Assessing the economic impacts of future fluvial flooding in six countries under climate change and socio-economic development

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Abstract

Floods are among the most frequent and costliest natural hazards. Fluvial flood losses are expected to increase in the future, driven by population and economic growth in flood-prone areas, and exacerbated in many regions by effects of climate change on the hydrological cycle. Yet, studies assessing direct and indirect economic impacts of fluvial flooding in combination with climate change and socio-economic projections at a country level are rare. This study presents an integrated flood risk analysis framework to calculate total (direct and indirect) economic damages, with and without socio-economic development, under a range of warming levels from <1.5°C to 4°C in Brazil, China, India, Egypt, Ethiopia and Ghana. Direct damages are estimated by linking spatially explicit daily flood hazard data from the Catchment-based Macro-scale Floodplain (CaMa-Flood) model with country and sector specific depth-damage functions. These values input into an economic Input-Output model for the estimation of indirect losses. The study highlights that total fluvial flood losses are largest in China and India when expressed in absolute terms. When expressed as a share of national GDP Egypt faces the largest total losses under both the climate change and climate change plus socio-economic development experiments. The magnitude of indirect losses also increased significantly when socio-economic development was modelled. The study highlights the importance of including socio-economic development when estimating direct and indirect flood losses, as well as the role of recovery dynamics, essential to provide a more comprehensive picture of potential losses that will be important for decision makers.

Keywords

fluvial flooding, economic impacts, climate change, socio-economic development

1. Introduction

Floods are among the most frequent and costliest natural hazards. Globally, floods have affected more than 3.8 billion people and caused direct economic damages of ~826 billion US$ between 1960-2019 (EM-DAT 2020). Fluvial flooding accounts for two thirds of these direct economic damages (*ibid.*). The Intergovernmental Panel on Climate Change (IPCC) report that since the mid-20th century socio-economic losses from floods have been increasing, mainly due to greater exposure and vulnerability of affected populations (Jiménez Cisneros et al. 2014). The impacts of fluvial floods are expected to increase in the future, predominantly driven by population and economic growth in flood-prone areas (Jongman et al. 2012; Tanoue et al. 2016). The intensification of the global hydrological cycle due to climate change will further increase future flood risks (Alfieri et al. 2017), exacerbating flood damages and posing a threat to future generations. Therefore, it is imperative to assess fluvial flood risks under scenarios of climate change and socio-economic development, to support decision-making regarding flood risk management and adaptation strategies.

Past efforts have largely focused on estimating future populations exposed to fluvial flooding (e.g. Hirabayashi and Kanae 2009; Hirabayashi et al. 2013; Arnell and Lloyd-Hughes 2014) and the estimation of direct damages (usually to urban areas) (e.g. Winsemius et al. 2013, 2016; Ward et al. 2013, 2017; Alfieri et al. 2017), under different scenarios of climate change and/or socio-economic development. Direct flood damages are typically assessed by linking physical properties of the hazard such as flood depth and area; exposure, in terms of the location of assets or land-use type; and vulnerability, derived from depth-damage functions that denote the damage that would occur at a given flood depth for a given asset or land-use type. Floods can also cause indirect damages, including reduced business production of affected economic sectors; the spread of these losses towards other initially non-affected sectors through inter-sectoral linkages; and the costs of recovery processes (Koks and Thissen 2016). Indirect damages may continue to be felt after the flood event has ended, reflecting the full time dimension of the event, as well as negatively and positively affecting regions outside of the original event (Carrera et al. 2015). Due to these factors indirect losses can be high, or even exceed direct damages (Koks et al. 2015). The scale and duration of indirect losses will be dependent on the severity of the event, the pre-existing state of the economy, and the ability of individuals, businesses and markets to adapt and recover. Yet, in terms of flood risks, indirect impacts and their wider macro-economic effects are still poorly understood (Carrera et al. 2015), and detailed estimation of joint direct and indirect flood-induced economic impacts are relatively rare (Sieg et al. 2019).

Given the potential scale of indirect losses, it is important to consider them alongside direct damages to provide a more complete picture of the economic consequences of flood events (Koks et al. 2019). However, only a limited number of studies assess the total economic impacts of future fluvial flooding in combination with climate change and socio-economic projections. Dottori et al. (2018) carried out a global fluvial flood risk assessment by estimating human losses, and direct and indirect economic impacts under a range of temperature and socio-economic scenarios. However, they only considered welfare or consumption losses as a proxy of indirect impacts, ignoring changes in sectoral outputs. Willner et al. (2018) assessed the economic losses from climate change-related fluvial floods in the near future (2035), mainly in China, the US, and the European Union, but with fixed socio-economic conditions. Koks et al. (2019) evaluated the total economic consequences of future fluvial flooding at a sub-national scale for

Europe, including indirect impacts and regional economic interdependencies for five aggregated sector groups. However, the authors noted the relatively simple approach to estimate the initial reduction in production capacity following a flood, from which indirect damages were calculated. This was based on the value of exposed assets per sector divided by the total asset value for each sector, assuming each sector needed a certain stock of assets to produce outputs. Furthermore, the study excluded damages to residential buildings, which are a significant part of direct flood impacts.

In addition, flood risk analysis is usually performed at a global, continental or aggregated multi-country level. Single-country analysis is less common, particularly studies that consider both direct and indirect losses under future scenarios of climate change alongside scenarios of socio-economic development. This is particularly true for developing countries in Africa, Asia, and Latin America, where rapid growth in population and economic activities is forecast to take place, driving large increases in flood exposure and economic losses (Jongman et al. 2012; Dottori et al. 2018) (see SM1.1 for a review of literature on the six countries covered in this study). Where country level studies do exist they often focus on specific cities or river basins only and are disparate, using different climate models, levels of global warming, economic and population data etc., hindering comparison.

