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Time of emergence of economic impacts of climate change

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Abstract

We introduce the concept of time of emergence of economic impacts (ToEI), which identifies the initial moment when the climate change impact signal exceeds a previously defined threshold of past economic output shocks in a given geographic area. We compute the ToEI using probabilistic climate change projections and impact functions from three integrated assessment models of climate change: DICE, RICE and CLIMRISK. Our results demonstrate that, in terms of the business-as-usual carbon emissions scenario, the global economy could reach its ToEI by 2095. Regional results highlight areas that are likely to reach the ToEI sooner, namely Western Europe by 2075, India by 2083, and Africa by 2085. We also explore local-scale variations in the ToEI demonstrating that, for example, Paris already reached the ToEI around 2020, while Shanghai will reach it around 2080. We conclude that the ToEI methodology can be applied to impact models of varying scales when sufficient historical impact data are available. Moreover, unprecedented impacts of climate change in the 21st century may be experienced even in economically developed regions in the US and Europe. Finally, moderate to stringent climate change mitigation policies could delay the extreme economic impacts of climate change by three decades in Latin America, the Middle East, and Japan, by two decades in India, Western Europe, and the US, and by one decade in Africa. Our results can be used by policymakers interested in implementing timely climate policies to prevent potentially large economic shocks due to climate change.

1. Introduction

Local estimates of economic impacts and risks related to climate change are gaining increasing importance in guiding decision-making about climate policy (Botzen *et al* 2019). Metrics of relative risk and time of exceedance of severe impacts provide insights that may prove relevant to both climate change policy and communicating the associated risk. We believe that a country's history of economic shocks can provide decision-makers with a useful reference baseline to gauge the severity of future climate-induced economic shocks and the challenges various emission trajectories imply for a society. Future climate impacts that exceed a certain high threshold of past total economic shocks could have severe implications for the economy. To guide climate policy towards preventing such climate shocks, it is important to have information about when, where, and under which greenhouse gas emission scenarios these shocks are more likely to occur.

The primary objective of this paper is to present a methodology for gaining insights into the time of emergence of economic impacts (ToEI) of climate change. We provide estimates of the ToEI by placing local-level climate damages in the perspective of historical country-level economic developments. We define ToEI as the first moment in time when future climate change impacts expressed as a percentage of GDP losses exceed a pre-defined threshold of economic GDP shocks due to climate and non-climate effects. Hence, the ToEI provides a historical context to the results of emerging climate impacts, which furnishes the following complementary insights for climate policy in addition to the common practice of expressing climate impacts as absolute monetary losses or losses as a percentage of GDP. It is likely that future climate change impacts that exceed historical economic shocks from both climate and non-climate causes will be experienced as severe and undesirable by society, which implies that policymakers would aim to prevent such shocks from occurring. For example, the financial crisis that started in 2008 resulted in severe economic shocks in many parts of the world, which negatively affected human well-being in countries with adverse macroeconomic conditions (Arampatzi *et al* 2019). As a response, additional financial sector regulations and safety nets were put in place in many countries to limit the risks of similar shocks occurring again in the future. Information on when climate impacts will exceed such historical GDP shocks and how this occurrence can be avoided or delayed by climate policy could be useful for proactive governments that aim to prevent severe societal impacts due to climate change. Moreover, the ability to delay the ToEI through reductions in greenhouse gas emissions can be viewed as providing time to implement adaptation measures to prevent severe economic shocks caused by climate change from materializing. The concept of time of emergence (ToE) has its origins in the climate sciences and can be defined as the date when the climate signal emerges from the background, natural climate variability. The methodology of ToE of climate signals is well described by Hawkins and Sutton (2012), who explore the long-term inter-annual temperature variability for various general circulation models and estimate the ToE for each of them. A similar methodology is applied by Mora *et al* (2013), who also identify the starting date when temperatures continuously exceed the natural climate variability of the post–industrial revolution era and may be harmful for biodiversity and society. Lyu *et al* (2014) estimate the ToE of sea-level rise relative to a 19 year baseline period (1986–2005).

