declines by 3.2% per year (Approach 1). We complement this finding with a model that accounts for extrapolations of historical trends based on cereal yields, generating an annual T decrease of 2.1% per year (Popp et al., 2017) (Supplementary material, Figure S.2). The difference between these two models is that the first represents *total* production, while the second refers only to production in the form of crop yields, reflecting intensification technologies such as industrial fertilisers for a given land area (although crop yields will be higher at lower levels of land use as more productive land is used). These models are relatively consistent in that they both result in significant decreases in land use impacts in 2100. Approach 1 implies that the land use impact at the end of the century will be only 0.07 of current levels (Table 7).

Table 7 Technology, T, in 2100 as related to levels in 2020 for climate and land use impacts; these data are also displayed in Figure 1

	Methods to project T		
Dimension	**Approach 1: Extrapolation of historical trends**	**Approach 2: STIRPAT-derived projections**	**Approach 3: Forecasts in previous research**
Climate	0.09	0.55	0.06
Land use	0.07	0.47	0.19

https://doi.org/10.1553/p-n5en-z38a

Sensitivity analyses

We further explore how changing trajectories of population, affluence and technology would change environmental impacts as seen through an IPAT lens. Here, we want to illustrate the importance of the time horizon and the difference in *T* across the two environmental dimensions and the three modelling approaches (Table 1). These aspects influence the extent to which changes in *P* and *A* will actually affect *I*. Our models can thus be used to highlight the relevance of addressing environmental concerns through policies aimed at reducing population or affluence.

Population

Given the very nature of an IPAT model, a 10% reduction in population in 2100 compared to the middle-of-the-road scenario would decrease the climate impact to the same extent as in Approach 1. For example, carbon emissions would be 0.47 of current levels instead of 0.52 (Table 8), which is a rather modest reduction. In this approach, the small *T* of 0.09 of current levels (Table 7) compensates for the relatively large anticipated values for *P* and *A* of 1.32 and 4.54, respectively, of today's readings (Figure 1). However, in the scenarios that are based on STIRPAT (Approach 2), the impact of a 10% decrease in population is much larger, as it implies that the carbon impact ($I = 2.91$) is considerably lower than in the middle-of-the-road scenario ($I = 3.28$) (Table 8). Put differently, a 10% decrease in population would reduce the impact in 2100 by 37% compared to current levels. Regarding forecasts in previous research (Approach 3), our models suggest that the effect of a 10% decrease in population would be less relevant for climate than for land use; *I* would be reduced from 1.13 to 1.02 of current levels for land use, compared to from 0.35 to 0.32 for climate (Table 8). In absolute terms, this suggests that population policies would have a larger effect on the land use impact than on the climate impact, although the relative impact would be similar in a strict IPAT-type framework.

Our IPAT models of environmental impact as related to the UN WPP's (2022) three population prospects illustrate that the high rates of growth implied by the constant fertility scenario have very large impacts in all cases, whereas low fertility rates are associated

Table 8 Impact *I* in 2100 compared to in 2020, showing ranges (and middle-of-the-road values) for ± 10% changes in population and affluence compared to the middle-of-the-road outcomes depicted in Figure 1

Policy	Dimension	Impact *I* Approach 1: Extrapolation of historical trends	Approach 2: STIRPAT-derived projections	Approach 3: Forecasts in previous research
P ± 10%	Climate	[0.47–0.58] (0.52)	[2.91–3.65] (3.28)	[0.32–0.39] (0.35)
	Land use	[0.40–0.49] (0.44)	[2.53–3.08] (2.80)	[1.02–1.24] (1.13)
A ± 10%	Climate	[0.47–0.58] (0.52)	[3.09–3.47] (3.28)	[0.32–0.39] (0.35)
	Land use	[0.40–0.49] (0.44)	[2.66–2.94] (2.80)	[1.02–1.24] (1.13)

https://doi.org/10.1553/p-n5en-z38a

Table 9 Impact I in 2100 compared to in 2020, assuming the UN WPP's (2022) three population projections: low, medium and constant fertility; all other models in this paper are based on the WPP's (2022) medium scenario

	Impact I in 2100 relative to 2020 for different population prospects		
Dimension	**Approach 1: Extrapolation of historical trends**	**Approach 2: STIRPAT-derived projections**	**Approach 3: Forecasts in previous research**
Climate	0.35 (low) 0.52 (medium) 0.97 (constant fertility)	2.12 (low) 3.28 (medium) 6.56 (constant fertility)	0.24 (low) 0.35 (medium) 0.66 (constant fertility)
Land use	0.30 (low) 0.44 (medium) 0.82 (constant fertility)	1.91 (low) 2.80 (medium) 5.17 (constant fertility)	0.76 (low) 1.13 (medium) 2.09 (constant fertility)

with much smaller effects (Supplementary material, Figures S.3 and S.4). Note that the STIRPAT-derived models (Approach 2) show a similar sensitivity to population as the other two approaches in relative terms (Table 9). This is because the elasticities for population are relatively close to one for both climate (1.12) (Table 4) and land use (0.99) (Table 5). However, in absolute terms, variations in population have the largest consequences in these models (Approach 2), because they imply that T is quite high in 2100 compared to current levels, at 0.55 for climate and 0.47 for land use (Table 7). Note further that the constant fertility scenario has a larger absolute impact on land use ($I = 2.09$ vs. 1.13 in the middle-of-the-road scenario) than on climate ($I = 0.66$ vs. 0.35) in the models that are based on forecasts in previous research (Approach 3). This suggest that population policies are of greater importance for land use than for climate change.