Lastly, existing flood risk projections do not always cover the plausible range of global warming, especially higher warming levels such as 3°C or above. Since the global mean temperature increase implied by countries' Nationally Determined Contributions (NDCs) under the Paris Agreement is estimated to be in the range of 2.7°C to 3.5°C by 2100 (Gütschow et al. 2018), it is important to examine a wide range of climate change impacts on flood risk. Likewise, an accurate understanding of the drivers of future fluvial flood risk is critical to help adopt effective risk reduction measures, but few studies have integrated both climate and socio-economic drivers (Muis et al. 2015; Winsemius et al. 2016). Winsemius et al. (2016) performed the first global fluvial flood risk assessment that separated the effects of climate change and socio-economic growth, but only estimated direct urban damages.

This study is novel in that it presents an integrated flood risk analysis focused on direct and indirect economic damages caused by floods, both with and without the inclusion of socio-economic development. A broad range of warming levels from <1.5°C to 4°C are considered. The framework is applied to six developing countries: Brazil, China, India, Egypt, Ethiopia and Ghana. This demonstrates the flexibility of the method to be applied to multiple countries, to facilitate regional comparison, and reflects a range of different climate impacts, geographies and levels of development.

2. Data and methods

2.1 Climate forcing and flood hazard data

The daily streamflow and flood inundation depth are simulated at 0.25° spatial resolution by using a physical model cascade, the Hydrologiska Byråns Vattenbalansavdelning (HBV) model and Catchment-based Macro-scale Floodplain (CaMa-Flood) model. The WATCH daily bias-adjusted reanalysis dataset (Weedon et al. 2014) for 1961-1990 was used as the climate forcing data for the baseline period (1961-1990). The climate forcing data for the future period (2086-2115) were generated by combining monthly observations, daily reanalysis data, and projected changes in climate from General Circulation Models (GCMs). The projected changes in climate for the specific warming levels considered here are <1.5°C, <2°C (which denote aiming to stay below 1.5°C and 2°C in 2100, respectively, with 66% probability), exactly 2.5°C, 3°C, 3.5°C and 4°C relative to pre-industrial levels (see Warren et al. (2020) of this special issue). To sample the uncertainty in regional climate change projections we use patterns of change simulated by five GCMs obtained from the Climate Model Intercomparison Project Phase 5 (CMIP5). A river discharge corresponding to a 1 in 100-year flood in the baseline period was selected as the hazard indicator, in line with several previous studies (e.g. Hirabayashi and Kanae 2009; Hirabayashi et al. 2013; Arnell and Lloyd-Hughes 2014; Arnell and Gosling 2016). Whilst adaptation is not modelled, the 1 in 100-year event is often used as a hazard indicator given flood protection works are often designed for this return period (with some exceptions e.g. the Netherlands). The time series of the simulated annual maximum daily river discharge in the baseline period for each grid, GCM and scenario were fitted respectively to a Gumbel distribution function using the maximum likelihood method. The magnitude of river discharge having a 100-year return period in the baseline was then calculated. The economic risks associated with the projected changes in flood hazard were calculated in the modelled inundation areas in which annual maximum discharge in the future period exceeds the baseline 1 in 100-year threshold. Details of climate forcing and flood hazard data used in this study are described in He et al. (2020) of this special issue.

2.2 Model experiment design

Projected changes in average annual economic damages for the future period (2086-2115) are compared to the baseline period (1961-1990). Two sets of model experiments are conducted: a “climate change only” experiment (CC), in which socio-economic conditions are kept constant at the baseline level for the six warming scenarios; and a “climate change and socio-economic development” experiment (CC+SE), which considers both climate change and socio-economic growth in parallel. The differences between the estimates can reflect the effect of socio-economic development alone on future flood risks. Here, socio-economic development refers to each country’s population, labour force, gross domestic product (GDP) and capital stock. The socio-economic data used to calculate the direct and indirect losses for both the baseline and future scenarios are described below.

2.3 Direct damages

For each flood event direct damages are calculated for agricultural, residential, commercial and industrial land-use sectors by linking the simulated flood depth and area with country and sector specific depth-damage functions and maximum damage values from Huizinga et al. (2017) and land cover maps from the European Space Agency Climate Change Initiative (ESA CCI) land cover product at 10-arcsec resolution (ESA 2017). The depth-damage functions provide estimates of the fractional damage (damage as a percentage of the associated maximum damage value) for a given flood depth per land-use class. Since it is difficult to establish depth-damage functions for the future, this study uses the same set of functions for both the baseline and future periods as in other studies (e.g. Alfieri et al. 2017; Dottori et al. 2018).

The land cover map from 1992, the earliest year available in the ESA CCI's product, is used for the baseline period and the map of 2015 for the future period, assuming a constant land cover after 2015. Employing two sets of land cover maps from the same data source means they are produced with the same approach and ensures consistency between estimates. Using different years can also account for the effect of land cover change, especially urban expansion, in the real world. This is beneficial as many studies do not allow for urban expansion (e.g. Rojas et al. 2013; Winsemius et al. 2013, 2016; Ward et al. 2017), which will be a key driver of increased future flood risks (Muis et al. 2015).