The ToE literature has thus far focused on variability in physical variables (e.g. temperature), whereas we are interested in the implications of climate change on economic output. In other words, we focus on identifying the ToE of severe climate change impacts that exceed historical economic output shocks. We define historical output shocks as deviations from a long-term economic trend, which we compute by using a set of time-series filters. We illustrate the ToEI using probabilistic climate change projections and impact functions from integrated assessment models (IAMs), which are a prominent framework for generating economic estimates of climate change impacts. The concept of IAMs is based on the seminal work by William Nordhaus (1992). Since then, many more IAMs have emerged (Nordhaus and Yang 1996, Bosetti *et al* 2007, Stern 2008, Dietz 2011, Hope 2011, Anthoff and Tol 2014, Admiraal *et al* 2016, Estrada and Botzen 2021, Van Vuuren *et al* 2018) with various model specifications and geographic scales, ranging from global (Nordhaus 2017) and regional (Hope 2011, Nordhaus 2011, Anthoff and Tol 2014) to the grid-cell level (Estrada and Botzen 2021, Estrada *et al* 2020, Ignjacevic *et al* 2020). These models attempt to measure a variety of climate-related impacts, including crop yield losses, industrial output losses, coastal and river flooding, and health impacts. Many of the abovementioned models monetize climate impacts and express them either in absolute terms or relative to annual gross domestic product (GDP). We apply the ToEI methodology to IAM impact functions of various spatial resolutions, covering a broad range of climate and socio-economic contexts. First, we compute the ToEI for the well-established DICE and RICE impact functions (Nordhaus 2017), demonstrating that this risk measure can readily be included in IAMs that cover different spatial scales[5]. We repeat the process using the local-scale CLIMRISK model (Estrada and Botzen 2021, Ignjacevic *et al* 2020)[6], establishing that the ToEI methodology can also exploit high-resolution IAMs.

The ToEI concept presented in this paper can be applied by researchers working with various climate change impact methodologies (Mendoza-Tinoco *et al* 2017, Xie *et al* 2018), including empirical studies (Burke *et al* 2015) and sectoral models that make future impact projections (Ermolieva *et al* 2018, Estrada *et al* 2020). Moreover, the results may be useful for policymakers interested in applying timely climate policies to prevent potentially large economic shocks due to climate change.

2. Methodology and data

The methodology of ToEI of climate change proposed in this paper focuses on identifying the *first year* in which future (climate) impacts will exceed historical economic shocks. Historical shocks may have been caused by non-climatic reasons. Irrespective of their cause, the severity of the economic impacts of such shocks matters for social welfare, and it is those economic impacts as a percentage of GDP that we use as a threshold for comparison with future climate impacts. Once this threshold has been crossed, the change is permanent unless temperatures decline in the long run—for example, due to stringent climate policy measures.

The procedure for estimating the ToEI of climate change is illustrated in figure 1. In short, climate

[5] Only the original impact functions from the DICE and RICE models are used in this study, rather than the entire IAM framework.

[6] SI 3.

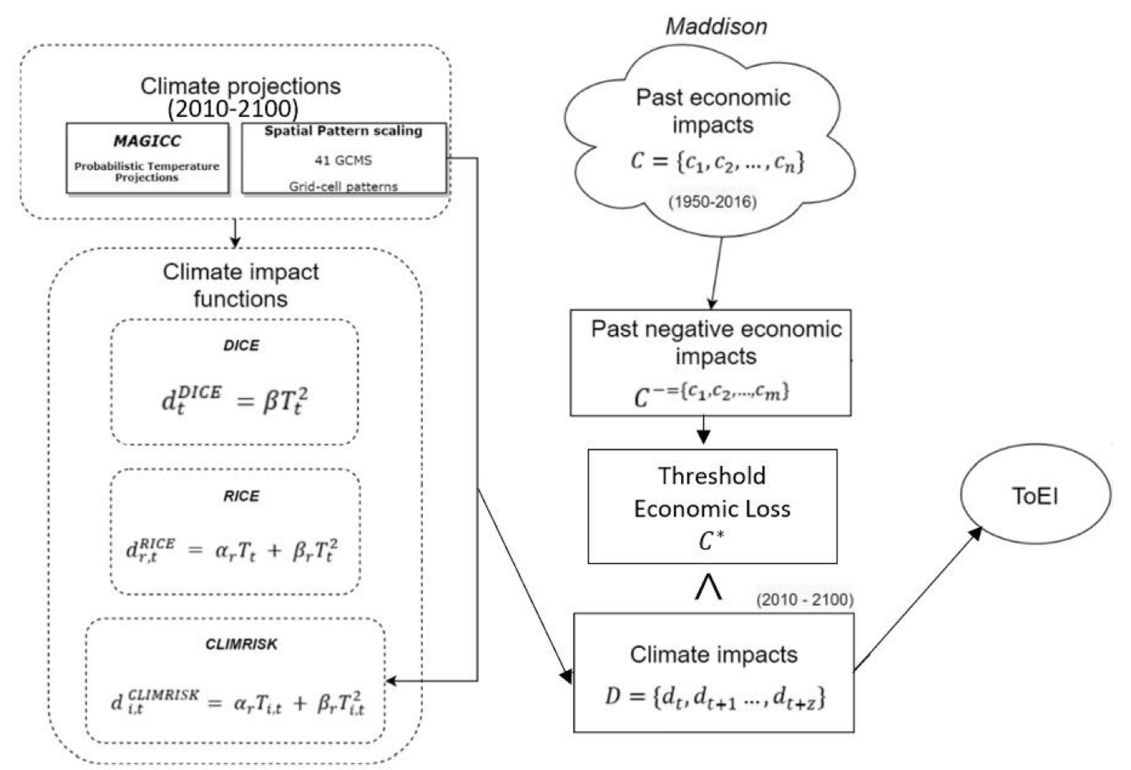

Figure 1. Flow diagram for estimating the ToEI of climate change using DICE, RICE and CLIMRISK models.

inputs (e.g. temperature) are fed into the impact function of choice in order to compute future climate impacts. Next, time-series filters are used to extract negative variations around the trend of historical economic data. The empirical distribution of these shocks is compared to the projected future impacts to determine the ToEI. The full details of the various components of the ToEI calculation summarized here are presented in the supplementary information (SI) (available online at stacks.iop.org/ERL/16/074039/mmedia).