Affluence

Table 8 shows variations in per capita affluence by ± 10% in 2100 compared to the middle-of-the-road scenario, and Figures S.5 and S.6 in the Supplementary material show the corresponding graphs. These variations imply proportional impacts in the models that are based on the extrapolation of historical trends (Approach 1) and forecasts in previous research (Approach 3) (Supplementary material, Figures S.5 and S.6). These two methods both imply that variations in A by ± 10% perfectly reflect the corresponding variations in P, which is an inherent effect of this type of IPAT modelling. The effects of ± 10% changes in affluence are the highest in the models in which T is the highest, the STIRPAT-based projections (Approach 2). Notably, these models result in impacts that vary quite a lot, from 3.09 to 3.47 for climate and from 2.66 to 2.94 for land use (Table 8). However, this also means that the relative changes in the impact are smaller, because in these models we assume that the elasticity of income is less than one for both climate (0.58) (Table 4) and land use (0.50) (Table 5).

https://doi.org/10.1553/p-n5en-z38a

Technology

Environmental impacts with different assumptions for T are shown in Figure 2 and Figure 3, and Section S5 in the Supplementary material lists values of I in 2100. The left panels in Figures 2 and 3 show that neither climate nor land use impact is particularly sensitive to ± 10% changes in T if historical trends continue (Approach 1). For example, these models imply that a 10% decrease in T results in climate impact that is 0.47 of current levels, compared to 0.52 in the middle-of-the-road scenario (Supplementary material, Table S.1). This is because reductions in T are very large in these scenarios, with $T = 0.09$ and $T = 0.07$ of current levels for climate impact and land use impact, respectively (Table 7).

The central panel in Figure 2 shows variations in climate impact as an effect of a range of STIRPAT elasticities in eq. 2, accounting for the first and the third quartile in the literature. It is noteworthy that none of these models result in climate impacts that are small enough to meet global goals, as they range from 2.22 to 5.45 of current levels (Supplementary material S6, Table S.2). Correspondingly, calculations of the land use impact in 2100 as related to different elasticities suggest that the effects will be much worse compared with current levels (Supplementary material S5, Table S.2).

Figure 2 IPAT projections of climate impact (I, red) as related to variations in assumptions for technology (T, green). The left panel shows projections in which technology is based on historical trends ± 10% (Approach 1); the central panel is based on STIRPAT estimates of climate impact elasticities, with the first and third quartiles in addition to the median (Approach 2); and the right panel shows trajectories based on the IPCC's SSP2 projection for different RCPs (Approach 3).

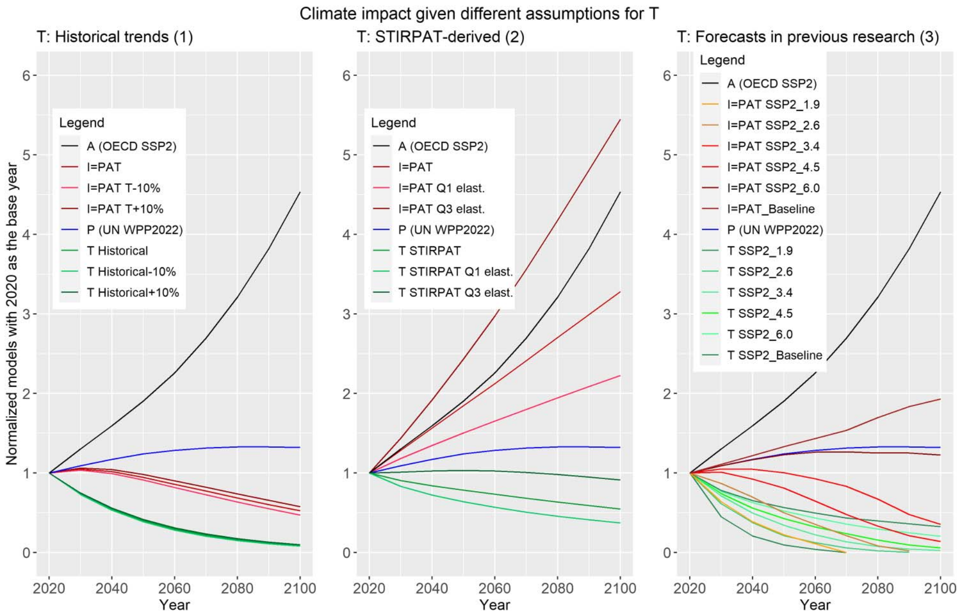
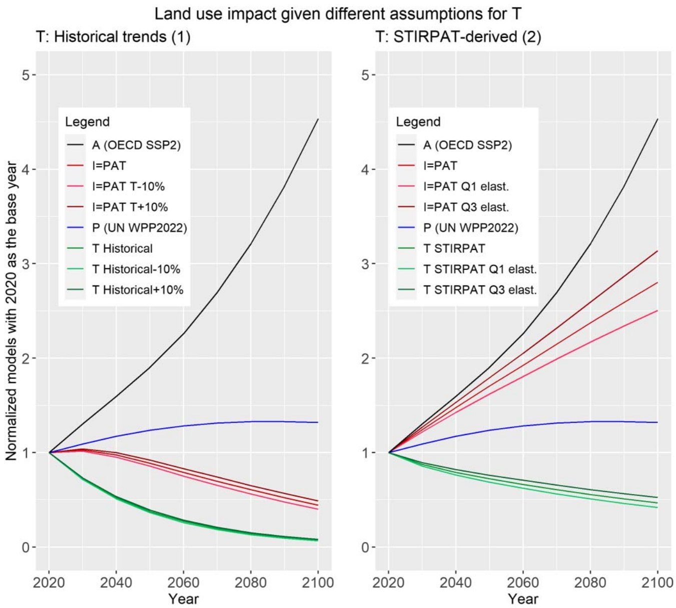