For the agricultural land-use sector, the cropland area is obtained directly from the ESA CCI land cover maps, then aggregated at the resolution of the flood hazard maps (0.25°). However, the global land cover data represents urban land as a single class and does not differentiate between residential, commercial, and industrial sectors. Therefore, the urban land class is disaggregated into these three sub-classes. In terms of the occupation of residential, commercial and industrial urban land-use sectors in cities, several previous studies assume uniform percentages across the globe (e.g. Dottori et al. 2018), ignoring differences between individual countries. Huizinga et al. (2017) suggest that the percentages that commerce and industry contribute to national GDP could be used to downscale the single urban land class. However, the contribution of a sector to national GDP does not necessarily relate to the land surface it occupies. In this case, the population in a sector would be more relevant to the occupied land area. Therefore, in this study the residential population and employment in commercial and industrial sectors are used as proxies to downscale the single urban land class. It is assumed that the percentages of occupation of each sector within cities are equivalent to those of the population in each sector. Population data from the World Bank World Development Indicators are used (World Bank 2019). To be consistent with the land cover maps, population data from 1992 and 2015 per country are used to calculate the country-specific percentages for the baseline and future scenarios respectively. Lastly, the estimated direct economic damages per sector are aggregated at a country level for estimating the indirect losses. All economic damages are expressed in 2010 US$ values.

2.4 Indirect damages

The method for estimating indirect damage from fluvial floods is based on the existing Flood Footprint model presented in Mendoza-Tinoco et al. (2020). The Flood Footprint model draws on the Adaptive Regional Input-Output (ARIO) model (Hallegatte 2008), a widely used model to calculate indirect economic impacts of disaster events. Other methods, such as Computable General Equilibrium (CGE) models (e.g. Rose and Liao 2005), are also used in this field. While CGE models are good at reflecting the inter-industry links, they require many parameters to be calibrated and tend to be overly optimistic about market flexibility (Carrera et al. 2015; Kajitani and Tatano 2017). In contrast, Input-Output models not only include sectoral interdependence, but also maintain a level of simplicity which makes them popular in indirect economic impact evaluation of disaster events (Okuyama and Santos 2014; Koks et al. 2016), and permits easy integration with external models and data (Galbusera and Giannopoulos 2018). For further review of recent modelling approaches focused on the indirect damage from fluvial floods see Mendoza-Tinoco et al. (2020).

Below we present an overview of the key model components and the modelling process regarding the CC+SE experiment. For a full description of the model please see SM1.2 and Mendoza-Tinoco et al. (2020).

The Flood Footprint model is run at a monthly time-step. The economy is initially in equilibrium, with total supply and demand balanced as follows[1]:

$$x_i^0 + im_i^0 = \sum_{j=1}^{n} a_{i,j} * x_j^0 + fd_i^0 \tag{1}$$

$$fd_i^0 = hc_i^0 + gc_i^0 + inv_i^0 + ex_i^0 \tag{2}$$

Where x_i^0, im_i^0 and fd_i^0 are output, imports and final demand of products in sector *i* in the pre-flood equilibrium (month before flooding $t = 0$). $a_{i,j}$ reflects the *i*th row and *j*th column element of the input coefficient matrix derived from the IOTs, reflecting the intermediate demand for product *i* required to produce one unit of product *j*. *n* represents the number of industrial sectors. Thus, the left-hand side of equation 1 represents the total supply of product *i*, while the right-hand side denotes its total demand.

Final demand consists of: 1) household consumption (hc_i^0), divided into basic demand (bd_i^0) and other consumption (ohc_i^0): $hc_i^0 = bd_i^0 + ohc_i^0$; 2) governmental expenditure (gc_i^0); 3) fixed capital formation or investment (inv_i^0); and 4) exports (ex_i^0).

Following a flood event supply and demand become imbalanced and the economy is no longer in equilibrium. On the supply side, direct flood damage to industrial capital and labour reduce the production capacity of affected sectors. Equations 3 and 4 show the industrial capital available for production in each month following flooding.

$$\alpha_i^t = \frac{\Delta k_i^t}{k_i^t} \tag{3}$$

$$k_i^t = (1-\alpha_i^t) * (k_i^{t-1} + \sum_j ra_{j,i}^{t-1}) \tag{4}$$

Here α_i^t is the proportion of damaged capital in sector *i* during month *t* and Δk_i^t is the direct damage to the capital stock (as estimated in section 2.3). k_i^t is the available capital of sector i at the beginning of month t. Available capital is defined as the remaining capital following a flood plus any recovered

[1] In this paper, we use bold capital letters to represent matrices (e.g. $\mathbf{I}$ and $\mathbf{A}$), italic bold lowercase letters for vectors (e.g. $\boldsymbol{x}$), and italic lowercase letters for scalars (e.g. n). Vectors are column vectors by default, and the transposition is denoted by an apostrophe (e.g. $\boldsymbol{x}'$). The conversion from a vector to a diagonal matrix is expressed as italic bold lowercase letters with a circumflex (e.g. $\hat{\boldsymbol{\alpha}}$).

capital during the previous month. ra_{ji}^t is the element of an $n*n$ recovery matrix $\mathbf{RA}^t$, which denotes the investment from sector *j* to restore capital in sector *i* in month *t*.

Capital production capacity, xk_i^t, is assumed proportional to available capital, k_i^t, in each month, relative to the pre-flood level:

$$xk_i^t = {k_i^t}/{k_i^0} * x_i^0 \tag{5}$$

Damaged physical capital includes industrial and residential capital. Available residential capital is calculated in the same manner as industrial capital above, but has no effect on production capacity as it is not involved in the production process[2]. Similarly, labour availability, l^t, can change in the aftermath of a flood reflecting casualties and transport disruptions which may delay or impede travel to work. In the model it is assumed that labour can flow freely across different industrial sectors, so that during each month the labour production capacity, xl_i^t, in each sector experiences the same percentage change as the total labour supply (a full description of labour availability and its recovery parameters are provided in the SM 1.2).