The ToEI calculation can be performed in the following way. Let X denote the logarithms of an economic time series, which in our application is economic output sample size n[7]:

$$X = \{x_1, x_2, \ldots, x_n\}. \tag{1}$$

Vector X can contain a single time series (e.g. global GDP) or can have a panel structure representing time series of economic output for different geographic locations. We collected the annual economic time series of output data (constant GDP) from the Maddison Project database (Bolt, Inklaar, de Jong & Luiten van Zanden, 2018). The latest version of this database (2018) covers 169 countries[8]. For most countries, the Maddison Project database covers a period of 67 years of modern historical GDP variability for the computation of the ToEI.

The past economic output time series X can be decomposed into a trend component (τ) and a cyclical component (c). For each country in year n, we have

$$x_n = \tau_n + c_n. \tag{2}$$

A variety of filters common in macroeconomic analysis of business cycles can be used for trend-cycle decomposition (Mills 2003). Examples of these filters include Hodrick-Prescott (HP; Hodrick and Prescott 1997), Christiano-Fitzgerald (CF; Christiano and Fitzgerald 2003), and Baxter King (BK; Baxter and King 1999). Care must be taken in parametrizing the functions of different filters to account for the length of business cycles and the frequency of time-series data (e.g. annual, semi-annual, monthly, etc.)[9]. The cyclical component constitutes a time series C with n time periods[10]:

$$C = \{c_1, c_2, \ldots, c_n\}, \tag{3}$$

where $C \subset \mathbb{R}$ (subset of real numbers).

[7] Economic output can refer to total, sectoral, firm-level, or other output.
[8] The lists of countries (SI table 11) and missing data (SI table 10) are presented in SI 4.
[9] SI 7.
[10] A detailed example of the calculation using three case study regions is presented in SI 4.1.

By isolating the negative values of the time series of the cyclical component, the set of past negative output deviations from the long-term trend can be constructed. We label this set of past economic shocks C^{-}, as it represents all historical negative shocks from economic, climate and a wide variety of other sources:

$$C^{-} = \{c_1, c_2, \ldots, c_m\}, \tag{4}$$

where $C^{-} \subset \mathbb{R}^{-}$ (subset of real negative numbers).

The set of shocks estimated for any given country is stored as a vector of values that can be compared against a user-defined shock threshold. We calculate the economic shocks between 1950 and 2016 per country, per region, and for the world.

Next, the time-series estimates of future impacts, defined as D, are required for comparison against past shocks. The units of future impact estimates D must correspond to the units used in C and C^{-}, as they are directly compared in equation (7). We express both historical shocks and future climate impacts as a percentage of GDP, because such historically severe percentage of GDP shocks are also likely to be severe in the future, even if society were to become richer[11].

$$D = \{d_t, d_{t+1} \ldots, d_{t+z}\} \tag{5}$$

where t and $t+z$ are the first and last years for which the projections are available and $t > n$, implying that the first year of impact projections must be after the last year of past observed impacts.

The ToEI is estimated by comparing the distribution of past economic shocks with the projected climate impacts generated by some impact function:

$$\text{ToEI} = t - 1 + \sum_{i=0}^{z} b_i \tag{6}$$

where b_i is a Boolean variable for year i indicating whether the impact projections have exceeded a predetermined shock threshold. Formally, it is defined as follows:

$$b_i = \begin{cases} 0 & \text{for } d_t \geqslant c^{*} \\ 1 & \text{for } d_t < c^{*} \end{cases} \tag{7}$$

where c^{*} represents a percentile value from the set C^{-}[12]. In this paper, two threshold values are chosen to illustrate the methodology: the 75th and 95th percentiles of past economic shocks. These percentile values are commonly used in uncertainty and risk analyses and cover a broad range of results.

We illustrate the concept of ToEI on various spatial scales by applying impact functions from three IAMs that estimate the same climate change impact categories, namely losses to major economic sectors such as agriculture, the costs of sea-level rise, adverse impacts on health, non-market impacts, and catastrophic impacts (see SI 1, 2, 3). First, we determine the extreme output shocks for the world as a whole and draw comparisons with the model using the DICE impact function for climate change-induced impact projections to calculate the global ToEI values[13]. For this, we use the standard DICE model impact function, which estimates damages due to climate change based on global average temperature rise and global GDP. Next, we divide the world into 12 regions corresponding to those in the RICE model, which is the regional version of DICE[14]. We then compute the regional ToEI estimates for the RICE model impact functions that are based on global average temperature rise (Nordhaus 2017). Lastly, we use the recently developed CLIMRISK model to compute grid-cell level ToEI estimates using pattern-scale temperature change projections.