Figure 3 IPAT-based projections of land use impact (*I*, red) as related to variations in technology (*T*, green). The left panel shows projections in which *T* is based on the extrapolation of historical trends ± 10% (Approach 1), and the right panel is based on STIRPAT-based estimates of population and income elasticities, accounting for the first and third quartiles in addition to the median in the literature (Approach 2). We did not find any variations in the literature regarding forecasts of land use (Approach 3).



As an additional robustness check we also generate a STIRPAT model based on findings in Liddle (2015), who highlighted the importance of accounting for differences across OECD countries and non-OECD countries, with larger elasticity estimates in the latter group. For income elasticity, we assume $c = 1.0$ (eq. 2) for non-OECD countries (Liddle, 2015), and our baseline value for OECD countries ($c = 0.58$) (Table 4). We then weigh these values based on OECD/non-OECD shares of global GDP in 2020 (World Bank, 2023), generating a global weighted average of $c = 0.75$. For the population elasticity, we assume Liddle's (2015) global estimate of $b = 1.0$. For comparison, note that our baseline model for climate impact assumes $b = 1.12$ and $c = 0.58$ (Table 4). The resulting graph (Supplementary material, Figure S.7) suggests that the climate impact in 2100 may be even more severe than in our baseline scenario, with $I = 4.10$ vs. $I = 3.28$ (baseline) of 2020 levels.

The right panel in Figure 2 shows the IPCC's SSP2 projections given different levels of radiative forcing in 2100 (see Supplementary material, Figure S.1). It includes the only climate scenario in this study in which emissions are below net zero in the 2050s (SSP2 and RCP 1.9), in alignment with global climate targets to keep global warming below 1.5 °C. However, as illustrated in our IPAT models, this scenario is associated with

https://doi.org/10.1553/p-n5en-z38a

exceptional improvements in the climate impact per unit of production. For example, it implies that T will be reduced to less than one-quarter of current levels already in 2040 (Figure 2).

Discussion

The IPAT framework connects to earlier studies on how societies can manage environmental challenges. While it was developed to highlight the role of population, it can be used to argue for nearly any relationship of the constituting elements (Chertow, 2000). Here we have shown that IPAT is a helpful tool for comparing future environmental impacts when the relative role of T compared to A and P varies. Articulating differences across domains is important because it improves our understanding of how the trade-offs involved diverge. Distinct forms of ethical and political reasoning may apply in different environmental dimensions. We have intuitively illustrated that larger reductions in T imply smaller effects of changing P and A in absolute terms. We have modelled this as either low elasticities between impact and affluence or population, or through exogenously defined trajectories.

Environmental ecology theories

The overall interlinkages of P, A and T have been discussed extensively in the environmental literature from a number of different theoretical perspectives. It is our hope that our IPAT-type modelling can clarify how these different theories implicitly (and occasionally explicitly) put different weights on the various parts of this identity. The original proponents of IPAT highlighted the negative consequences of anticipated growth in P and A (Ehrlich and Holdren, 1971), and they were thus sceptical of improvements in T. Contemporary environmentalists who focus on degrowth are similarly sceptical of such improvements, but they concentrate almost entirely on A. In contrast, researchers proposing green growth put considerable emphasis on mitigation through T. Our models have highlighted how substantive such technology improvements must be in light of mainstream forecasts of global GDP, especially if one considers contemporary consumption to be (already) above sustainable levels – a view that is common in the environmental literature. Broadly, our models are consistent with previous research that reasoned that the IPAT framework highlights T as the most dynamic and important part of the equation (Chertow, 2000). They are especially helpful for pinpointing the situations in which large reductions in T are feasible, and P and A are therefore of less relative importance. Our models also illustrate the extent to which technological improvements underlie different actors' forecasts.

Green growth perspective

Our projections relate to different perspectives within environmental ecology. Broadly, the results can be seen as consistent with the green growth theory, or modernisation in the

https://doi.org/10.1553/p-n5en-z38a

framing of York et al. (2003a), at least in the limited sense that they imply relative (weak) decoupling of the environmental impact from economic growth. In a comparison of levels in 2100 and 2020, T decreases while A increases in all our models. However, the results of only a few of the models imply that an absolute (strong) decoupling of the growth of affluence A from impact I is likely to occur. Indeed, in many of our models, I in 2100 is projected to increase from current levels.

Nevertheless, the projections that are grounded in the extrapolation of historical trends (Approach 1) support modernisation, as they imply that both climate and land use impacts will be lower at the end of the century than they are now (Figure 1, left panel). It is, however, important to be aware that both of these models assume exceptionally small values of T in 2100 (Table 7), which implies a massive adoption of environmentally-friendly policies and technologies in the 21st century. In the case of land use, the models assume enormous increases in yields for a given amount of land.