The available production capacity of sector *i* in month *t*, $xcap_i^t$, is determined by the minimum capacity of labour and capital in that month, where 'min' is the minimum value between xk_i^t and xl_i^t:

$$xcap_i^t = \min(xk_i^t, xl_i^t) \tag{6}$$

The importing capacity, $imcap_i^t$, is assumed to be constrained by the surviving capacity of the transport sector, $xcap_{tran}^t$. If the remaining capacity of the transport sector '*tran'* declines by $x\%$ in month t, then the imports will contract by the same percent relative to the pre-flood level, im_i^0.

$$imcap_i^t = \frac{xcap_{tran}^t}{x_{tran}^0} * im_i^0 \tag{7}$$

Demand fluctuations are also incorporated in the Flood Footprint model. A new type of final demand arises due to the need for reconstruction and replacement of damaged physical capital, including industrial and residential capital. For example, $rd_{i,j}^t$ is the element of an $n*n$ reconstruction demand matrix $\mathbf{RD}^t$, which denotes the investment that is needed for sector i to support the capital reconstruction of industrial sector j:

[2] Although damage to residential capital can have indirect effects on the production process as its recovery results in a non-negligible part of the total reconstruction demand, competing with industrial capital for reconstruction resources.

$$rd_{i,j}^{t} = \max\left\{\left[(1+r_s)*k_j^{t-1} - k_j^t - \sum_{m=1}^{t-1} rasto_j^m\right]*d_i, 0\right\} \tag{8}$$

Where 'max' is the maximum, r_s is the targeted growth rate of capital stock, and $\sum_{m=1}^{t-1} rasto_j^m$ is the accumulative capital under construction before month t. Capital under construction does not contribute to a productivity increase until it is fully recovered. Therefore, the demand for capital reconstruction in sector j reflects the gap between the capital target, $(1+r_s)*k_j^{t-1}$ and the actual amount of capital minus the capital already under construction. Such demand is allocated to sector i according to the contribution of that sector to capital reconstruction, which defines d_i. Reconstruction demand of the residential sector, $rd_{i,res}^{t}$, is defined in the same way.

Furthermore, strategic adaptive behaviour in the aftermath of floods can also drive people to ensure a continued consumption of basic commodities, such as food, clothes and medical services (Mendoza-Tinoco et al., 2017). The coexistence of reconstruction and basic demand delimits the boundary of final demand in the model (see SM 1.2 for further details).

Given disruptions to both the supply and demand sides, industrial sectors choose their optimal production, $x_i^{t,*}$, and imports, $im_i^{t,*}$, under production, import and consumption constraints, to maximize the total economic supply each month during the post-flood recovery. This in turn determines the amount of final demand, $fd_i^{t,*}$, that could be satisfied:

$$fd_i^{t,*} = x_i^{t,*} + im_i^{t,*} - \sum_j a_{i,j} * x_i^{t,*} \tag{9}$$

The remaining final products, after satisfying the basic demand, are then proportionally allocated to the reconstruction demand and other categories of final demand. Capital is recovered through reconstruction, while labour is recovered exogenously (see SM 1.2 for further details). This iterative process continues until the total supply and demand of the economy are in equilibrium and the economic output recovers to the targeted growth trajectory.

Total indirect economic damage is calculated as the loss of monthly GDP compared to its potential:

$$va_i^{t,*} = x_i^{t,*} - \sum_{j=1}^{n} a_{j,i} * x_i^{t,*} \tag{10}$$

$$IndirectDamage = \sum_t \left[\left(1+r_g\right)^t * \sum_{i=1}^{n} va_i^0 - \sum_{i=1}^{n} va_i^{t,*}\right] \tag{11}$$

Here $va_i^{t,*}$ refers to the value added of sector *i* in month *t*, which is the extra value of final products created above intermediate input. Summation of value added in all sectors, $\sum_{i=1}^{n} va_i^{t,*}$, constitutes the national GDP for month t, where r_g is the targeted growth rate of national GDP. The total indirect damage is the accumulative losses of GDP over all months. This reflects the method for the CC+SE experiment, whereby the economy can recover to a target level above the pre-flood level, based on the exogenous growth trajectory. However, in the CC only experiment economic recovery is constrained to the pre-flood level. Constraints on physical capital, labour, output and imports are set so that they cannot grow larger than the pre-flood level. In this case r_g is set to zero, which indicates no economic growth.

Economic data used for the indirect damage estimation includes information on national Input-Output tables (IOTs), GDP, capital stock and labour force (see SM Table S1 for an overview of data used to calculate the flood-induced indirect damages in the baseline and future periods for the CC and CC+SE experiments). For each of the countries IOTs are obtained from their national statistical websites, providing information on intermediate demand, final demand, value-added, output, imports and exports at the country level. For each country, the earliest version IOT available is used to approximate the economy during the baseline period. For the CC experiment, the same IOT is used for both the baseline and future periods. Under the CC+SE experiment the economic structure is assumed to vary in the future. This variance is represented by using the same IOT as used in the CC only experiment in the baseline but the most recent version of the IOT available for each country in the future period (see SM Table S2 for country specific details on the IOTs used). This, to some extent, reflects the structural change from the baseline economy to the future one, given difficulties in projecting IOTs for 2100. The IOTs also provide data on the sectors involved in capital reconstruction from the investment column contained in the final demand block. The share of each sector investing in fixed capital formation indicates its contribution to the reconstruction process, namely the values of d_i. The annual IOT data is lastly divided by twelve to represent a monthly value.