CLIMRISK is a global model that assesses the dynamic economic impacts of climate change at the local scale (0.5° × 0.5°) for various socioeconomic and climate change projections. This is done by combining local GDP exposure information (Grübler *et al* 2007) with annual global temperature projections obtained using the MAGICC climate model and scaling patterns from the climate models included in the CMIP5 (Kravitz *et al* 2017, Lynch *et al* 2017). The CLIMRISK impact module encompasses a broad range of economic sectors and assumptions about impact dynamics, and makes a distinction between urban and non-urban areas by accounting for the urban heat island (UHI) effect (Estrada *et al* 2017). The result is a global, dynamic, IAM that projects climate impacts on a local, regional and global scale (Estrada and Botzen 2021, Ignjacevic *et al* 2020)[15]. Detailed descriptions of each model and impact function parameters are presented in SI.1 (DICE), SI.2 (RICE), and SI.3 (CLIMRISK).

[11] The reason is a similar % GDP shock would result in higher absolute GDP losses when future GDP levels are higher.

[12] There exist two special cases, where $\sum_{i=0}^{z} b_i = z$ (i.e. all values of $b_i = 1$) and $\sum_{i=0}^{z} b_i = 0$ (i.e. all values of $b_i = 0$). The first case implies that the ToEI was never reached within the specified horizon, and ToEI $> t+z-1$. In the latter case, the ToEI is exceeded in the first period of evaluation or before, and ToEI $< t$. In this paper, $t = 2010$, $z = 91$, meaning that we are evaluating the ToEI between 2010 and 2100.

[13] SI 1.

[14] SI 2.

[15] SI 3.

Table 1. ToEI of climate change for the DICE model impact function under various RCP scenarios and historical shock thresholds; HP filter.

DICE global	ToEI 75th	ToEI 95th
RCP 4.5	2059	2095
RCP 8.5	2044	2062

3. Results

The ToEI of climate change can be computed for any climate-economy IAM using the method proposed in this paper. We first present the ToEI results for the well-established DICE and RICE impact functions before proceeding to the local-scale CLIMRISK impact function, with an added focus on results for urban areas. Although the scale of the results is different across the three models, the impact functions are consistent and can be readily compared with one another. However, the CLIMRISK model takes advantage of local scale temperature and economic output projections and takes the UHI effect into account.

The results are available for various Representative Concentration Pathways (RCPs; Moss *et al* 2010). To illustrate the advantages of climate change mitigation, the results are presented for the RCP 4.5 and RCP 8.5 scenarios, which can be interpreted as an emission scenario consistent with full compliance with the global mitigation effort described in the current nationally determined contributions and a high-emission scenario with no climate policy, respectively[16].

Although we focus on results generated using the HP filter, SI 6.4 presents a sensitivity analysis using other filters. The results are presented for two different historical impact thresholds, the 75th and 95th percentiles. Although both represent high historical impacts, the proposed methodology can produce results for any other percentile calculated from the past negative shock distribution.

3.1. DICE model impact function

Whereas the climate impacts under the RCP 2.6 would not exceed past extreme output shocks (95th percentile), under the RCP 4.5, they would do so by 2095, and, under the RCP 8.5, by 2062 (table 1). A lower shock threshold (75th percentile) is exceeded some decades earlier, including for the RCP 4.5 scenario. This is because at this threshold, future climate impacts are compared with smaller past output shocks when estimating the ToEI. In summary, the DICE results demonstrate that at a global level, the ToEI occurs between years 2044 (75th shock percentile) and 2062 (95th shock percentile) in a scenario without climate policy (RCP 8.5). The dates for ToEI can be significantly delayed by adopting moderate (RCP 4.5) or more ambitious climate change mitigation strategies. In other words, mitigation can buy valuable time to adapt to severe climate change. Since this example relies on the global DICE impact function, no location-specific information can be extracted about where and when such severe effects might occur.

3.2. RICE model impact functions

Table 2 presents the estimates of ToEI under the RCP 4.5 and RCP 8.5 scenarios for the 12 regional RICE model impact functions, in combination with the HP filter[17].