Human ecology and political economy perspectives

Our projections based on forecasts (Approach 3) imply that the impacts in 2100 will be much larger than what many argue are sustainable levels, as the climate impact is projected to be far above zero and the land use impact is even projected to be above current levels. These predictions support the human ecology and political economy perspectives. Even more disconcerting, the models based on STIRPAT (Approach 2) imply that both environmental impacts *increase* as an effect of anticipated growth in P and A because the impact elasticities for both factors are above zero (Tables 4 and 5). Thus, theories that argue for degrowth, such as the political economy perspective, and those that promote the need for population policies, such as the human ecology view, find the most support from these models.

While population size contributes to the environmental impacts in all our models, in some scenarios this effect is small relative to the impact of the projected growth in affluence. The importance of changing A and P can be considered in relation to the size of T in the different projections. For example, it becomes clear that the higher T in forecasts of land use (Approach 3) implies that the relative importance of anticipated growth in P and A is greater for this environmental dimension than it is for climate (Table 7). This suggests that land use impacts are harder to mitigate than climate impacts through means other than reduced consumption or fewer people. An emphasis on the importance of population policies for mitigating environmental challenges is consistent with the human ecology perspective. Thus, this perspective may be more relevant for land use impacts than for climate impacts.

How do population and affluence affect environmental impacts?

In line with earlier research using this approach, our STIRPAT-type modelling has highlighted the difficulties in disconnecting affluence and population from environmental impacts. These models, which are derived from observed trends over time and across regions, consistently give the highest environmental impacts. They suggest that to

https://doi.org/10.1553/p-n5en-z38a

reach global environmental goals, our economic, technological and political systems may need to work in fundamentally different ways than they have in recent decades. Business-as-usual scenarios likely imply limited decoupling of I from and P or A. In our STIRPAT-based models, the differences between projections across environmental dimensions are driven by variations in the impact elasticities of P and A, which imply alternative paths for T. Thus, our models highlight that in standard climate models such as the SSP2 RCP 4.5, substantial weight is given to future technological improvements, and the near-total decoupling of affluence and population from climate impacts is assumed. As such, the IPCC's middle-of-the-road prediction clearly reflects a green growth perspective.

Another inference that can be drawn from our models is that population policies ("fewer people") and degrowth ("less consumption") are less relevant strategies for addressing climate impacts than land use impacts if the mainstream SSP2 trajectories are assumed to be realistic. This is because there are promising technologies for mitigating climate impacts, especially within the energy supply sector (see Davis et al., 2018). By contrast, for land use change, population policies or reduced consumption appear to be more relevant. This is underlined in our STIRPAT-based approach, which indicates that land use impacts will increase substantially from levels that many argue are already unsustainable. We are not aware of many empirical and analytical studies on land use in the scientific literature that would clearly contradict such a perspective.

Our models suggest that climate impacts may be decoupled from affluence (and, relatedly, from population). These findings are supported by existing technologies and policies that would substantially reduce climate impacts, as shown in the right panel in Figure 1. Still, it is important to note that achieving green growth in the context of climate change means that the impact per dollar spent needs to decrease *steeply* for I to go down sufficiently. The reduction in T must be larger than the anticipated increase in $P \times A$; for example, if $P = 1.2$, and $A = 5$, then T must be $1/6$ for a constant I, or $1/12$ for reductions in I by half in a green growth scenario. Assuming access to clean energy, it is imaginable that the carbon elasticities of population can be reduced to near zero, which implies that there will be no additional climate impact of an extra person in the world. We have one IPAT trajectory that reflects this positive trend (Figure 2, right panel).

However, we have found little evidence of the corresponding pattern for land use change. Our models have thus illustrated that the anticipated technological and behavioural developments in carbon intensity do not necessarily translate into improvements in land use systems. Instead, our models have shown that while achieving green growth may be a realistic goal in the context of climate change, it is less applicable to land use. Consequently, the political economy view that calls for a stagnant economy (degrowth) is likely to be more relevant for mitigating land use impacts than for addressing climate impacts. In parallel, our results suggest that population policies, which are related to the human ecology perspective, may have a larger effect on the likelihood of reaching global goals for land use change than for climate change. Policymakers need to be aware of the different approaches that will be required to address these different environmental impacts.

https://doi.org/10.1553/p-n5en-z38a

Limitations

Our models are generalisations of the world, and therefore suffer from several limitations. They are based on several theoretical simplifications, the most important of which is probably that we have largely avoided examining potential endogeneities between *P*, *A* and *T*. By harmonising the different types of models into one framework, we have thus excluded some of the causal ways that these aspects may be linked; hence, our models should primarily be seen as putting different approaches into a similar scale and a similar theoretical perspective to allow for comparisons. The models should be considered in this light, rather than as precise projections of environmental impacts. Consequently, we see this article as mainly representing a theoretical contribution. Any single IPAT-type model we have presented can be discussed, as different operationalisations or competing models in the secondary literature could have been chosen and may have been equally plausible. Nevertheless, we have found that this exercise has been helpful in interpreting the radically diverse perspectives found in the environmental literature.