Industry data from the IOTs are aggregated to ten sector groups per country: Agriculture (AGR), Mining (MIN), Food Manufacturing (FDM), Other Manufacturing (OTM), Utilities (UTL), Construction (CON), Trade (TRA), Transport (TRA), Public services (PUB) and Other Services (OTS) (see also SM Table S2). Where sectoral-level data is not available, such as for capital stock, it is disaggregated to the ten sector groups based on their proportional contribution to national GDP.

In line with the direct damage estimation, data on GDP, population and labour force are derived from the World Bank World Development Indicators (World Bank 2019). Data on capital stock is from the Investment and Capital Stock (ICSD) dataset from the IMF (IMF 2015). Capital stock is divided into industrial and residential capital based on land use from the land cover maps (ESA 2017). Under the CC experiment data on GDP, population, labour force, and capital stock are set as constant to restrict any socio-economic change. In the CC+SE experiment these data are dynamic. For the baseline scenarios this reflects reported trends in data from 1961-1990. For the warming scenarios, trends in data are based on the SSP2 projections whereby social, economic, and technological trends do not shift markedly from historical patterns (Riahi et al. 2017).

The shock of the flood event is represented by data on physical damage to capital assets (section 2.3) and labour loss. While the same depth-damage functions are used for the estimation of direct losses for both baseline and future periods, the calculated direct damages are scaled prior to use in the I-O model, based on the baseline and projected GDP per capita, according to the power law functions provided by Huizinga et al. (2017). Exponents in the power law functions are smaller than one, indicating that direct damage is not proportional to GDP per capita and grows slower than GDP per capita. The scaled damage is disaggregated into specific industrial sectors in proportion to their capital stock.

Population exposure to fluvial flooding for each country is provided by He et al. (2020) of this special issue. Affected labour is derived by multiplying the exposed population by the labour participation rate, from the World Bank (World Bank, 2019). The number of affected employees during each flood are divided into four categories: the dead, the heavily injured, the slightly injured, and others affected by flood-induced traffic disruptions. The ratios between these categories are determined based on the historical average of recorded floods for each country from the EM-DAT Dataset (EM-DAT 2020). This data feeds into the labour calculations in the I-O model (described in SM 1.2).

3. Results

3.1 Direct and indirect fluvial flood damages

Figure 1 presents estimates of direct and indirect economic damage for each country and climate scenario, under the CC and CC+SE experiments (results are plotted on the same axis to compare risk, see SM Figs S1 and S2 for results plotted on separate axis per country for more detail). The results reflect the underlying data provided from the flood hazard model, highlighting increasing economic damages, above the baseline, in line with the increasing warming scenarios. For Egypt, the largest increases in average damage occur up to scenario 3: 2.5°C, after which damages continue to increase albeit at a smaller rate. This reflects the findings of He et al (2020), who note that the proportional area of the Nile River Basin that experiences a decrease in the return period of a 1 in 100-year event (increase in flood frequency) changes little from scenario 1: <1.5°C to 6: 4°C.

Under the CC experiment, direct damages under scenario 1: <1.5°C are 399 (+95%, relative to baseline, Brazil), 1,713 (+80%, China), 427 (+13,783%, Egypt), 54 (+341%, Ethiopia), 11 (+255%, Ghana) and 719 (+435%, India) million US$ per year. Direct damages increase to 4,267 (+1,979%, relative to baseline, Brazil), 5,759 (+506%, China), 1,495 (+48,508%, Egypt), 147 (+1,108%, Ethiopia), 79 (+2,401%, Ghana), and 7,888 (+5,767%, India) million US$ per year under scenario 6: 4°C. The indirect damages, though much lower than direct damages, display similar trends (Figure 1). The Economic Amplification Ratio (EAR), defined as the ratio of total costs to direct costs (Hallegatte et al. 2007), is relatively constant across the warming scenarios for each country. As an average across the warming scenarios the EAR is 1.23 (Brazil), 1.15 (China), 1.61 (Egypt), 1.36 (Ethiopia), 1.22 (Ghana) and 1.26 (India).

Under the CC+SE experiment the magnitude of direct damage increases significantly for all countries, reflecting the increasing population and economic assets at risk. Under scenario 1: <1.5°C direct damages range from 0.13 billion US$ per year (Ghana) to 42 billion US$ per year (China). Losses increase to 1.12 billion US$ per year (Ghana) and 129 billion US$ per year (China) under scenario 6: 4°C. The magnitude of indirect damages not only increase but also surpass the direct damages (Figure 1). Indirect losses range from 1.7 billion US$ per year (Ghana) to 51 billion US$ per year (China) under scenario 1: <1.5°C, increasing to 12 billion US$ per year (Ghana) and 256 billion US$ per year (China) under scenario 6: 4°C. As an average across the warming scenarios the EAR increases to 10.97 (Brazil), 2.36 (China), 16.21 (Egypt), 12.05 (Ethiopia), 12.94 (Ghana) and 6.62 (India).

The increase in direct damage under the CC+SE experiment reflects the steady growth in capital stock, population and GDP under the SSP2 trajectories, resulting in larger flood exposure in the future period compared to the baseline. Indirect losses are significantly larger than direct losses as indirect losses in the CC+SE experiment accumulate over time and reflect the potential for a continuous slowdown in economic growth from the projected growth trajectory if no floods occurred. In other words, the indirect flood damages presented here do not only result in a short-term impact on economic output, but have the potential to restrict longer-term economic growth (discussed further in section 3.4, Figures 4 and 5). Thus, the inclusion of socio-economic development results in large increases in total losses when compared to the equivalent CC experiment run; for example, under scenario 6: 4°C, the total losses will increase by 3,613% (Brazil), 5,670% (China), 5,265% (Egypt), 6,095% (Ethiopia), 13,447% (Ghana) and 5,503% (India).