The results highlight that under the RCP 8.5 scenario, the RICE regions of Africa, India, and Western Europe are expected to experience climate impacts comparable to extreme economic shocks (95th percentile) that occurred in the past 50 years by the years 2085, 2083, and 2075, respectively. Highly developed regions, such as the US, Japan and other high-income countries, are expected to reach the ToEI threshold by 2098, 2087, and 2084, respectively. If a lower shock threshold (75th percentile) is used, then the ToEI occurs in the middle of the century in several regions and even earlier in Africa. Even on the coarse spatial scale of the RICE model, highly developed regions such as Western Europe, Japan, and the US are expected to exceed both thresholds (75th and 95th percentiles) during the current century under the high emission scenario (RCP 8.5) and in Western Europe possibly even under the moderate climate policy scenario (RCP 4.5). Nevertheless, the advantages of climate mitigation policies are evident once again, with no regions expecting a ToEI that corresponds to the 95th percentile impact threshold in the 21st century under the moderate mitigation scenario (RCP 4.5). Such moderate mitigation would provide many regions with several decades to adapt to extreme climate change impacts.

3.3. CLIMRISK model impact functions

The CLIMRISK model allows local-level socio-economic and climate data to be used to obtain more spatially detailed ToEI estimates (figure 2). In the case of the RCP 4.5 scenario, several areas within Africa and almost all grid cells in India have ToEI values before 2040 when the 75th percentile threshold is considered. By contrast, under the RCP 8.5 scenario, the occurrence of ToEI during the present century is widespread, including in most of Europe (around 2050–2060) and the US (2060–2070). When considering the 95th percentile threshold, most of the US and Europe have ToEI values occurring during the last two decades of this century, and most of India,

[16] For results using alternative climate scenarios, damage functions, and filters, please refer to SI 6.

[17] Shock values for all RICE regions are presented in SI table 3. For the full list of Maddison Project database countries belonging to each RICE region, see SI table 11.

Table 2. ToEI of climate change using the RICE model impact functions under various RCP scenarios and historical shock thresholds; HP filter. The gray areas represent cases where ToEI was not reached within the current century. Reprinted from [Ignjacevic, P. *et al*], Copyright (2020), with permission from Elsevier.

	RCP 8.5		RCP 4.5	
RICE region	ToEI 75th	ToEI 95th	ToEI 75th	ToEI 95th
United States	2082	2098		
Western Europe	2052	2075	2077	
Japan	2073	2087		
Russia	2086			
Eurasia[18]				
China[19]	2100			
India	2048	2083	2068	
Middle East	2064	2094	2096	
Africa	2042	2085	2053	
Latin America	2069	2100	2099	
Other High Income	2064	2084	2096	
Other Asia	2046	2083	2063	