Moreover, it is important to keep in mind that we have relied solely on experts in this study, as our modelling inputs are grounded in a literature review. Thus, the study has assumed that this literature is sufficiently rich to capture key dynamics. While the STIRPAT literature on climate impacts is relatively extensive, it has been more challenging to find related studies on land use. Moreover, we have assumed elasticities to be temporally constant, and it could be argued that our STIRPAT models for climate change are simplistic compared to models that also include factors such as energy use and future energy prices (Kaya and Yokobori, 1997; Liddle and Huntington, 2020). Our method is a simplification, which also relates to variations across income levels. There is only limited research on how elasticities change over different levels of affluence, but the few studies on this topic have suggested that the estimates are relatively robust (see e.g., Liddle, 2015). The modelling in this study is based on our own assessments of what constitutes relevant empirical inputs. For example, we have assumed that the slightly different definitions of climate impact that we adopt in the three modelling approaches (Table 1) do not have a large influence on the findings in general. Thus, our modelling assumes that variations in climate impact over time are not fundamentally different across these different specifications.

Another related limitation is that our STIRPAT-based climate impact model (Approach 2) uses the *median* of the listed studies in two literature reviews (Liddle, 2015; Pottier, 2022), even though Liddle (2015) argued that published studies in this field are sometimes flawed. Nevertheless, we note that the values that we assume in our baseline model are within a reasonable range based on Liddle's (2015) recommended estimates, as discussed in the subsection Technology in the sensitivity analysis. Furthermore, the results of our sensitivity analysis that specifically accounts for Liddle's (2015) recommended values (Supplementary material, Figure S.7) largely mirror our baseline results (Figure 1, central panel), although they also suggest that the climate impacts in 2100 may be even more severe than in our baseline projection. We refer to Liddle (2015) and Liddle and Huntington (2020) for more thorough discussions on the wide-ranging estimates for carbon emissions elasticities of population and affluence in the literature, for example, relating to cross-sectional dependence and variations over time.

https://doi.org/10.1553/p-n5en-z38a

Another potential concern is that we use a single set of trajectories for *P* and *A* in our IPAT modelling, while the various forecasting scenarios that we base our models on use different, but related, trajectories. The most important difference between these approaches is that we use the UN WPP (2022), while many SSP-based projections have used population forecasts from the Wittgenstein Centre for Demography and Global Human Capital and IIASA (KC and Lutz, 2017). The harmonisation of a diverse set of scenarios was necessary in our approach, which aimed to synthesise a sprawling literature and a large set of models with different assumptions regarding *P* and *A*. This highlights the importance of interpreting our results primarily as a theoretical tool for understanding conceptual differences, rather than as competing forecasts of environmental problems.

Conclusion

Our models are generally consistent with common views in the environmental sciences of how affluence and population affect environmental challenges. They show the following: (i) Consumption and wealth are the largest drivers of many environmental challenges. (ii) As the impact of population on environmental challenges is often close to one-to-one, population reductions will likely affect many environmental problems proportionally, rather than substantially less or more. There are both empirical and theoretical reasons to see population as a scalar to environmental impacts. (iii) Green growth is possible and is likely in the sense of relative decoupling in which declining *T* is combined with increasing A; in contrast, it is much more challenging to achieve absolute decoupling involving decreasing *I* over time, which implies very small values for *T* in long-term scenarios in which $P \times A$ is expected to increase considerably. (iv) Some environmental challenges, such as achieving zero emissions energy production or radical decreases in the climate impact per unit of consumption, seem more feasible than others, such as radically changing land use and halting conversions of forests to farmland. (v) Even though large-scale technological transformation is viewed as plausible by the scientific community (e.g., the IPCC), such scenarios assume dramatic reductions in environmental impacts per unit of consumption (*T*). We believe that using IPAT to harmonise models across different types of impacts can help to improve our understanding of and inform our conclusions about the strategies for addressing environmental challenges.

Supplementary material

Available online at https://doi.org/10.1553/p-n5en-z38a

Supplementary file 1. Climate impact for different RCPs given projections of *P* and *A* in the SSP2 (S1); Land use impact assuming the continuation of historical trends (S2); Environmental impacts as related to variations in population (S3); Environmental impacts as effects of variations in per capita affluence (S4); Environmental impacts as related to variations in technology (S5); Climate impact as an effect of variations of *T* in STIRPAT accounting for differences across OECD/non-OECD countries (S6).

Acknowledgements

This work was supported by the Global Challenges Foundation as well as the Bank of Sweden Tercentenary Foundation (Riksbankens Jubileumsfond) [M17-0372:1, P17-0330:1]. We are grateful for helpful suggestions and comments from the participants of the Population and Climate Change conference at the Wittgenstein Centre in Vienna and the Sustainable Populations workshop at the Institute for Futures Studies in Stockholm.

ORCID iDs

Emma Engström https://orcid.org/0000-0002-5290-5704

Martin Kolk https://orcid.org/0000-0002-7175-4040

References

Alexandratos, N., and Bruinsma, J. (2012). *World agriculture towards 2030/2050: The 2012 revision* (ESA Working paper No. 12-03). Food and Agriculture Organization of the United Nations (FAO).

Al-Mulali, U., and Ozturk, I. (2016). The investigation of environmental Kuznets curve hypothesis in the advanced economies: The role of energy prices. *Renewable and Sustainable Energy Reviews*, *54*, 1622–1631. https://doi.org/10.1016/j.rser.2015.10.131

Antweiler, W., Copeland, B., and Taylor, S. (2001). Is Free Trade Good for the Environment? *The American Economic Review*, *91*(4), 877–908.

