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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 differences across environmental dimensions, climate and land use impacts were modelled using middle-of-the-road projections for population and per capita income. Different forecasting methods were implemented, including historical extrapolations, models based on stochastic IPAT (STIRPAT), and technological forecasting trajectories in the literature. The different approaches were compared within the IPAT framework. We also explored consequences of alternative trajectories for P, A and T, and we discussed implications for reaching global goals, with a basis in our modelling. Further, our findings were analysed in light of three theories in environmental sociology that give different emphasis on the different components of IPAT. We argue that the large technological mitigation assumed in many forecasts makes affluence and population relatively irrelevant for climate change. However, both factors will likely be influential determinants of land use impact in the twenty-first century.

Keywords: IPAT, environmental Kuznets curve (EKC), green growth, human ecology, STIRPAT model, land use impact

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Introduction

For more than half a century, environmental sciences have highlighted how increasing consumption contribute to environmental problems. In an influential school of thought, such impacts have been conceptualized as the product of the number of people (*P*), per capita affluence (*A*), and a conversion factor (*T*) that translates consumption into environmental impact (*I*). Ehrlich and Holdren (1971) and Commoner (1971) introduced the IPAT identity to illustrate this point. This conceptualization has been influential in both theoretical work and empirical studies relating to the sources of the world's growing environmental problems. A further development of the IPAT with respect to carbon emissions was created by Kaya and Yokobori (1997) that distinguished between energy use per unit of consumption and the carbon intensity of energy consumption.

For many environmental problems, the historical empirical evidence of a strongly positive correlation between environmental impact and both population and affluence is relatively robust. Over the last decade, more scientists and social scientists have highlighted the importance of population for many contemporary environmental challenges (Bongaarts & O'Neill, 2018; Lidicker, 2020). Other researchers have focused primarily on consumption and downplayed the role of the population in many environmental problems (Wiedmann et al., 2020). The IPAT framework have 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 argued for either population policy (smaller *P*) or reduced economic growth and consumption (smaller *A*) as possible solutions to environmental problems. For example, Ehrlich and Holdren's (1971) original work focused on meeting future environmental challenges by limiting population growth. In contrast, more recent research has primarily focused on technological solutions to environmental problems, seeing mitigation through affluence or population as infeasible or indefensible.

In this article, we take a theoretical approach in which we use IPAT-type modelling to examine how IPAT-based reasoning gives different answers depending on the environmental issue at hand. Instead of using IPAT to motivate why any one part of the identity is a *universal* tool to understand all kinds of environmental challenges (which is how IPAT-based arguments have often been used in the past), we show that IPAT is perhaps equally or more useful to understand how *diverse* environmental dimensions relate to various part of the identity. Further, we point out the usefulness of examining a number of models of environmental impact, such as forecasts by the *Intergovernmental Panel on Climate Change*'s *(*IPCC), into the IPAT-framework to better understand how their implications. This illustrates the importance of considering the specifics of each environmental challenge. We look at a variety of aspects, such as time scales, possibilities for technological solutions, as well as the elasticity of impact with respect to population and consumption. This way, we show why population and affluence may have different relevance for different types of challenges.

We created IPAT-type models for climate impact and land use change using mainstream population and income projections with a set of different assumptions for how to calculate the *T* factor in IPAT. We then modelled alternative population, affluence and technology trajectories and discussed their implications for finding sustainable solutions ahead. These environmental dimensions represent two of the most critical challenges facing humanity in the twenty-first century. They both constitute issues in which human transgressions risk destabilizing 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 urgent planetary boundary, biosphere integrity, because biodiversity loss is to a large extent attributable to habitat destruction by means of forest conversion to farmland (Dasgupta, 2021).

However, while both climate 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 distinct. In terms of drivers, a notable difference is that land use impact is dominated by agriculture and forestry, whereas the climate change has additionally been attributed to four other sectors (energy systems, industry, buildings, and transport) (IPCC, 2022). Moreover, climate and land use contrast in how researchers judge the feasibility to decouple impact from consumption. For climate impact, many countries have given zero-emission pledges, and mainstream models typically include global near zero-emissions at some point in this century (IPCC, 2022). Even though historical trends are often not compatible with decoupling environmental impacts from population and affluence growth (Haberl et al., 2020), many researchers see the IPCC scenarios as feasible, though challenging to reach. In contrast, land use challenges are much less explored, and in the available literature researchers have highlighted substantial challenges in reversing the increasing human land use impact (Bimonte & Stabile, 2017; Pontarollo & Serpieri, 2020). Thus, our cases serve as illustrations for different scenarios in which the possibility to decouple consumption from environmental impact 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 different 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 can help clarify, for example, why population policy has often been shown to be of limited relevance when it comes to climate change (e.g., Budolfson & Spears (2021)), while it could still be of importance for other environmental issues. In the rest of this article we present background and theory in relation to the IPAT-equation (Section 2), the methodology that we used, with underlying models and empirical inputs (Section 3), the results of the modelling (Section 4), and a discussion and concluding commentary around their implications (Section 5).

Theoretical and empirical background

A large body of literature has in different ways connected economic growth and population growth to environmental impacts. In this section, we highlight important concepts and theoretical perspectives in this research.

Economic growth and environmental impact

A universal finding in studies of human environmental impacts is that they are tightly linked to economic consumption, and that richer countries, because they consume more, have larger impact than poorer ones (York et al., 2004). Contemporary societies also have a vastly larger impact than historical societies with lower incomes, both in total and per capita. Most research also suggests that, while environmental consequences tend to increase with income, the rise is less than linear with economic growth (Haberl et al., 2020; Vadén et al., 2020; York et al., 2003b). A society that doubles its income will increase its environmentally harmful consumption less than twice as much.

Several theoretical concepts have been introduced to relate economic growth to impact. First presented by Grossman & Krueger (1991), the *environmental Kuznets curve* (EKC) describes a societal evolution where the relationship between environmental impact and affluence has an inverse U-shape, with less environmental degradation in more affluent societies. It parallels the Kuznets (1955) curve which linked income inequality to economic growth. Related, *green growth*, or green economy, is a concept introduced by Pearce et al. (1989) to describe scenarios where increased affluence is not related to increased environmental consumption. Different explanations for the EKC and green growth include a growth in scale of the economy, a change in its composition in terms of structural shifts from agrarian to industrial to information-intensive service-based, as well as the adoption of novel environmentally-friendly production techniques, policies, or investments (Antweiler et al., 2001; Coxhead, 2003; Panayotou, 1993; Shafik & Bandyopadhyay, 1992; Stern, 2004). In their background study for the World Development Report 1992, Shafik and Bandyopadhyay (1992) reported strong support for the EKC (also discussed in Shafik (1994)). In later work, a range of studies have found empirical support for EKC in different contexts (Cole, 2003; Grossman & Krueger, 1995; Lean & Smyth, 2010), as reviewed in Tan et al. (2014). For example, Lean and Smyth (2010) found that long-run estimates supported EKC in a study of five Association of Southeast Asian Nations (ASEAN) countries from 1980 to 2006. However, as highlighted by Stern (2004), the EKC may not apply to all types of environmental impacts.

One can further distinguish between a weak and a strong version of green growth and decoupling. In the weak format, this notion simply means that as societies get richer, the relative impact of increased affluence gets lower. Hence, impact increases less than proportional to affluence. The stronger version implies that richer societies also have a lower absolute impact. This can be conceptualized as a situation in which the elasticity between affluence and impact transforms fundamentally, not only from a value between zero and one, but to a negative value at some (high) level of affluence. The weak case can be described as relative decoupling, and the strong case as absolute decoupling. While the evidence for relative decoupling is strong across many environmental impacts, it is weak for *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).

Specifically, few or no studies have found evidence of absolute decoupling at the global level for either climate change or land use, 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 EKC was observed for per capita carbon dioxide (CO_2) emissions in Denmark, Finland, Iceland, and Sweden, but not in Norway

(Urban & Nordensvärd, 2018). A literature review of research in 27 advanced economies found that the majority (41 of 55) of the examined studies had found support for the EKC hypothesis and absolute decoupling for CO_2 emissions and gross domestic product (GDP) at national levels (Al-Mulali & Ozturk, 2016).

Studies of the relationship between land use and affluence are rarer and 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 for 42 Romanian counties from 2000–2014 and found an *inverted* EKC. These results agreed with earlier work relating land consumption and per capita GDP in 20 Italian regions over the period 1980–2010 (Bimonte & Stabile, 2017). The latter study instead 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 scenarios for climate change and land use imply relative, but not absolute, decoupling.

Population influences on the environment

Links between population growth, population size, land use, productivity and wages go back to classical economic writing on the links between population and economy by economists and demographers such as Malthus (1798). During the 1960s and 1970s, when human population growth reached its historical maximum (Lam, 2011), there was growing concern that this aspect was a major cause of environmental problems. The theoretical perspectives we apply in this article, most predominantly 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 impact (York, Rosa, & Dietz 2003).