Figure 1 also illustrates that there is a large range in uncertainty, shown as the ensemble maximum and minimum values, which also increases under higher warming levels. This reflects the variance seen in the flood model outputs, representing differences in climate change patterns projected by the five GCMs.

[Figure 1]

3.2 Percentage change to national GDP

Figure 2 presents the average annual indirect economic damage as a share of national GDP. Under both the CC and CC+SE experiments Egypt suffers the largest reductions to national GDP, reaching 2.3% and 3.0% under scenario 6: 4°C, respectively. This highlights the high population density and the fact that most economic activities, including agriculture, take place in the Nile Valley (Aliboni 2012). While flood risk was low in the baseline period in Egypt this increases in the future, driven by increased precipitation upstream in Sudan and Ethiopia which increases river flows and flood risk along the Nile (He et al. 2020).

Under the CC experiment, Ethiopia and India face the next largest impacts to GDP, after Egypt, equating to 0.73% and 0.76% of GDP respectively, under scenario 6: 4.0°C. However, for Ethiopia losses decline from the baseline (1.09% of GDP) when socio-economic development is included, ranging from 0.09% to 0.28% of GDP under scenarios 1 to 6. This reflects the different baseline and future projections of socio-economic growth in Ethiopia, which makes the country appear more resilient when viewed in relative terms, to the costs of fluvial floods under future projections of climate change (see also SM Fig S3 and S4). A similar trend is seen in China when considering socio-economic development. Winsemius et al. (2016) also highlight how socio-economic change can be a driver for reduced future flood risk, in relative terms, particularly in higher income countries.

Brazil faces the lowest indirect damages of all countries as a proportion of GDP under the CC experiment (0.16% under scenario 6: 4°C), but the second largest losses under the CC+SE experiment (1.80% under scenario 6: 4°C). Whilst losses as a proportion of GDP initially decline at lower warming levels, increases are seen from scenario 3: 2.5°C onwards. A similar trend is seen for India and Ghana. For India, indirect losses as a proportion of GDP initially decline from the baseline at lower levels of warming, before increases are seen from scenario 4: 3°C onwards, suggesting a tipping point where increasing flood risk outweighs any relative benefits of socio-economic development. Similar trends in direct flood damage were reported by Dottori et al. (2018) for several regions in the world, with damage as a share of GDP declining with warming, particularly for fast growing economies, although the trend was reversed when damages were reported in absolute terms (as in Figure 1 above). Hence, it is important to consider changing socio-economic characteristics such as population change, land-use change and economic growth trajectories, alongside climate change.

[Figure 2]

3.3 Sectoral distribution of fluvial flood damages

A further benefit of the methodology is that it allows sectoral disaggregation of flood damages. Figure 3 shows a subset of the results for the six countries, split by direct and indirect losses (see SM Fig S5 for full results). Direct and indirect losses to sectors increase in line with increasing warming scenarios. As above, they are significantly higher, with a greater share of indirect losses, under the CC+SE experiment.

Under the CC experiment the agricultural sector (AGR) faces some of the largest losses in China, Ethiopia, Egypt, Ghana and India, as well as other manufacturing (OTM) and public (PUB) and other services (OTS). This is similar to findings of Dottori et al. (2018) who found pronounced agricultural losses in low-income regions with a higher share of agricultural GDP. In Brazil, the largest impacts are felt by other manufacturing (OTM), public (PUB) and other services (OTS), whilst Ethiopia also sees large losses to its food manufacturing (FDM) sector. Whilst the losses increase from scenario 1: <1.5°C to 6: 4°C, the sectoral distribution of losses in each country remains similar. However, under the CC+SE experiment the results also reflect underlying changes in the economic structure of the countries, including the expansion of service sectors of the economy. For example, there are increasing losses to public services (PUB) and other services (OTS) under scenario 6: 4°C for countries such as India and Ghana, who predominantly saw losses to the agricultural sector (AGR) under the CC experiment.

[Figure 3]

3.4 Recovery Dynamics

When calculating indirect damages under the CC experiment it is assumed that the economy recovers to the pre-flood level (section 2.4). Figure 4 illustrates the dynamic percentage change of monthly GDP for each country, under the baseline and six warming scenarios, relative to the pre-flood level. The fluctuations highlight each occurrence of flooding and the post-flood recovery period. Fluvial flood losses to monthly GDP range from up to 2.9% in Ethiopia (Baseline) and up to 15.2% in Egypt (scenario 6: 4°C). For all countries, it usually takes several months for GDP to recover to pre-flood levels. The frequency of events, scale of losses, and recovery time increase in severity in line with the increasing warming levels.

In terms of flood frequency, it can be seen that during the 30-year baseline, in large countries which have some of the world's largest rivers (e.g. China, Brazil and India), there will be more than 25 years with 1 in 100-year floods. Although flood-induced damages are aggregated to the national scale, these floods may occur in different areas of the country, particularly for countries with more than one major river. During the future period, a flood exceeding the baseline 1 in 100-year threshold will no longer be a 1 in 100-year flood, thus extreme flood events from the baseline perspective become more frequent in the future under the warming scenarios.

Focusing on the dynamics of individual flood events over time, and their indirect losses, is beneficial as it highlights the different magnitude of impacts between flood events. It also highlights the potential impact, in terms of the magnitude of losses and duration for recovery, of successive flood events that may occur while the country is still in a recovery period, as shown in China and Egypt around month 50.