Bimonte, S., and Stabile, A. (2017). EKC and the income elasticity hypothesis Land for housing or land for future? *Ecological Indicators*, *73*, 800–808. https://doi.org/10.1016/j.ecolind.2016.10.039

Bongaarts, J., and O'Neill, B. C. (2018). Global warming policy: Is population left out in the cold? *Science*, *361*(6403), 650–652. https://doi.org/10.1126/science.aat8680

Boserup, E. (1965). *Conditions of Agricultural Growth* (1 ed.). Routledge. https://doi.org/10.4324/9781315016320

Budolfson, M., and Spears, D. (2021). Population Ethics and the Prospects for Fertility Policy as Climate Mitigation Policy. *The Journal of Development Studies*, *57*(9), 1499–1510. https://doi.org/10.1080/00220388.2021.1915481

Chertow, M. R. (2000). The IPAT Equation and Its Variants. *Journal of Industrial Ecology*, *4*(4), 13–29. https://doi.org/10.1162/10881980052541927

Climate Watch. (2022). *Historical GHG Emissions*. World Resources Institute. Retrieved 2 February 2023, from https://www.climatewatchdata.org/ghg-emissions

Cole, M. A. (2003). Development, trade, and the environment: How robust is the Environmental Kuznets Curve? *Environment and Development Economics*, *8*(4), 557–580. https://doi.org/10.1017/S1355770X0300305

Commoner, B. (1971). *The Closing Circle*. Knopf.

Coxhead, I. (2003). Development and the Environment in Asia. *Asian-Pacific Economic Literature*, *17*(1), 22–54. https://doi.org/10.1111/1467-8411.t01-1-00013

Dasgupta, P. (2021). *The Economics of Biodiversity: The Dasgupta Review*. London: HM Treasury. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/962785/The_Economics_of_Biodiversity_The_Dasgupta_Review_Full_Report.pdf

Davis, S. J., Lewis, N. S., Shaner, M., Aggarwal, S., Arent, D., Azevedo, I. L., Benson, S. M., Bradley, T., Brouwer, J., Chiang, Y.-M., Clack, C. T. M., Cohen, A., Doig, S., Edmonds, J., Fennell, P., Field, C. B., Hannegan, B., Hodge, B.-M., Hoffert, M. I., … Caldeira, K. (2018). Net-zero emissions energy systems. *Science*, *360*(6396), eaas9793. https://doi.org/10.1126/science.aas9793

Dellink, R., Chateau, J., Lanzi, E., and Magné, B. (2017). Long-term economic growth projections in the Shared Socioeconomic Pathways. *Global Environmental Change*, *42*, 200–214. https://doi.org/10.1016/j.gloenvcha.2015.06.004

Dietz, T., and Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human Ecology Review*, *1*(2), 277–300.

https://doi.org/10.1553/p-n5en-z38a

Dietz, T., and Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences*, *94*(1), 175–179. https://doi.org/10.1073/pnas.94.1.175
Dietz, T., Rosa, E. A., and York, R. (2007). Driving the Human Ecological Footprint. *Frontiers in Ecology and the Environment*, *5*(1), 13–18.
Ehrlich, P., and Holdren, J. (1971). Impact of Population Growth. *Science*, *171*(3977), 1212–1217.
Evenson, R. E., and Gollin, D. (2003). Assessing the Impact of the Green Revolution, 1960 to 2000. *Science*, *300*(5620), 758–762. https://doi.org/10.1126/science.1078710
Fan, S., and Lu, Z. (2022). Research on the Peak Carbon Dioxide Emission Strategy of Chinese Port Based on Carbon Emission Estimation. *Frontiers in Environmental Science*, *9*, 789970. https://doi.org/10.3389/fenvs.2021.789970
Fricko, O., Havlik, P., Rogelj, J., Klimont, Z., Gusti, M., Johnson, N., Kolp, P., Strubegger, M., Valin, H., Amann, M., Ermolieva, T., Forsell, N., Herrero, M., Heyes, C., Kindermann, G., Krey, V., McCollum, D. L., Obersteiner, M., Pachauri, S., … Riahi, K. (2017). The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. *Global Environmental Change*, *42*, 251–267. https://doi.org/10.1016/j.gloenvcha.2016.06.004
Fujimori, S., Hasegawa, T., Ito, A., Takahashi, K., and Masui, T. (2018). Gridded emissions and land-use data for 2005–2100 under diverse socioeconomic and climate mitigation scenarios. *Scientific Data*, *5*(1), 180210. https://doi.org/10.1038/sdata.2018.210
Grossman, G. M., and Krueger, A. (1991). *Environmental Impacts of a North American Free Trade Agreement* (w3914; p. w3914). National Bureau of Economic Research Working papers. https://doi.org/10.3386/w3914
Grossman, G. M., and Krueger, A. B. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443
Haberl, H., Wiedenhofer, D., Virág, D., Kalt, G., Plank, B., Brockway, P., Fishman, T., Hausknost, D., Krausmann, F., Leon-Gruchalski, B., Mayer, A., Pichler, M., Schaffartzik, A., Sousa, T., Streeck, J., and Creutzig, F. (2020). A systematic review of the evidence on decoupling of GDP, resource use and GHG emissions, part II: Synthesizing the insights. *Environmental Research Letters*, *15*(6), 065003. https://doi.org/10.1088/1748-9326/ab842a
International Energy Agency. (2022). *Global Energy Review: CO2 Emissions in 2021*. IEA. Retrieved 1 April 2023, from https://www.iea.org/reports/global-energy-review-co2-emissions-in-2021-2
International Institute for Applied Systems Analysis. (2023). *SSP Public Database (Version 2.0, December 2018)*. IIASA. Retrieved 23 March 2023, from https://tntcat.iiasa.ac.at/SspDb/
International Monetary Fund. (2022). *World Economic Outlook Database October 2022. Gross domestic product, current prices. U.S. dollars*. IMF. Retrieved 23 February II2023, from https://www.imf.org/en/Publications/WEO/weo-database/2022/October/weo-report?a=1&c=001,&s=NGDPD,PPPGDP,&sy=1990&ey=2019&ssm=0&scsm=1&scc=0&ssd=1&ssc=0&sic=0&sort=country&ds=.&br=1
IPCC. (2022). IPCC, 2022: Summary for Policymakers. In: *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_SPM.pdf
Jia, J., Deng, H., Duan, J., and Zhao, J. (2009). Analysis of the major drivers of the ecological footprint using the STIRPAT model and the PLS method—A case study in Henan Province, China. *Ecological Economics*, *68*(11), 2818–2824. https://doi.org/10.1016/j.ecolecon.2009.05.012
Kaya, Y., and Yokobori, K. (Eds.). (1997). *Environment, energy, and economy: Strategies for sustainability*. United Nations University Press.
KC, S., and Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Global Environmental Change*, *42*, 181–192. https://doi.org/10.1016/j.gloenvcha.2014.06.004
Kolk, M. (2021). Government Transfers to Parents and Population Policy in a Global Perspective: An Economic Demographic Perspective. *The Journal of Development Studies*, *57*(9), 1483–1498. https://doi.org/10.1080/00220388.2021.1915480
Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, *45*(1), 1–28.