More recently, many studies have empirically assessed the association between population growth and environmental impact at the regional, national, and global levels. Broadly, while estimates of the elasticity between affluence and environmental impact vary widely, both empirical and theoretical discussions of the link between population size and environmental impact have often found that the relationships are close to *one* (York, Rosa, & Dietz 2003). That is, everything else being equal, most environmental impacts are directly proportional to population size. Note that these calculations account for the effect of population *net* of the level of affluence, so an individual in a high-income society still contributes more to environmental problems than someone in a low-income society. The evidence for relationships that diverge distinctly from one is rather limited (Rosa et al., 2004), even though one can theoretically expect elasticates 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 organization.

Social theories on population, affluence, and impact

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

Second, *modernization*, or environmental economics from a neo-classical perspective, asserts that environmental challenges can largely be solved through current social, political, and economic institutions (York et al., 2003a). Accordingly, this view argues that current levels of economic growth, capitalism, and globalization can be maintained without fundamentally harming the Earth System. This theory hence implies a relationship between environmental quality and economic development that reflects green growth or EKC. Modernization implies that IPAT models generate values of I that is curvilinear with income, that is, above a certain level of income, I decreases, despite that A increases. Such relationships have been shown to hold for some pollutants, for instance air pollution in the form of sulphur dioxide (Grossman & Krueger, 1991), while there is less evidence for sector-wide decoupling, as discussed above.

Third, the *political economy* perspective holds that economic production is the most important factor (York et al., 2003a). This position maintains that neither technological development nor political reforms will suffice to adequately reduce environmental impact. As producers develop technology and other methods to reduce labour costs, they will increase the use of shared, ecological resources, which implies that environmental externalities are inevitable. Economic elites will not internalize costs voluntarily, and their political power will challenges any reform to fundamentally change this structure (York et al., 2003a). This perspective maintains that even technology that reduces environmental impacts will in the end increase damage because the increases in profits will be used to escalate growth and thus increase environmental impacts. The only solution is an end to economic growth. The perspective is thus consistent with the degrowth perspective and a fundamental restructuring of society. Hence, in IPAT models, this suggests that for total environmental impact (I) to decrease, affluence (A) inevitably has to 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 impacts (Chertow, 2000):

$$I = PAT \quad (1)$$

where I represents the total environmental impact, P is population, A is affluence, and T is impact per unit of economic activity. This equation has been challenged as a simplification because interactions and dependencies may occur between A, P, and T; nevertheless, while any interpretations of results deriving from IPAT will have to relate to such aspects, this equation formalizes essential components of the relationship between environmental impact and population, consumption, and technological development. Chertow (2000) provided a discussion around strengths and weaknesses relating to various versions of IPAT in the literature.

IPAT implies, by design, that the different factors contribute equally to environmental impacts, and so 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, and instead it considers that these associations can be estimated from data:

$$I = aP^bA^cT^de \quad (2)$$

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, 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 impact, while higher values imply that 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 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 populations 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 impact, population, and affluence in different contexts (Dietz & 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 OECD countries from 2010 to 2050. Several related studies have addressed China's carbon emissions in the coming century (Fan & Lu, 2022; Li et al., 2016). Li et al. (2016) predicted China's GHG emissions from 2015 to 2035, with parameters deriving from a STIRPAT-based analysis of data from 1998 to 2014. They made projections based on three emission scenarios, and they considered variations in population, affluence, carbon emission intensity, urbanization, energy consumption structure, and economic structure (Li et al., 2016). The current study builds on this work, although it evaluates two environmental dimensions and three forecasting approaches.

Methods and empirical inputs

We developed broad, quantitative projections of climate impact and land use impact between 2020 and 2100 using IPAT as the theoretical foundation. Specifically, we evaluated normalized trajectories of impact, $\frac{I}{I_0}$, population, $\frac{P}{P_0}$, affluence, $\frac{A}{A_0}$, and technological development, $\frac{T}{T_0}$, where subscripts with 0 represent the values of *I*, *P*, A and *T* in 2020, our base year. For population and affluence we relied on generic, commonly cited middle-of-the-road forecasts in the literature. Regarding *P*, we used the United Nations (UN) World Population Prospects (WPP) Medium variant (2022). 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 projections of A, we used global GDP in IPCC's middle-of-the-road scenario Shared Socioeconomic Pathway 2 (SSP2) (Dellink et al., 2017; Fricko et al., 2017; Riahi et al., 2017). These data were obtained from the © SSP Public Database, hosted by the International Institute for Applied Systems Analysis (IIASA) (2023).

The last part of IPAT, *T*, is inherently difficult to measure and predict, because 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 organizational), and the development of technologies that allow actors to produce a given amount of outcome with less impact. In this article, we have therefore used a *set* of model families that can be seen as different methods for estimating *T*. Grounded in the literature, they represent three distinct conceptual approaches. The first is centred around the continuation of current trends for *T* at a constant rate, which is invariable with *P* and A. The second accounts for elasticities between environmental impact and population as well as affluence, and it implies that the *T* trajectory varies with *P* and A. The third is based on more elaborate forecasts developed in SSP2. The three approaches are summarized in Table 1 and will be described in the following subsections.

Table 1. Assumptions in our three different approaches to develop trajectories for *T*.

Approach	Explanation
1) Historical trends	Historical trends in annual impact per level of GDP, in which changes in *T* are estimated from observed changes in *I* and GDP. The *T* derived from the historical data is then assumed in the future, given our assumed trajectories for *A* and *P*.
2) STIRPAT-derived	STIRPAT with estimated elasticities in the literature, b and c in eq. 3 and 4, in combination with assumed projections for *P* and *A*. Here, *T* depends explicitly on *P* and *A*.
3) Literature forecasts	Trajectories of *I* are taken from existing scenarios that directly model impact. They are then used with our trajectories for *P* and *A* to calculate projections for *T*.

Approach 1: Historical trends

In our first approach to calculate *T*-trajectories, we used estimates on climate and land use impact in the literature and we fitted a value of *T* based on these historical data. This approach was based on the assumption that technological advancements in the form of reduced environmental impact per unit of production will be fixed. Further, *T* will be independent of how *A* and *P* changes in the future, although its value is derived from how *I*, *P* and *A* have changed historically. Thus, this approach assumes that *T* will reduce at a constant rate that reflects average annual improvements in recent history.

For climate impact, we used data accounting 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). These data implied an average decline in emissions of 3.00% per year between 1990 and 2019. In our models (Approach 1), we set the annual *T* reduction to this value. This was consistent with literature estimates, for example the International Energy Agency (2022) reported that the emissions intensity of GDP declined by approximately 3% per year in the U.S and the E.U (2010-2021), and by 40% in China between 2000-2021 (i.e., around 3% per year).

Table 2. Global historical GDP and GHG calculated as CO_2e measured in 1990 and 2019. These data were used to generate models based on historical trends (Approach 1).

Dimension	**IPAT-entry**	**1990**	**2019**	**Comment**
Climate impact [Gton CO_2e]	*I*	32.52	49.76	Historical GHG calculated as CO2-equivalents (Climate Watch, 2022).
GDP [billion (bn) US$ 2022 prices]	*P*×*A*	23,663	87,654	World Economic Outlook Database October 2022, global GDP (International Monetary Fund (IMF), 2022).
Carbon intensity [Gton CO_2e per bn US$]	*T*	1.37	0.57	An average decrease by 3.00% per year.

Regarding land use impact, we accounted 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)) as compared with 2005/2007 (1,592 mn ha). This resulted in an average decrease of 3.2% per year (Alexandratos & Bruinsma, 2012) (Table 3). We used this value in our land use models (Approach 1). It was relatively consistent with literature findings, for example Lamb et al. (2021) reported that the land needed per unit of agricultural and forestry production declined by in average 2.7% annually between 2010 and 2017.

Notably, the calculation of total land use impact in this approach responds to population growth and affluence. An important assumption when fitting this value to an IPAT framework and setting $T = I/(A \times P)$ is that total environmental impact has been a function of economic consumption historically. This assumes that changes in GDP per capita drive land use change, which is appropriate if human land use is proportional to economic activity. However, if humanity is instead seen in a more ecological sense, in which each human has similar caloric needs, land use needs are probably very similar across all levels of affluence. Most likely, the reality is somewhere in between and varies for different types of land use. Another association between land use and affluence is reflected in our STIRPAT estimates, as shown below.

Table 3. Global area of arable land used for crop production and GDP in the 1960s and 2000s, which were used to calculate models based on 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 for crop production in hectares (Alexandratos & Bruinsma, 2012).
GDP [constant 2015 bn US$]	$P \times A$	11,918 (1962)	59,025 (2006)	National Accounts data on GDP obtained from the World Bank Database (2023).
Crop land use per unit of total production	T	0.115	0.027	This results in an average annualized T decrease of 3.2% per year.