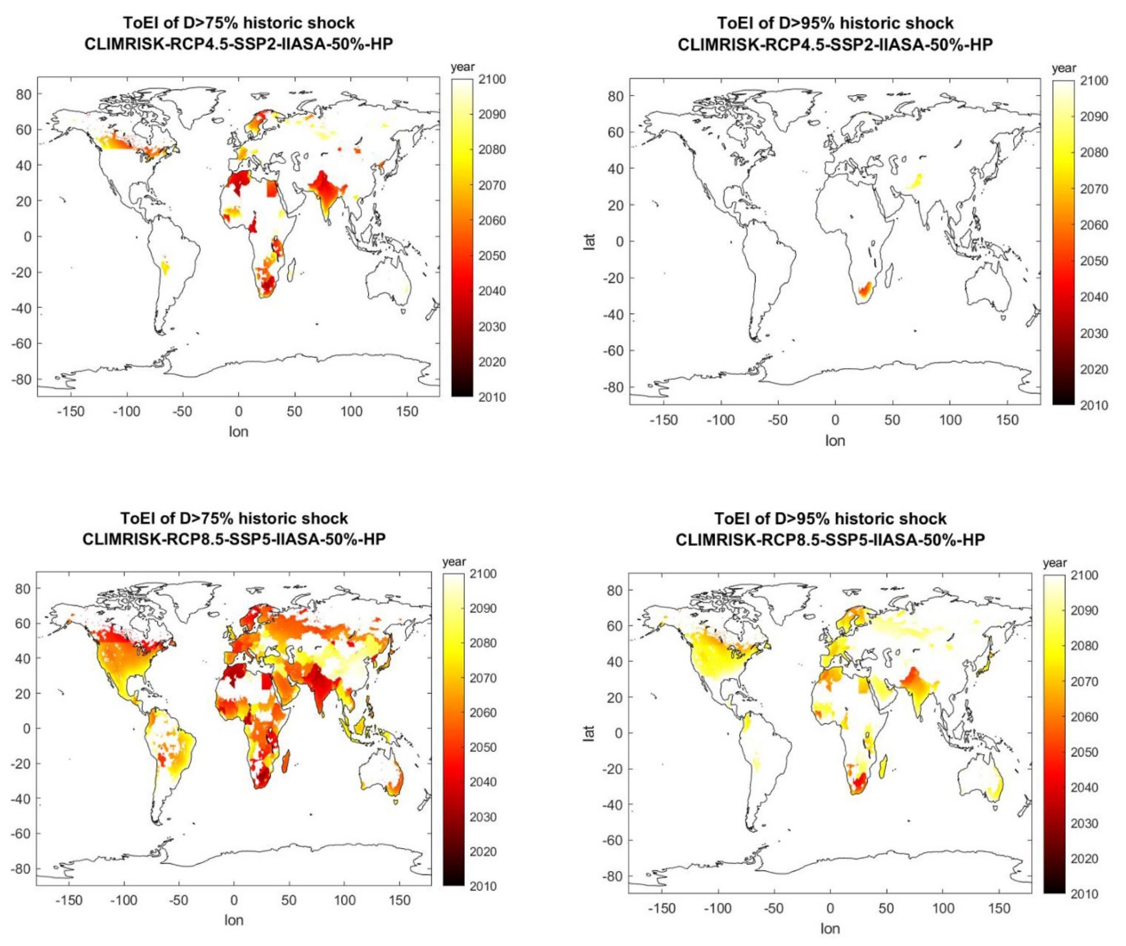

Figure 2. ToEI for the CLIMRISK model under the RCP 4.5 (top) and RCP 8.5 (bottom) scenarios for the 75th and 95th percentiles of shock threshold. HP Filter.

Southern Africa, and North Africa would exceed this threshold by mid-century.

3.4. Urban areas

One of the main advantages of CLIMRISK is the inclusion of the UHI effect in its temperature estimates and impact functions, which rely on the Shared

[18]The lack of ToEI in the Eurasian region in the 21st century can be explained by the relatively low sensitivity of the RICE damage function to increases in global temperature (SI table 2).

[19]The relatively high ToEI value in China could be attributed to the 1960s Great Chinese Famine, which had severe impacts on the economy and is regarded as one of the greatest man-made disasters in human history.

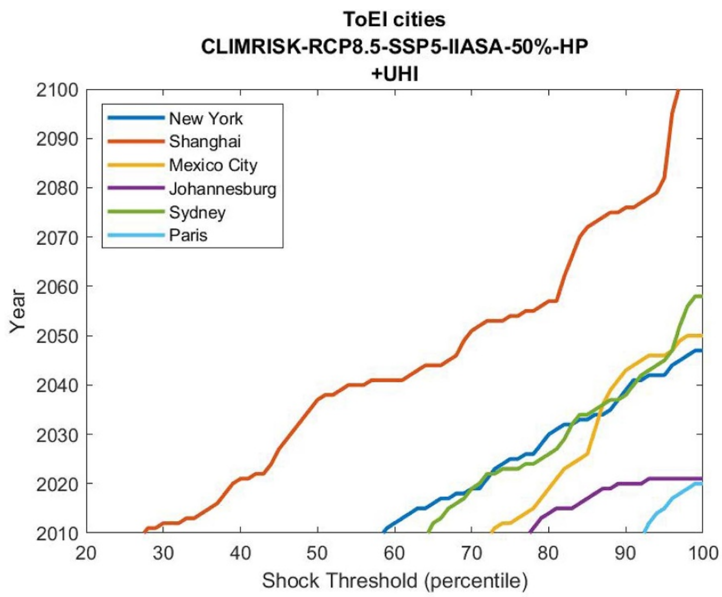

Figure 3. ToEI for selected cities for the median realization of temperature projections for the RCP 8.5—SSP5 scenario combination. HP Filter[21].

Socioeconomic Pathway (SSP) projections[20]. Due to the joint effect of global and local climate change at the city level, we can expect that in highly populated cells we refer to as city-cells, the ToEI would occur sooner than in rural areas. As we lack observed city-level data of historical economic output on a global scale, we assume that country-level economic shocks are to a large degree experienced by the city-cells in a given country.

Figure 3 presents ToEI estimates across various shock thresholds for selected global cities. The steepness of the line is inversely related to the level of risk: the steeper the line, the later the specific shock threshold is exceeded. For example, while Paris is expected to exceed the 95th percentile of its past economic shocks around 2020, Shanghai would expect its equivalent around 2080 under the RCP 8.5 and SSP5 scenario combination. The ability to observe such local-scale climate differences is only possible through the use of an IAM with a detailed spatial resolution, such as CLIMRISK.

4. Discussion

The ToEI is a flexible risk measure and can be adjusted to reflect the user's preferences and information needs. The user can set the emissions and socio-economic scenarios and the threshold of economic shocks, as well as choose from a variety of impact functions and select the time horizon over which climate impact shocks are assessed. Climate scenarios, impact functions, and damage thresholds are all adjustable parameters that form the climate risk uncertainty bounds. Although the purpose of our application of the ToEI to the impact functions of three IAMs was to illustrate that the concept can be applied at various scales, this does not necessarily mean it is equally useful at every scale. For example, there may be a mismatch between the location of historical economic shocks in a country or region and the location where severe future climate impacts occur[22]. One could argue the country scale is most suitable since the ToEI can inform climate change mitigation and adaptation policy decisions of national governments. Nevertheless, global results can inform international climate policy agreements, while city level results can inform city climate adaptation planning.