[Figure 4]

Under the CC+SE experiment the economy can recover to a level above the pre-flood economy based on the exogenous growth data used within the I-O model (2086-2115 for the climate scenarios, and 1961-1990 for the baseline scenario). In this case, the level of recovery required to re-establish the pre-flood trajectory is larger (Figure 5). Consequently, indirect impacts can continue to accumulate over time as they also account for the overall slowdown in the growth rate of the economy from its potential trajectory, highlighted by the downward sloping trends in Figure 5. Fluvial flood losses to monthly GDP range from up to 1.5% in Egypt for scenario 1: <1.5°C and up to 4.7% in Egypt for scenario 6: 4°C. Indirect damage as a share of monthly GDP is generally lower than under the CC experiment given the future economic growth trajectories (see Fig S3). Yet, although the impact of individual flood events, in terms of the potential loss to monthly GDP, is more severe under the CC experiment, when totalled over time the accumulated impacts are higher under the CC+SE experiment.

[Figure 5]

Figure 5 also shows how the trajectory of trends under the baseline period (i.e., navy blue lines) differ to those of the climate scenarios, ranging from 0.6% in Egypt up to 4.8% in China. The differences reflect the different frequency and intensity of flood events, with the economy able to recover fully between events in many instances. Typically, when absolute economic growth continues over time full economic recovery is impossible, as the growth continues at a slower rate than under the pre-flood economy. Full recovery usually occurs in periods of economic recessions (Fig. S4) when other constraints (e.g., droughts and famine) become more severe than flood constraints and dominate economic trajectories. These deviations result in spikes, or downward trends, in Figure 5 when displayed as a percentage change in monthly GDP from the pre-flood economy. These periods of economic recession reflect that the baseline is based on historical growth data and these time series do not always follow a smooth trajectory. In contrast, the future scenarios are based on deviations from projected growth data between 2086-2115 from the SSP2 scenario. These trajectories do follow a smooth pathway hence another reason for the difference in the baseline trajectories when compared to the climate scenarios in Figure 5. Thirdly, while absolute losses increase under the warming scenarios, in relative terms losses to GDP may appear smaller in the future given the level of projected economic growth, as seen in China when comparing the baseline to future scenarios (Figure 2). This is consistent with the results of Dottori et al. (2018), which implies that some economies grow faster than flood-induced direct damage with warming.

4. Discussion and Conclusions

The above analysis provides an assessment of the direct and indirect economic impacts of fluvial flooding in six countries under future scenarios of climate change and socio-economic development. It covers a range of climate scenarios reflecting ambitious targets as well as higher levels of warming. The study demonstrates the importance of including socio-economic development when projecting direct and indirect flood losses, and the implications of this for damage estimates. Population change, land-use change and economic growth can be just as, or more, important than climate change in terms of understanding the future dynamics of fluvial flood risk (Dottori et al. 2018). The methodology considers direct and indirect economic impacts, providing a more comprehensive assessment of total damages at the national level, while facilitating comparison across countries.

Results highlight the potential for large increases in flood related losses under future warming scenarios. Absolute fluvial flood losses are largest in China and India. However, as a share of national GDP Egypt faces the most serious consequences, under both the CC and CC+SE experiments. The magnitude of indirect losses also varies largely when comparing between the CC and CC+SE experiments, becoming particularly severe in Egypt, Ghana and Ethiopia under the CC+SE experiments.

The method is also beneficial in that dynamic recovery is considered. This provides valuable insights into the role of recovery dynamics in influencing losses, and paves the way for further research in this area, particularly important given the past knowledge gap in considering such dynamics in I-O models (Meyer et al. 2013). The results highlight the potential lost opportunity costs, in terms of economic development, due to fluvial flooding in the future. The baseline CC+SE results also emphasise the importance of other exogenous constraints (such as droughts and famine) that may be felt in successive years or in combination with flooding constraints, causing different recovery dynamics and loss estimates.

In terms of validating results, the lack of empirical data on the dynamics of business recovery (Koks et al. 2019), and documented economic data on the indirect costs of flooding makes comparison difficult. Direct damage estimates for the baseline period under the CC+SE experiment can be compared with data from the EM-DAT database (EM-DAT 2020). Total direct damages for the baseline period modelled here are 6,640 (Brazil), 25,123 (China), 87 (Egypt), 215 (Ethiopia), 86 (Ghana), and 4,050 (India) million US$. Damages reported by EM-DAT during the same period are 4,185 (Brazil), 10,219 (China), 14 (Egypt), 0.92 (Ethiopia), 75 (Ghana), and 5,744 (India) million US$. For Brazil, Ghana and India the estimates are comparable to those reported by EM-DAT (around 15-60% difference). For the other three countries the estimates are much larger than reported data. This likely reflects the underreporting of economic damages in the EM-DAT database, particularly for developing countries in past decades (Kundzewicz et al. 2014).

Regarding the percentage change in direct damages relative to the baseline, results can be compared with Alfieri et al. (2017). Their estimates were made under three warming scenarios (1.5°C, 2°C, and 4°C), assuming constant socio-economic conditions and using the same set of depth-damage functions as this study (Huizinga et al. 2017). Estimates presented here under the CC experiment for Brazil, China and India are in good agreement with those reported by Alfieri et al. (2017). However, the estimates for the three African countries in this study are much larger. This discrepancy is also noted by He et al. (2020) when comparing population exposure to flooding with that of Alfieri et al. (2017). Consequently, the higher estimates for the three African countries in this study likely reflect higher increasing flood occurrences projected by the flood hazard model.