Approach 2: STIRPATs in previous research

In the second approach we used projections of technological development grounded in the STIRPAT framework (eq. 2), which implied that *T* ahead was explicitly dependent on population and affluence. We used elasticities in STIRPAT that had been estimated under the assumption that the error term, *e*, included *T* and its coefficient, *d* in eq. 2. This approach is consistent with the early STIRPAT literature which assumed that it is not possible to operationalize *T* (Dietz et al., 2007; Dietz & Rosa, 1994, 1997; Rosa et al., 2004). However, 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, was correlated with carbon outputs, arguing that it should be a measure of *T* in STIRPAT. Other factors accounted for in STIRPAT include urbanization, financial development, trade openness, as well as renewable and non-renewable energy consumption (Jia et al., 2009; Usman et al., 2022). Nevertheless, there is still a lack of consensus regarding how *T* should be operationalized in the literature, and therefore we opted for the standard approach of keeping *T* in the error term. Specifically, we made projections of the total environmental impact, *I*, based on our projections for *P* and *A* (detailed above), using literature estimates of elasticities b and c. Then, we calculated *T* by the IPAT identity, according to:

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

From this, when we examined changes over time, we got:

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

In this equation, $\frac{T}{T_0}$ slopes downward for elasticities below one (b < 1 and c < 1) if population and affluence increase monotonically. For higher elasticities (b > 1 and c > 1), $\frac{T}{T_0}$ 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 were grounded in a review of previously estimated STIRPAT models. For climate impact, we used 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 used in Approach 1, which was based on CO_2e. This approach thus assumed that general trends were consistent across these different definitions. Regarding elasticities with respect to population, we used the median of the cross-national, inter-temporal STIRPAT studies listed in Liddle (2015); in this data set, we excluded short-run data when long-run data were available, and we used disaggregate estimates (per income level), rather than overall estimates when both of these data were published (N = 29 data points). Concerning elasticities with respect to affluence, we additionally considered the review by Pottier (2022), who presented income elasticities of GHG or CO_2 emissions from various countries and time periods. From that study, we used the upper bound in cases in which no other data were listed (N = 36 data points). We used the median of the entries in Liddle (2015) and Pottier (2022) in our climate models in Approach 2 (Table 4).

Table 4. Elasticities of population and affluence with respect to climate impact in the two literature reviews that we considered. We used the median values in our models in 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)

For land use impact, we used elasticities of population and affluence published by Rosa et al. (2004), in which STIRPATs were estimated using data from 142 countries (Table 5). As we depended only on this one study to model land use impact, the elasticities that we used were less reliable than those that we used for climate impact, which reflected two literature reviews. This imbalance was unavoidable considering that the literature on STIRPAT has mainly focused on climate impact (e.g., Wang et al. (2011) and Xiong et al. (2019)). While there are alternative approaches, for instance focusing on ecological footprint, which is a general measure that aggregates over many types of environmental stress (Dietz et al., 2007; Jia et al., 2009; Usman et al., 2022), the STIRPAT literature using land use as the dependent variable is still scarce. Therefore, we used the estimates in Rosa et al. (2004), and we assumed that arable land and grazing were proxies for land use.

Thus, the literature suggests that impact elasticities of population are near unity for both climate impact and land use impact. Elasticities of income are generally below one, which signals relatively inelastic relationships where environmental effects increase at a slower rate than GDP. Consistently, the median elasticity of income for climate impact was 0.58 (Table 4), which was only slightly larger than the elasticity for land use impact, 0.50 (Table 5). Note further that for climate impact *b* was above unity (1.12) while *c* was not (0.58), implying that *T* depended on the relative difference between changes in *P* and *A*. For land use, however, elasticities of both population and income were less than unity, which means that increasing *P* and *A* implied declining *T*, impact per unit of production, over time.

Table 5. Elasticities of population and affluence with respect to land use. In our models, we used the mean of two analyses in Rosa et al. (2004), one for grazing and one for arable land (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)

Approach 3: Literature forecasts of environmental impacts

Lastly, we considered literature forecasts of impact *I* and we examined how they related to *T* in the IPAT framework (Approach 3). For climate, we applied IPCC's most recent models (IPCC, 2022), which use a scenario matrix architecture in which socioeconomic patterns are reflected in five key SSPs, and 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 (Appendix A, Figure A.1). These levels reflect different Representative Concentration Pathways (RCPs), which represent various mitigation schemes, accounting for behavioural trends and efforts to curb emissions relating to energy generation, novel technologies, and transportation, for example.

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

For land use, we accounted for forecasts in IPPC's middle-of-the-road scenario SSP2. This assumes that current trajectories in the land sector will continue, with medium levels of regulation and technological change, material-intensive consumption, an increase in animal calorie share, as well as ongoing tropical deforestation (Popp et al., 2017). It considers 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 accounted for this development in relation to the projection of GDP in SSP2 (Dellink et al., 2017) to calculate the annual decrease in *T* (Table 6). The approach thus considers that *T* responds to the inverse of $A \times P$.

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 increased enormously. This approach thus assumes that the levels of agricultural intensification, mechanisation, capital investments, and nutritional inputs to the land that have taken place since the 1960s (i.e., the *Green Revolution*) will continue over the twenty-first century

(Evenson & Gollin, 2003). For low-income countries, this reflects the adoption of agricultural intensification practices that have mainly taken place 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 & Gollin, 2003).

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 (a World Bank WDI), hosted by IIASA (2023), and the 2100 forecast was from 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.

Note that a major simplification in our models is that we largely do not consider that A, P and T are endogenously related to each other. This diverges from historical trends and forecasts in which endogenous relationships can be either explicit, as in IPCC's models, or indirect, 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 about independence and temporal invariance in the relationships we have studied. Our approach therefore contrasts with researchers who have theorized that *P* and *T* are dependent on each other (Boserup, 1965). However, it is still conceptually helpful as it allows us to use IPAT as a theoretical tool to explore how different forecasting methods relate to one another.

Effects of changing *P*, *A* and *T*

In the last section of our results, we examined to what extent changing different parameters would 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 modelled population using four diverging trajectories, where our standard middle-of-the-road trajectory was the medium scenario in WPP (2022). We first changed the medium scenario with 10% in 2100 and assumed a linear change up to that point. We also used the projections for low and constant fertility in 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 policy reducing fertility could imply non-coercive support for family planning or less government support for childrearing, and scenarios promoting it could instead involve increased socialization of childrearing (Kolk, 2021).

For variations in affluence, which are directly related to degrowth from a theoretical perspective, we similarly modelled per capita GDP based on a 10% increase and decrease as compared to the 2100 levels 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 mitigate environmental challenges. It is therefore associated with the political economy viewpoint.

We also explored the impact of a range of expectations about technological development. First, we considered variations in *T* by 10% in the models based on historical data (Approach 1). Second, we considered the first and third quartile of impact elasticities of population and affluence in the reviewed STIRPAT literature (Approach 2). Third, we considered different radiative forcings in 2100 in SSP2 (IPCC, 2022) (Approach 3) (Appendix A, Figure A.1, left panel). These levels imply varying *T*, since they assume that socioeconomic patterns (*P* and *A*) are similar, while climate behaviours, policies, and technologies differ. We could therefore obtain projections for *T* by dividing climate forecasts with population and GDP trajectories in SSP2 (Appendix A, Figure A.1, right panel). This assessment relates to the modernization perspective as it focuses on *T*. The corresponding method could not be used for land use, because we only found one relevant forecasting scenario in the literature (Approach 3).

IPAT projections and interpretations

Climate and land use impacts

IPAT models for climate and land use impacts are shown in Figure 1. The historical extrapolations resulted in climate impact at the end of the century that is about half of current levels (Approach 1; Figure 1, left panel). This was relatively similar to 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 by around 2.7°C (IPCC, 2022). This model also illustrated that even scenarios such as 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). This echoes the substantial increases in population and affluence that are expected by then, since standard trajectories imply levels of *P* and *A* that are 1.32 and 4.54 of current readings, respectively.

Even more alarming, the model reflecting STIRPAT elasticities (Approach 2) generated effects that were closer to the more catastrophic climate impacts (e.g., SSP5 RCP 8.5), and much larger T = 0.55 of current levels (Table 7). Also in sharp contrast with environmental targets, our STIRPAT-based projections of land use (Approach 2) and literature forecasts (Approach 3) suggested that impacts will *increase* rather than decrease in 2100. The latter indicated 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 current levels (Table 7). This is thus an example of weak decoupling, since A is expected to rise considerably by then. The lack of strong decoupling here is disconcerting considering environmental studies that argue that 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 land use impact assuming that historical trends continue and that T declines by 3.2% per year (Approach 1). We complemented this with a model that accounted for historical trends based on cereal yield, generating an annual T decrease by 2.1% per year (Popp et al., 2017) (Appendix B, Figure B.1). The difference between these two models was that the first one represented *total* production, while the latter related only to production in the form of crop yield, reflecting intensification technologies such as industrial fertilizers for a given land area (although crop yield 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 impact. Approach 1 implies that land use impact at the end of the century will be only 0.07 of current levels (Table 7).