With the DICE model impact functions, global GDP data were used. These results demonstrate that the ToEI can be computed for the case of a single global annual impact, but information on local heterogeneity of impacts is lacking. Using spatially explicit impact functions allowed us to identify regions and countries in which the ToEI would occur relatively soon, meaning that such areas would experience greater climate change shocks relative to historical economic shocks. Particularly vulnerable regions are Africa, India, and Western Europe. Remarkably vulnerable countries in Africa are Algiers, Cameroon, Egypt, and the Republic of South Africa, while, in Europe, Sweden, Norway, and France are most

[20] These SSP population projection scenarios are explained in full detail in SI 3.3.

[21] See also SI figures 4 and 5 for results under various temperature realizations as a measure of climate uncertainty.

[22] This potential mismatch in scale may be less serious than one might initially expect since our results demonstrate that most climate impacts occur in cities in which most (past and future) GDP is earned.

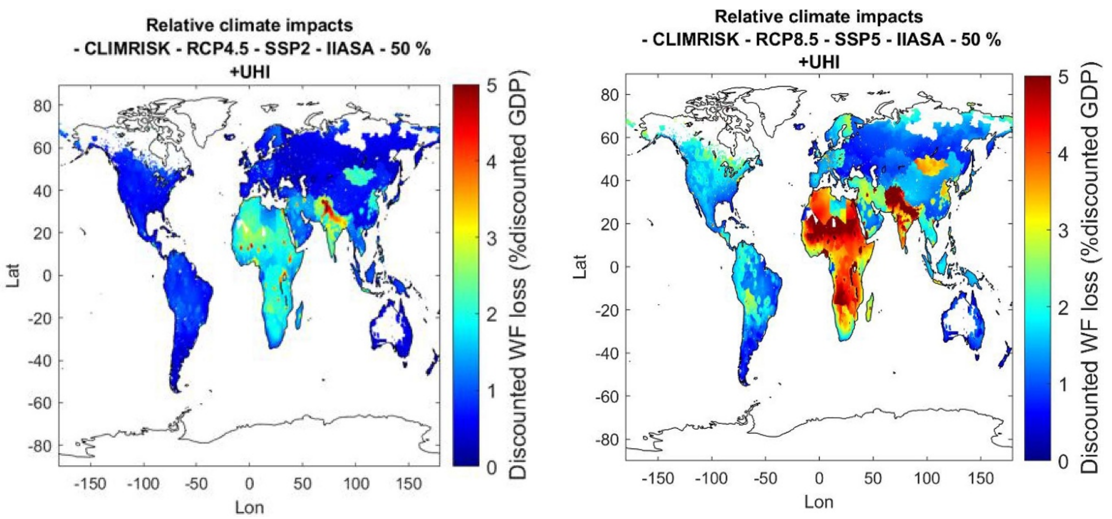

Figure 4. Relative climate impacts in the CLIMRISK model, expressed as percentage losses of GDP for the RCP 4.5—SSP2 and RCP 8.5—SSP5 scenario combinations.

vulnerable. These areas could be seen as hotspots of economic climate risk where the benefits of climate change adaptation and mitigation policies would be especially large. The new risk metric also helps to illustrate the effects of international mitigation efforts in delaying the worst economic impacts of climate change and the benefits of such measures in providing more time for adaption.

The ToEI results imply that economically stable, developed countries in Western Europe and the US could experience severe relative impacts of climate change, similar to those of some developing countries. This important implication can be derived from the ToEI methodology: the historical GDP impact threshold is lower for the regions with less severe past GDP shocks, making it more likely that future impacts will exceed this predetermined value. In other words, the ToEI is reached relatively early (late) in regions which experienced relatively small (large) GDP fluctuations in the past. This is an intentional design and serves as an alternative to more traditional impact monetization practices. For example, it is at odds with the notion that high levels of economic development make developed countries safer in the face of climate change. Figure 4 presents the results of climate change impacts that are expressed as percentage losses of GDP; by this traditional measure, low-income areas in Africa and India are expected to fare much worse than developed areas such as the US and Western Europe. We propose that developed countries may also be more likely to perceive the effects of climate change impacts as severe shocks to their economies, whereas developing countries may have more experience with political conflict and economic crises. Nevertheless, our finding that according to the ToEI metric, developed countries mainly in Europe are vulnerable to severe climate impacts does not mean that these risks are not high for several developing countries as well. For example, some regions in Africa and India experience the ToEI even sooner than Europe.

The significantly later occurrence of ToEI under the RCP 4.5 scenario suggests that even moderate climate mitigation can buy countries up to several decades of time to adapt to climate change. Moreover, abiding by climate policy consistent with the Paris Agreement can significantly delay ToEI occurrence to well beyond the 21st century[23].

However, many areas in the world are not expected to experience ToEI in the 21st century. This can be explained either by the high damage threshold to which future climate impacts are compared (large historical GDP shocks) or by relatively low climate impacts in a particular area[24].