However, as with any economic impact study of climate change it is extremely challenging to capture all aspects of the subject within a single framework. Several studies highlight that flood risk assessments are sensitive to the choice of GCMs or climate driving datasets (Sperna Weiland et al. 2012; Ward et al. 2013; Alfieri et al. 2015). However, in this study, the overall patterns seen with increasing warming levels are consistent among the five GCMs, which sample a reasonable proportion of the overall uncertainty in modelled precipitation in the wider CMIP5 (He et al. 2020).

The study also focuses on economic losses relating to floods whose magnitude exceeds a baseline 1 in 100-year return period. Smaller events, which may still have an economic effect, are not considered, leading to a potential underestimation of losses. Conversely, as the flood data from CaMa-Flood does not consider flood protection (He et al. 2020), focusing on a 1 in 100-year flood event can reduce the potential of overestimating risks given many flood protection defences are designed at protection levels lower than the 100-year return period. While beyond the scope of this study, more recently available global flood defence data could be used to investigate the role of adaptation further in the future (Scussolini et al. 2016). Winsemius et al. (2016) found that including improvement in flood protection levels over time would significantly reduce economic damages, although this extension to the modelling has its own limitations in terms of the availability and accuracy of data for this parameter (Tanoue et al. 2016).

There is also uncertainty associated with the depth-damage functions used. Dottori et al. (2018) employed the same set of functions in their study and claimed that the associated uncertainty would exceed ±50%, as also noted by Huizinga et al. (2017). Given there are no alternative, globally consistent databases available, it is not feasible to assess the effect of the depth-damage functions used in this study. Nevertheless, the database of depth-damage curves used in this study is beneficial as it accounts for heterogeneity across the six countries as well as facilitating a country comparison.

This study also assumes a constant land cover after 2015 in the CC+SE experiment. When socio-economic growth is modelled with constant land cover the exposure value per unit area increases more in the model than in reality where the area constructed on will grow. Though predicted future land cover maps exist (e.g. van Vuuren et al. 2017), they are often at a coarser resolution and subject to several assumptions (*ibid*) which can introduce further uncertainty into the economic calculations.

Lastly, there are uncertainties arising from the underlying data, parameterisation of the I-O model and assumptions on recovery dynamics used for the estimation of indirect losses, which would benefit from future research. For example, the IOTs used for the baseline and future analysis were dependent on the latest years of data available for each country, which differed, with the classification of certain sectors varying for some countries (SM Table S2). However, modelling the future structure of an economy, particularly when applied to multiple countries, is always difficult (Koks et al. 2019).

Nonetheless, the analysis presented here is beneficial in many aspects as discussed at the start of this section. Going forwards, the provision of more comprehensive estimates of fluvial flood risk, that account for both the effects of climate change and uncertainty under a range of warming scenarios, and the role of socio-economic development, will provide important insights to support decision-making regarding flood risk management, and in terms of investment needs for adaptation (Mokrech et al. 2015). Being able to apply the analysis at a country level is important for future research as economic losses will be related to the level of development of the specific society, and could capture any flood prevention measures in place which can differ regionally and overtime as income levels rise (Jongman et al. 2015). And, as noted by other authors (e.g. Koks et al., 2019), the study also contributes to the objectives of the Sendai Framework for Disaster Risk Reduction to better understand disaster risk (UNDRR, 2015), essential to help inform and support the development of post-disaster recovery and adaptation strategies.

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Figure Captions

Fig. 1 Average annual direct and indirect fluvial flood damages calculated across the 30-year time period for the baseline and six warming scenarios in each country. Damages in panel A are expressed in million US$/yr for the CC experiment and in panel B in billion US$/yr for the CC+SE experiment. Bars represent the five model ensemble average, with whiskers indicating the ensemble maximum and minimum.

Fig. 2 The average annual indirect economic damage as a share of national GDP (%) (model ensemble average) caused by fluvial flooding for the baseline and future scenarios in the six countries.

Fig. 3 Loss in million US$/yr, under the 1.5°C and 4°C climate scenarios with (CC+SE) and without (CC) socio-economic change for the six countries. The bars represent total losses, with the share of direct and indirect losses indicated by the shading. Results are presented for ten sectors: Agriculture (AGR); Mining (MIN); Food Manufacturing (FDM); Other Manufacturing (OTM); Utilities (UTL); Construction (CON); Trade (TRD); Transport (TRA); Public Services (PUB); Other Services (OTS).

Fig. 4 Percentage change in monthly GDP (%) due to fluvial flooding for the baseline and climate scenarios under the CC experiment. Lines represent the five model ensemble average.

Fig. 5 Percentage change in monthly GDP (%) due to fluvial flooding from the pre-flood economy for the baseline (based on actual exogenous growth data between 1960-1993) and climate scenarios (based on projected exogenous growth data between 2085-2118).

Declarations

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Conflicts of interest/Competing interests

The authors declare that they have no conflict of interest.

Availability of data and materials

Data and models used are outlined in the text and listed in full in the references.

Code availability

Not applicable

Authors' contributions

Zhiqiang Yin and Dabo Guan designed the study. Zhiqiang Yin and Yixin Hu performed the analysis. Zhiqiang Yin carried out the direct damage modelling and Yixin Hu carried out the indirect damage modelling. Zhiqiang Yin, Yixin Hu and Katie Jenkins interpreted the results, and prepared the manuscript. Katie Jenkins prepared the figures and Supplementary Material. Yi He provided the flood hazard data. Nicole Forstenhäusler prepared the land cover data. Lili Yang contributed to the input-output modelling. Rhosanna Jenkins contributed to the literature review in Supplementary Material. Rachel Warren and Dabo Guan coordinated and supervised the project, and reviewed the manuscript.