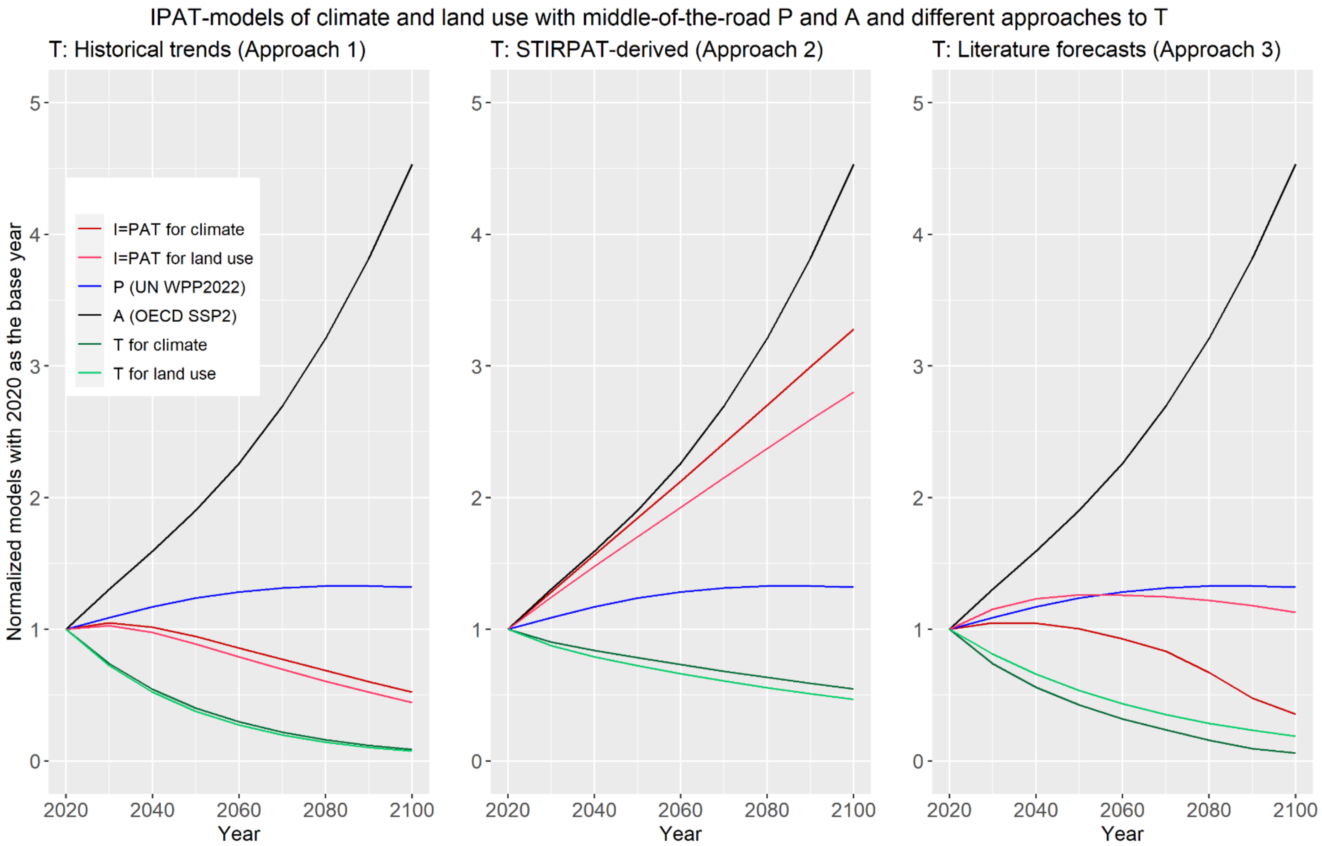

Figure 1. IPAT-projections of impact, *I*, for climate impact (red) and land use impact (light red). In all three panels, the same assumptions apply for population (*P*; blue) and affluence (*A*; black), while *T* varies. The left panel shows projections in which *T* for climate impact (green) and land use impact (light green) are based on 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 IPCC's SSP2 (RCP 4.5) (Fricko et al., 2017; Riahi et al., 2017) and land use impact derives from SSP2 (Popp et al., 2017) (Approach 3).

Table 7. Technology, *T,* in 2100 as related to levels in 2020 for climate and land use impact. These data are depicted in the *T* graphs in Figure 1.

Dimension	**Technology *T***		
	Approach 1) *T*: **Historical trends**	**Approach 2)** *T*: **STIRPAT-derived**	**Approach 3)** *T*: **Literature forecasts**
Climate	0.09	0.55	0.06
Land use	0.07	0.47	0.19

Scenario analyses

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

Population

Given the very nature of an IPAT model, reductions in population by 10% in 2100 as compared with the middle-of-the-road scenario would decrease climate impact with a similar share in the models that are based on historical data (Approach 1). For example, carbon emissions would be 0.47 of current levels instead of 0.52 (Table 8), a reduction which is rather modest. 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 carbon impact ($I = 2.91$) is considerably lower than the middle-of-the-road scenario ($I = 3.28$) (Table 8). Put differently, a 10% decrease in population would reduce impact in 2100 by 37% as compared to current levels. Regarding literature forecasts (Approach 3), our models further suggest that the effect of a decrease in population by 10% would be less important for climate than land use; in the latter case, *I* would be reduced from 1.13 to 1.02 of current levels, as compared with a reduction from 0.35 to 0.32 for climate (Table 8). In absolute terms, this suggests that population policy would have a larger effect on land use impact than climate impact, though the relative impact would be similar in a strict IPAT-type framework.

Table 8. Impact *I* in 2100 as compared to 2020. It shows the range (and middle-of-the-road value) for ±10% changes in population and affluence as compared to the middle-of-the-road outcomes depicted in Figure 1.

Policy	**Dimension**	**Impact *I***		
		Approach 1) *T*: **Historical trends**	**Approach 2)** *T*: **STIRPAT-derived**	**Approach 3)** *T*: **Literature forecasts**
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)

Further, IPAT models of impact as related to 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 with effects that are consistently substantially smaller (Appendix C, Figure C.1 and C.2). Note that the STIRPAT-derived models (Approach 2) show similar sensitivity to population as the other two approaches in relative terms (Table 9). This is because 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 as compared to current levels is quite high in 2100: 0.55 and 0.47 for climate and land use, respectively (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 climate ($I = 0.66$ vs. 0.35) in the models that are based on literature forecasts (Approach 3). This suggest that population policy is of greater importance for land use.

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

Dimension	**Impact *I* in 2100 relative 2020 for different population prospects**		
	Approach 1) ***T*: Historical trends**	**Approach 2)** ***T*: STIRPAT-derived**	**Approach 3)** ***T*: Literature forecasts**
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)

Affluence
Variations in per capita affluence by ± 10% in 2100 as compared to the middle-of-the-road scenario are listed in Table 8 and graphs are shown in Appendix D, Figure D.1 and D.2. They imply proportional impacts in the models that are based on historical trends (Approach 1) and literature forecasts (Approach 3) (Appendix D, Figure D.1 and D.2). These two approaches 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 models (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, note that this approach also means that the relative changes in impact are smaller, because in these models assume that the elasticity of income is less than one for both climate impact (0.58) (Table 4) and land use impact (0.50) (Table 5).

Technology
Environmental impacts assuming different scenarios for *T* are shown in Figure 2 and Figure 3, and Appendix E 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,* assuming that 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, as compared to 0.52 in the middle-of-the-road scenario (Appendix E, Table E.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 (first and third quartile based on the literature review). 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 (Appendix E, Table E.2).

Likewise, calculations of land use impact in 2100 as related to different STIRPAT elasticities suggest that effects will be severely worsened as compared to current levels (Appendix E, Table E.2).

The right panel in Figure 2 shows IPCC's SSP2 projections given different levels of radiative forcing in 2100 (see Appendix A). 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 exceptional improvements in 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).