https://doi.org/10.1553/p-n5en-z38a

Lam, D. (2011). How the World Survived the Population Bomb: Lessons From 50 Years of Extraordinary Demographic History. *Demography*, *48*(4), 1231–1262. https://doi.org/10.1007/s13524-011-0070-z

Lamb, W. F., Wiedmann, T., Pongratz, J., Andrew, R., Crippa, M., Olivier, J. G. J., Wiedenhofer, D., Mattioli, G., Khourdajie, A. A., House, J., Pachauri, S., Figueroa, M., Saheb, Y., Slade, R., Hubacek, K., Sun, L., Ribeiro, S. K., Khennas, S., de la Rue du Can, S., … Minx, J. (2021). A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. *Environmental Research Letters*, *16*(7), 073005. https://doi.org/10.1088/1748-9326/abee4e

Lean, H. H., and Smyth, R. (2010). CO2 emissions, electricity consumption and output in ASEAN. *Applied Energy*, *87*(6), 1858–1864. https://doi.org/10.1016/j.apenergy.2010.02.003

Li, L., Lei, Y., He, C., Wu, S., and Chen, J. (2016). Prediction on the Peak of the CO_2 Emissions in China Using the STIRPAT Model. *Advances in Meteorology*, *2016*, 1–9. https://doi.org/10.1155/2016/5213623

Liddle, B. (2011). Consumption-Driven Environmental Impact and Age Structure Change in OECD Countries: A Cointegration-STIRPAT Analysis. *Demographic Research*, *24*, 749–770. https://doi.org/10.4054/DemRes.2011.24.30

Liddle, B. (2015). What are the carbon emissions elasticities for income and population? Bridging STIRPAT and EKC via robust heterogeneous panel estimates. *Global Environmental Change*, *31*, 62–73. https://doi.org/10.1016/j.gloenvcha.2014.10.016

Liddle, B., and Huntington, H. (2020). Revisiting the Income Elasticity of Energy Consumption: A Heterogeneous, Common Factor, Dynamic OECD & non-OECD Country Panel Analysis. *The Energy Journal*, *41*(3). https://doi.org/10.5547/01956574.41.3.blid

Lidicker, W. Z. (2020). A Scientist's Warning to humanity on human population growth. *Global Ecology and Conservation*, *24*, e01232. https://doi.org/10.1016/j.gecco.2020.e01232

Malthus, T. (1798). *An Essay on the Principle of Population*. Printed for J. Johnson, in St. Paul's Church-Yard. http://www.esp.org/books/malthus/population/malthus.pdf

McGee, J. A., Clement, M. T., and Besek, J. F. (2015). The impacts of technology: A re-evaluation of the STIRPAT model. *Environmental Sociology*, *1*(2), 81–91. https://doi.org/10.1080/23251042.2014.1002193

O'Neill, B. C., Liddle, B., Jiang, L., Smith, K. R., Pachauri, S., Dalton, M., and Fuchs, R. (2012). Demographic change and carbon dioxide emissions. *The Lancet*, *380*(9837), 157–164. https://doi.org/10.1016/S0140-6736(12)60958-1

Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. *ILO Working Papers 992927783402676*.

Pearce, D. W., Markandya, A., and Barbier, E. (1989). *Blueprint for a green economy*. Earthscan.