4.1. Sensitivity analysis

The results of the ToEI model are dependent on the choice of the impact threshold. Relatively high values (>90th percentile) represent high historical impacts that are less likely to be exceeded by future climate change developments. The results appear robust across different socioeconomic scenarios, as past economic shocks are scenario-independent. An exception is the UHI effect, which depends on urban population, but ToEI results are not very sensitive to assumed SSPs (SI 6.2). The sensitivity analysis does indicate that the assumed damage function influences ToEI values, since accounting for persistence in impacts and the UHI implies ToEI values are experienced sooner, especially in developing countries (SI 6.3). Increasing the realized temperature

[23] SI figure 1.

[24] This also implies a low PoEI value, as the probability of any given run exceeding the threshold is low.

leads to an earlier ToEI across all cells (SI 6.1). However, this finding does not affect the main conclusion of this paper about the distribution of ToEI across cells.

The sensitivity of the results to climate is further illustrated through the probability of emergence of impacts (PoEI) metric, which is based on the number of times each cell's climate impact estimate exceeds the previously defined extreme threshold in 500 temperature realizations used to sample climate uncertainty. The PoEI is 100% under RCP 8.5, but is reduced to 26% under RCP 4.5 and approximates zero under the significant emission reductions projected under the RCP 2.6 scenario (95th shock percentile; SI 6.6).

4.2. Limitations

Limitations and the usefulness of IAM impact functions are widely discussed in literature (Ackerman *et al* 2009, Van Den Bergh and Botzen 2015, Tol 2018). Here we highlight three main limitations in our study. First, it has been argued that the IAM impact function specifications may be incomplete in capturing the relationship between temperature and economic impacts due to missing cost categories (Stern 2013). Second, there is aggregation of hazard and exposure across time and space making it difficult to isolate the effects of extreme climate events or economic impacts on a particular industry (e.g. agriculture). Third, the past economic shock data we used in estimating the ToEI is on a country-level, which reduces the accuracy of local-scale ToEI estimates in the CLIMRISK model. Our study is a first attempt to illustrate the ToEI concept. Our approach for estimating the ToEI compared future climate impacts with historical GDP shocks from any cause (including climate and non-climate events). This was done on purpose because it places future climate impacts in the context of experienced historical GDP fluctuations, including extreme economic shocks such as the 2008 financial crisis.

It should be noted that comparing projected climate impacts to historical GDP shocks alone could represent an overly reductionistic approach to estimate the future ToEI. For example, such thresholds do not fully account for climate adaptation and economic development which can be expected to be very different in the future. Nevertheless, we hope that the ToEI measure we presented in this manuscript represents a solid first step in a growing body of literature on the TOI of climate change. Future research could apply this methodology to estimate the ToEI of future climate impacts exceeding historical GDP shocks caused by historical climate events alone. Comprehensive ToEI assessment could be conducted for the entire economy or any sector, such as agriculture and using updated thresholds that account for economic development and adaptation levels.

5. Conclusion

IAMs of climate change tend to express negative impacts of climate as an absolute value or as a fraction of lost economic output, usually GDP. However, this approach does not place climate impacts in the context of past economic shocks, which would measure the severity of impacts on the economy relative to those experienced before. We have introduced ToEI as a novel risk measure that can be applied to various impact studies and integrated assessment and sectoral models that form future impact projections. We apply this methodology to impact functions from three climate IAMs of varying resolution—DICE, RICE, and CLIMRISK—to determine the ToEI associated with various levels of climate policy.

The ToEI identifies the first year in which projected impacts exceed historically observed impacts. Using the methodology developed in this paper, users can define an impact threshold and calculate the ToEI for their specific applications.

Three key conclusions emerge from this paper concerning both the ToEI methodology in general and the ToEI of climate change. First, the methodology of ToEI can be applied to impact models of different spatial scales when sufficient past impact data are available, as demonstrated by the results presented above using impact functions from three IAMs of varying scales. The advantages of a local-scale IAM can be fully exploited through the ToEI methodology, such that regional and local impact heterogeneities emerge, as is the case with the CLIMRISK model.

Second, even though climate change is expected to affect low-income countries the most when losses are expressed using traditional impact measures (e.g. absolute output loss or fraction of annual output lost), developed countries in Europe could experience the ToEI in a way not much different from that of the developing countries. The impacts of climate change may be most negative in the highly developed cities around the world, where the ToEI may soon be exceeded. This conclusion is in line with the idea that relative impacts matter and that highly developed areas have not experienced such large negative economic shocks in the past 50 years.

Finally, moderate to stringent climate mitigation policy can significantly reduce the risk of ToEI occurrence, potentially 'buying' enough time for implementation of climate adaptation measures. The results presented here underline the importance of compliance with the Paris Agreement in order to seriously limit climate change risks, but they also demonstrate the important benefits that can result from intermediate mitigation efforts.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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