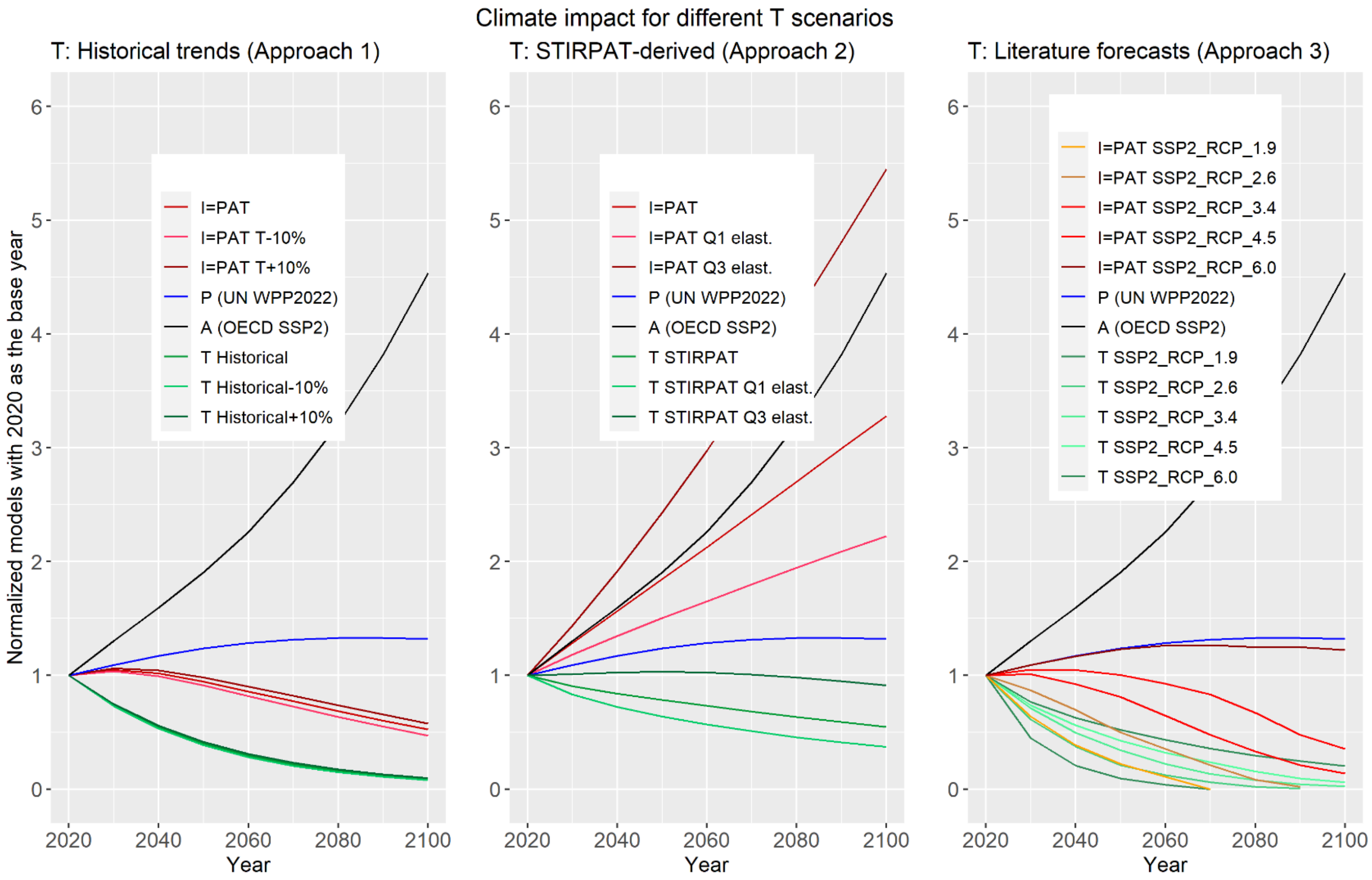

Figure 2. IPAT-projections of climate impact (*I*; red) as related to variations in scenarios for technology (*T*; green). The left panel shows projections in which technology is based on historical trends ±10% (Approach 1), the central panel is based on STIRPAT estimates of climate impact elasticities,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

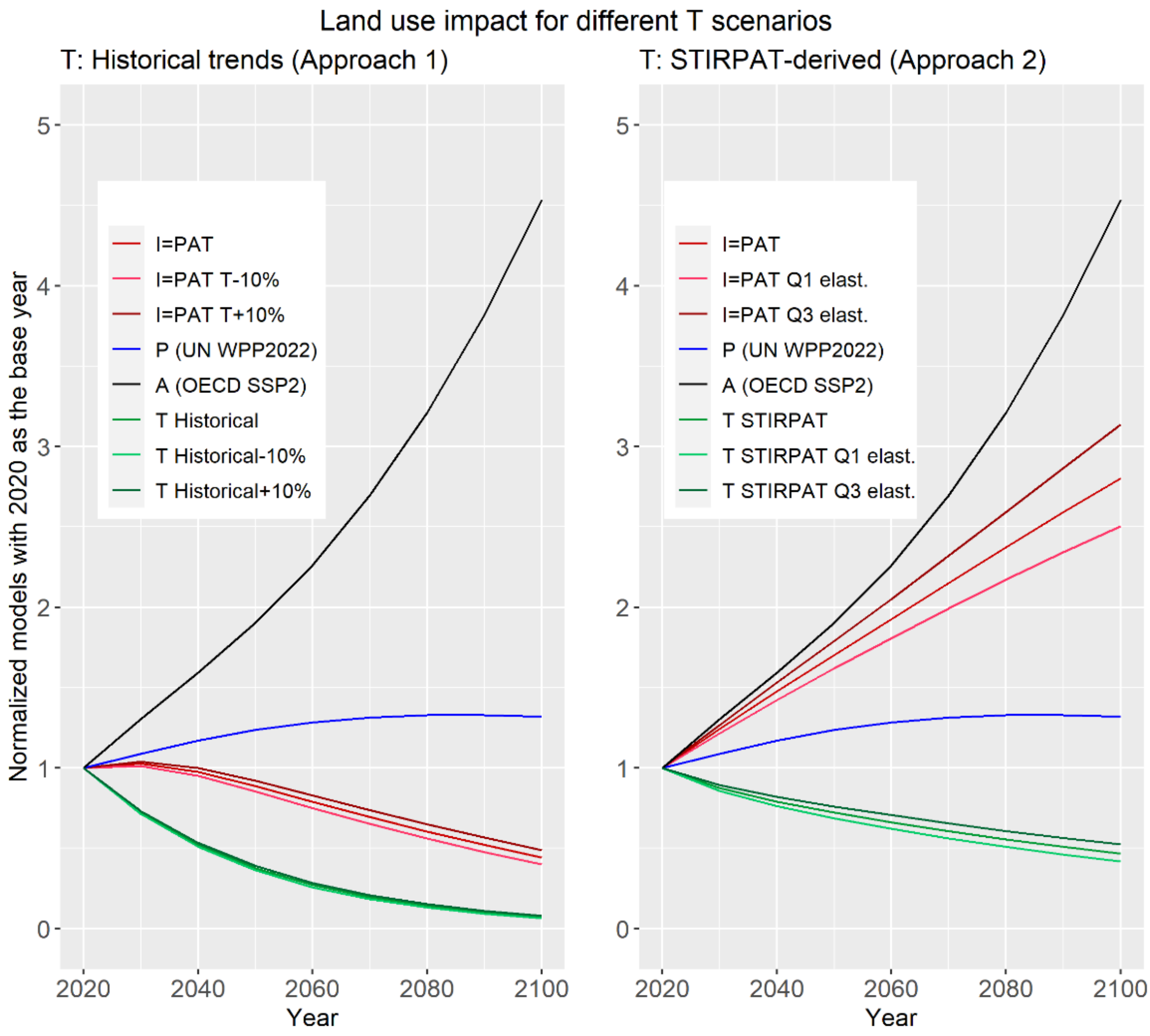

Figure 3. IPAT-based projections of land use impact (*I*; red) as related to variations in technology (*T*; green). The left panel shows projections in which *T* is based on historical trends ±10% (Approach 1), and the right panel is based on STIRPAT-based estimates of population and income elasticities, 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, so Approach 3 is not shown.

Environmental ecology theories

Our projections relate differently to theories within environmental ecology. The results are broadly consistent with the green growth theory, or modernization in the framing of York et al. (2003a), at least in the limited sense that they imply relative (weak) decoupling between environmental impact and economic growth. In a comparison of levels in 2100 and 2020, *T* decreases while *A* increases, in all our models. However, only a few of them imply absolute, (strong) decoupling between growth of affluence *A* and impact *I*; in many of our models, *I* in 2100 is projected to increase from current levels.

Nevertheless, the projections that are grounded in historical trends (Approach 1) do support modernization, 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); however, be aware that these models both assume exceptionally small values of *T* in 2100 (Table 7), implying a massive adoption of environmentally friendly policies and technology. In the case of land use, they involve enormous increases in land productivity for a given amount of land.

On the other hand, our projections based on forecasts (Approach 3) imply that impacts in 2100 will be much higher than what many argue to be sustainable levels, as climate impact is projected to be far above zero and land use impact is 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 of these environmental impacts *increase* as an effect of the anticipated growths in *P* and *A*, because the impact elasticities for both of these 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 policy, such as the human ecology view, find the most support from these models.