Pontarollo, N., and Serpieri, C. (2020). Testing the Environmental Kuznets Curve hypothesis on land use: The case of Romania. *Land Use Policy*, *97*, 104695. https://doi.org/10.1016/j.landusepol.2020.104695

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., … Vuuren, D. P. van. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, *42*, 331–345. https://doi.org/10.1016/j.gloenvcha.2016.10.002

Pottier, A. (2022). Expenditure elasticity and income elasticity of GHG emissions: A survey of literature on household carbon footprint. *Ecological Economics*, *192*, 107251. https://doi.org/10.1016/j.ecolecon.2021.107251

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., … Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., … Foley, J. A. (2009). A safe operating space for humanity. *Nature*, *461*(7263), 472–475. https://doi.org/10.1038/461472a

Rosa, E. A., York, R., and Dietz, T. (2004). Tracking the Anthropogenic Drivers of Ecological Impacts. *AMBIO: A Journal of the Human Environment*, *33*(8), 509–512. https://doi.org/10.1579/0044-7447-33.8.509

https://doi.org/10.1553/p-n5en-z38a

Shafik, N. (1994). Economic Development and Environmental Quality: An Econometric Analysis. *Oxford Economic Papers*, *46*(Supplement_1), 757–773. https://doi.org/10.1093/oep/46.Supplement_1.757
Shafik, N., and Bandyopadhyay, S. (1992). *Economic growth and environmental quality: Time series and cross-country evidence*. Policy Research Working Paper Series. https://EconPapers.repec.org/RePEc:wbk:wbrwps:904
Shi, A. (2003). The impact of population pressure on global carbon dioxide emissions, 1975–1996: Evidence from pooled cross-country data. *Ecological Economics*, *44*(1), 29–42. https://doi.org/10.1016/S0921-8009(02)00223-9
Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., and Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 1259855. https://doi.org/10.1126/science.1259855
Stern, D. I. (2004). Environmental Kuznets Curve. In *Encyclopedia of Energy* (pp. 517–525). Elsevier. https://doi.org/10.1016/B0-12-176480-X/00454-X
Tan, F., Lean, H. H., and Khan, H. (2014). Growth and environmental quality in Singapore: Is there any trade-off? *Ecological Indicators*, *47*, 149–155. https://doi.org/10.1016/j.ecolind.2014.04.035
United Nations (2022). *World Population Prospects 2022, Online Edition*. United Nations, Department of Economic and Social Affairs, Population Division. Retrieved 23 March 2023, from https://population.un.org/wpp/Download/Files/1_Indicators%20(Standard)/EXCEL_FILES/2_Population/WPP2022_POP_F01_1_POPULATION_SINGLE_AGE_BOTH_SEXES.xlsx
Urban, F., and Nordensvärd, J. (2018). Low Carbon Energy Transitions in the Nordic Countries: Evidence from the Environmental Kuznets Curve. *Energies*, *11*(9), 2209. https://doi.org/10.3390/en11092209
Usman, A., Ozturk, I., Naqvi, S. M. M. A., Ullah, S., and Javed, M. I. (2022). Revealing the nexus between nuclear energy and ecological footprint in STIRPAT model of advanced economies: Fresh evidence from novel CS-ARDL model. *Progress in Nuclear Energy*, *148*, 104220. https://doi.org/10.1016/j.pnucene.2022.104220
Vadén, T., Lähde, V., Majava, A., Järvensivu, P., Toivanen, T., Hakala, E., and Eronen, J. T. (2020). Decoupling for ecological sustainability: A categorisation and review of research literature. *Environmental Science & Policy*, *112*, 236–244. https://doi.org/10.1016/j.envsci.2020.06.016
Wang, M., Che, Y., Yang, K., Wang, M., Xiong, L., and Huang, Y. (2011). A local-scale low-carbon plan based on the STIRPAT model and the scenario method: The case of Minhang District, Shanghai, China. *Energy Policy*, *39*(11), 6981–6990. https://doi.org/10.1016/j.enpol.2011.07.041
Wiedmann, T., Lenzen, M., Keyßer, L. T., and Steinberger, J. K. (2020). Scientists' warning on affluence. *Nature Communications*, *11*(1), 3107. https://doi.org/10.1038/s41467-020-16941-y
World Bank. (2023). *World Development Indicators (WDI). Databank. World GDP (constant 2015 US$). World Bank National Accounts Data, and OECD National Accounts Data files*. The World Bank. Retrieved 16 March 2023, from https://databank.worldbank.org/reports.aspx?source=2&series=NY.GDP.MKTP.KD#
Xiong, C., Chen, S., and Huang, R. (2019). Extended STIRPAT model-based driving factor analysis of energy-related CO2 emissions in Kazakhstan. *Environmental Science and Pollution Research*, *26*(16), 15920–15930. https://doi.org/10.1007/s11356-019-04951-3
York, R., Rosa, E. A., and Dietz, T. (2003a). Footprints on the Earth: The Environmental Consequences of Modernity. *American Sociological Review*, *68*(2), 279. https://doi.org/10.2307/1519769
York, R., Rosa, E. A., and Dietz, T. (2003b). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, *46*(3), 351–365. https://doi.org/10.1016/S0921-8009(03)00188-5
York, R., Rosa, E. A., and Dietz, T. (2004). The Ecological Footprint Intensity of National Economies. *Journal of Industrial Ecology*, *8*(4), 139–154. https://doi.org/10.1162/1088198043630487

https://doi.org/10.1553/p-n5en-z38a