In all models, population size contributes to environmental impact, but in some scenarios, this effect is small relative to the impact of 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, this way it becomes clear that the higher *T* in forecasts of land use (Approach 3) implies that the relative importance of anticipated growths in *P* and *A* is greater for this environmental dimension than for climate (Table 7). This suggests that land use is harder than climate to mitigate except through reduced consumption or fewer people. An emphasis on the importance of population policy to mitigate environmental issues is consistent with the human ecology perspective. Thus, this perspective may be more relevant for land use than climate.

Discussion and conclusion

The IPAT framework connects to a number of earlier studies about how societies can manage environmental challenges. It was developed to highlight the role of population, but it can be used to argue for nearly any relationship of the constituting elements (Chertow, 2000). We have shown that it is a helpful tool when comparing across future environmental impacts when the relative role of *T* as compared to *A* and *P* differs. Articulating variations across domains is important because it enables understanding of how the trade-offs involved differs. Distinct ethical and political reasoning may apply across various 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.

The overall interlinkages with *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. Original proponents of IPAT highlighted the negative consequences of anticipated growths in *P* and *A* (Ehrlich & Holdren 1971), and they were thus sceptical of improvements in *T*. Contemporary environmentalists focusing on degrowth are similarly sceptical, but they concentrate nearly entirely on *A*. In contrast, researchers proposing green growth put a large emphasis on mitigation through *T*. Our models have highlighted how substantive such improvements must be, particularly in light of mainstream forecasts of global GDP, and even more so if one considers contemporary consumption to be (already) above sustainable levels. This view is common in the environmental literature. Broadly, our models are consistent with previous research that has reasoned that the IPAT framework highlights *T* as the most dynamic and important part of the equation (Chertow, 2000). They are especially helpful to pinpoint the situations in which large reductions in *T* are considered to be feasible, and therefore when *P* and *A* are of less relative importance. Our models also illustrate the extent to which technological improvements underlay different actors' forecasts.

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

Another conclusion based on our models is that population policy ("fewer people") and degrowth ("less consumption") may be less relevant strategies for climate than land use if one assumes the mainstream SSP2 trajectories to be realistic. The reason is promising technology, especially within the energy supply sector (see Davis et al. (2018)). For land system change, population policy or reduced consumption may be more relevant. This is underlined in our STIRPAT-based approach, which implies substantially increasing land use impacts, from levels that many argue are already unsustainable. We are not aware of much empirical and analytical studies in the scientific literature that would radically contradict such a perspective with respect to land use.

Our models suggest that environmental impacts may be decoupled from affluence (and, relatedly, population) for climate impact. These findings are supported by extant technologies and policies that would substantially reduce climate impact, as shown in the right panel in Figure 1. Still, note that green growth in the context of climate change means that 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 $A \times P$; for example if $A = 5$ and $P = 1.2$, 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 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 anticipated technological and behavioural developments in carbon intensity do not necessarily translate to improvements within land systems change. They have indicated that green growth may be a realistic perspective for climate change, but that it is less applicable to land use. Consequently, the political economy view, implying a stagnant economy (degrowth), is likely to be more relevant for land use than climate impact. In parallel, our results suggested that population policy, related to the human ecology perspective, may have a larger effect on the possibility to reach global goals within land use change than climate change. Policymakers need to be aware of these differences.

The results in this study should be interpreted with regards to its limitations. First, our modelling approaches are based on a number of theoretical simplifications. The most important is that we largely avoid 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 a way of putting different approaches into a similar scale and theoretical perspective, which allows for comparisons. The models should be considered in this light, rather than seen as precise projections of environmental impacts. Consequently, we see this article as mainly a theoretical contribution. Any single IPAT-type model we present can be discussed, and different operationalizations 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 environmental literature.

Second, 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 assumes that this literature is sufficiently rich to capture key dynamics in the future. While the STIRPAT literature on climate impact is relatively vivid, it has been more challenging to find the corresponding studies for land use impact. Furthermore, in our STIRPAT-based models, we have assumed elasticities to be temporally constant. There have been only limited studies examining how elasticities may change over different levels of affluence, and the few studies doing this have suggested that they are relatively robust (see, e.g., Liddle (2015)). The modelling 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. Our modelling thus assumes that variations in climate impact over time are not fundamentally different across these different specifications.

Third, another concern is that we used a single set of trajectories for P and A in our IPAT modelling, while the different forecasting scenarios that we base our models on use different, but related, trajectories. The most important difference is that we used UN WPP (2022) while many SSP-based scenarios have used population forecasts from the Wittgenstein Centre for Demography and Global Human Capital and IIASA (KC & Lutz, 2017). Harmonising a diverse set of scenarios was a consequence of our approach, which aimed to synthesize a sprawling literature and a wide set of models with different assumptions on P and A. This highlights the importance of interpreting our results primarily as theoretical tools for understanding conceptual differences rather than as competing forecasts of environmental problems.

In conclusion, our models are generally consistent with mainstream views in the environmental sciences. They show the following: i) Consumption and wealth are the largest drivers of many environmental challenges. ii) The impact of population on environmental impacts is often close to one-to-one, so population reductions will likely affect many environmental problems proportionally, neither substantially less nor more. iii) Green growth is possible and likely in the sense of relative decoupling, declining T combined with increasing A, although it seems more challenging for absolute decoupling involving decreasing I over time, which implies nearly infinitesimal T in the long-term scenarios, seeing that $P \times A$ is expected to increase considerably. In scenarios with relative decoupling, increasing affluence and population will aggravate environmental impacts. iv) For some environmental challenges, such as zero-emission energy, radical decreases in climate impact per unit of consumption seem more feasible than for others, such as land use impact. v) Even though large-scale technological transformation is judged possible by the scientific community such as the IPCC, they inevitably imply dramatic reductions in environmental impact per unit of consumption (T). We believe that the IPAT-type harmonisation of models that we have presented here helps to understand and motivate these conclusions.

Acknowledgements

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Appendix A. Climate impact for different RCPs given projections of *P* and *A* in SSP2.

Figure A.1 shows climate impact projections as inferred from six RCPs, given SSP2 (IPCC, 2022), using 2020 as the base year. All these projections assume the same development for *P* and *A*, while *I* varies according to the RCPs (Figure A.1).

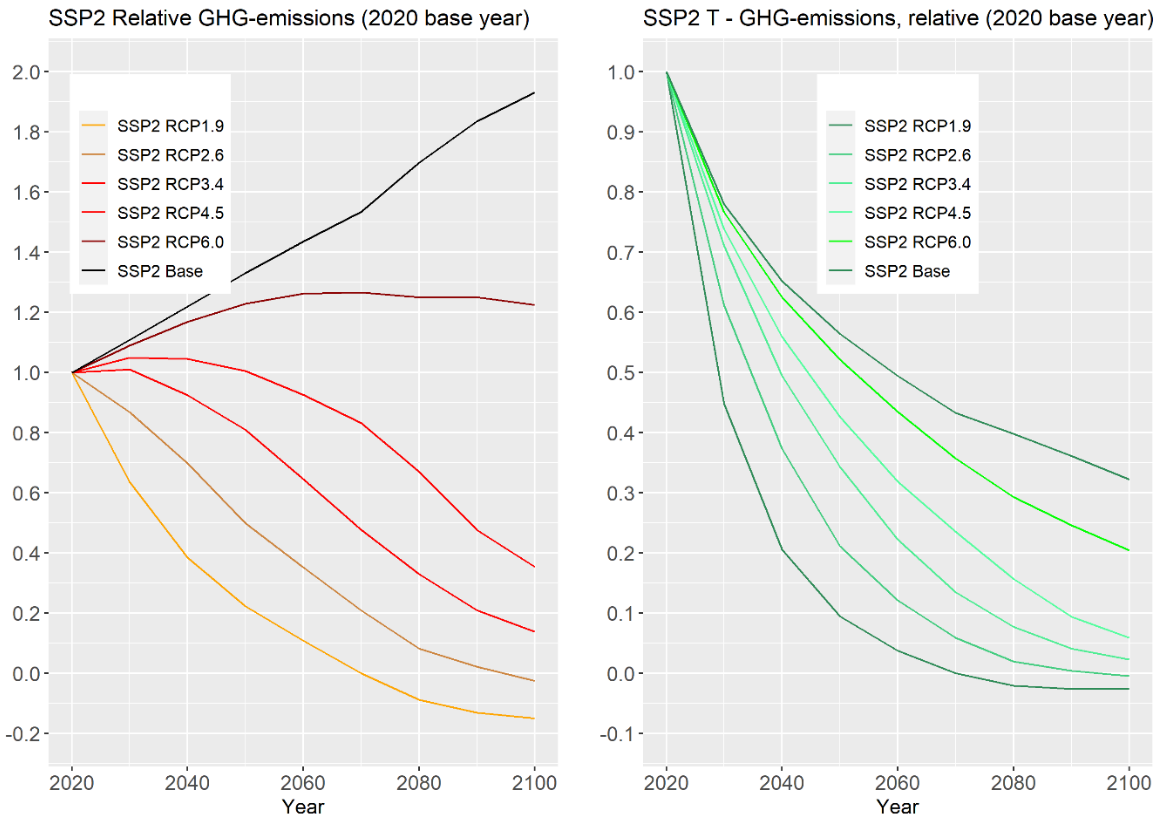

Figure A.1 The left panel shows emissions of Kyoto gases for each of the RCPs given SSP2, that is, total impact *I*. The right panel displays the corresponding *T* curves, calculated assuming $T = I/(P \times A)$. It considers that all RCPs given SSP2 imply the same assumptions for *P* and *A*. For both panels, data were downloaded from the © SSP Public Database, hosted by IIASA (2023).

Appendix B. Land use impact assuming the continuation of historical trends.

Land use impact assuming the persistence of historical developments with different assumptions for *T* are shown in Figure B.1 (Approach 1).

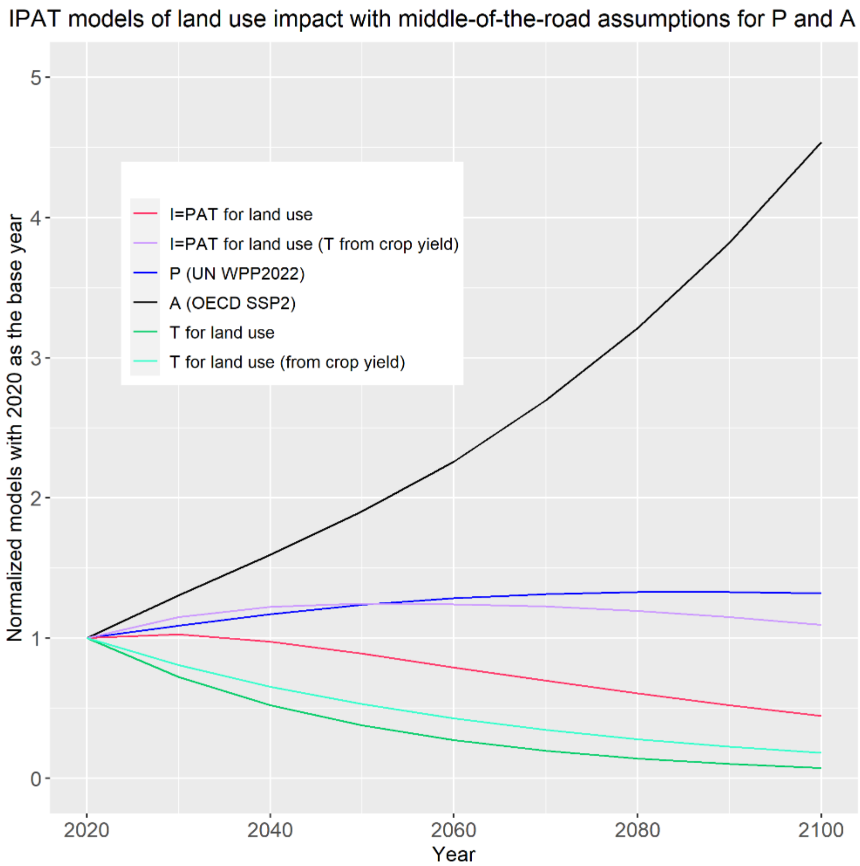

Figure B.1 Land use impact in the middle-of-the-road scenario (Approach 1) with different assumptions for *T*. The lower *T*-curve (green) and the corresponding *I* (light red) assume *T* reductions of 3.2% per year, that is, the same as in Figure 1 (Table 3) (Alexandratos & Bruinsma, 2012). The upper *T*-curve (cyan) and the corresponding *I* (light purple) are based on global average cereal yield in 1960 (1.3 tonnes/ha) *versus* 2005 (3.3 tonnes/ha), that is, a *T* reduction by 2.1% per year (Popp et al., 2017).

Appendix C. Environmental impact as related to variations in population.

Figure C.1 (climate impact) and Figure C.2 (land use impact) depict environmental impact as related to the three population prospects in UN WPP (2022).

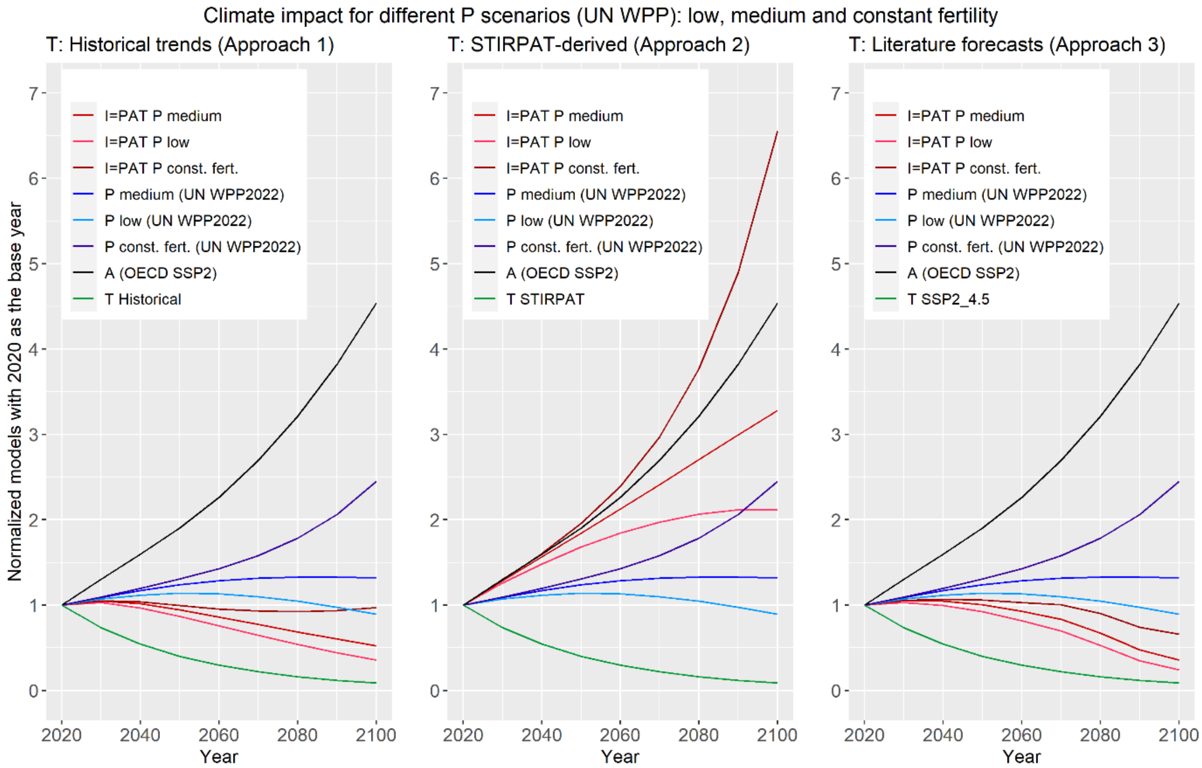

Figure C.1 Climate impact for the three population prospects in UN WPP (2022) in the three modelling approaches described in Table 1.

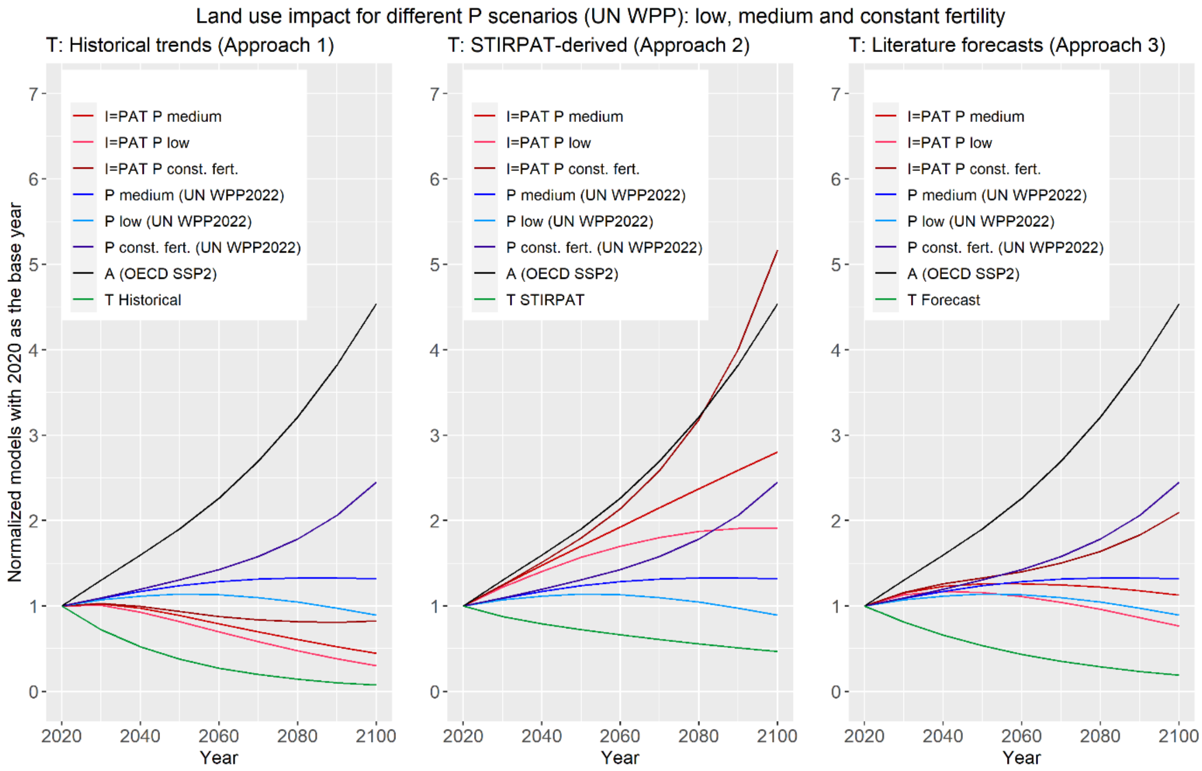

Figure C.2 Land use impact for the three population prospects in UN WPP (2022) in the three modelling approaches described in Table 1.

Appendix D. Environmental impact as an effect of variations in per capita affluence.

Climate and land use impacts *I* as related to variations in per capita affluence *A* (±10%) are shown in Figure D.1 and Figure D.2.

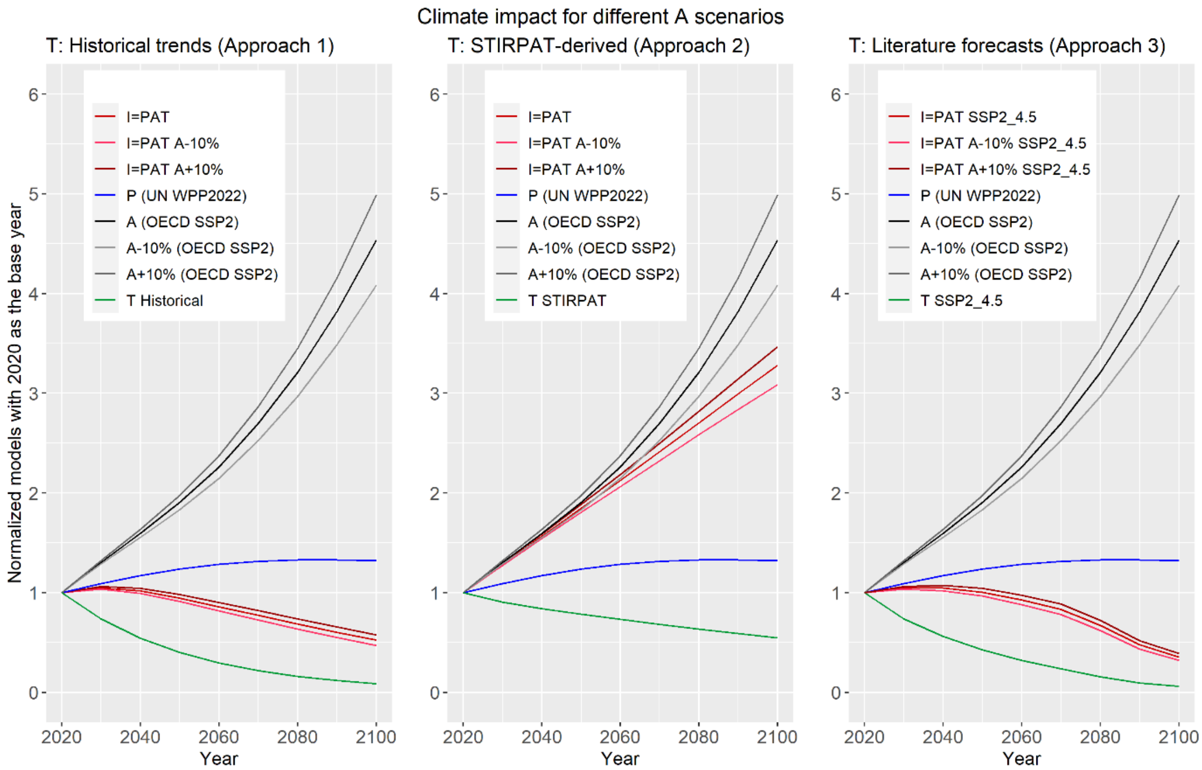

Figure D.1 Climate impact assuming variations in *A* by ±10% in the three modelling approaches explained in Table 1.

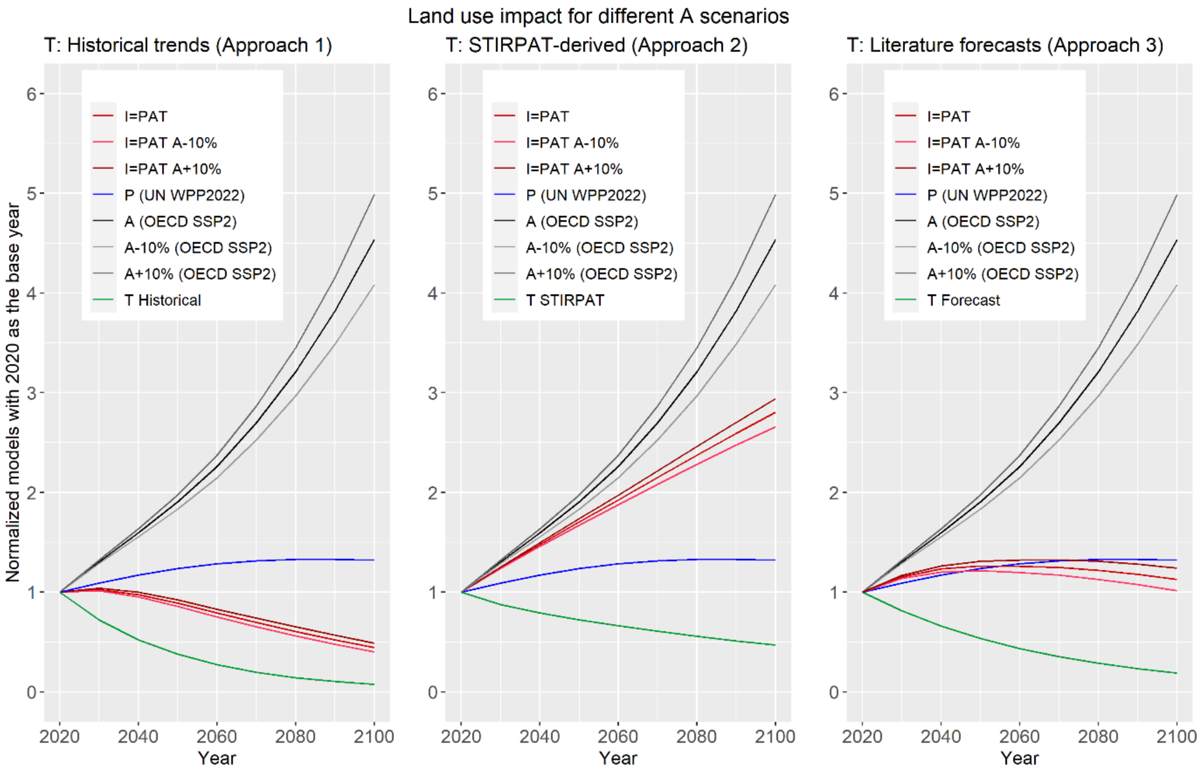

Figure D.2 Land use impact in relation to variations in *A* by ±10%.

Appendix E. Environmental impact as related to variations in technology.

Impacts *I* in 2100 as related to 2020 as an effect of different scenarios for *T* are listed in Table E.1-E.3. Graphs of these data are shown in Figure 2 and Figure 3.

Table E.1: Impact *I* in 2100 as related to 2020 assuming historical trends with varying *T* (±10%) (Approach 1).

Dimension	Impact *I (*Approach 1)		
	T-10%	T middle-of-the-road	T+10%
Climate	0.47	0.52	0.58
Land use	0.40	0.44	0.49

Table E.2: Impact *I* in 2100 as related to 2020 for climate impact and land use impact assuming STIRPAT-derived *T*, varying from the first to the third quartile in the literature (Approach 2).

Dimension	Impact *I (*Approach 2)		
	First quartile	Median	Third quartile
Climate	2.22	3.28	5.45
Land use	2.50	2.80	3.14

Table E.3: Impact *I* in 2100 as related to 2020 for climate impact with *T* derived from IPCC's forecasts in SSP2, varying with the different RCP forcings (Approach 3).

RCPs in SSP2	Impact *I (*Approach 3)
RCP 1.9	-0.15
RCP 2.6	-0.03

RCP 3.4	0.14
RCP 4.5	0.35
RCP 6.0	1.22
RCP Baseline	1.93

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