Factorial CGE-Based Analysis for the Indirect Benefits of the Three Gorges Project

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Key Points:

- A factorial computable general equilibrium approach is developed to estimate the indirect impacts of large-scale hydraulic projects.
- The environmental and macroeconomic indirect impacts of the Three Gorges Project are investigated.
- Increased maintenance and regulations of the Three Gorges Project can mitigate long-term flood-related losses.

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Abstract

Large-scale hydraulic projects (LHPs) have become increasingly significant in river basin flood-risk management. Although LHPs' direct flood-retention benefits have been clearly shown, there has been a dearth of a comprehensive examination of their indirect implications, which can be more long-lasting and substantial in both environmental and economic terms. Thus, this study develops a factorial CGE-based LHP-effect analysis approach (FLEA) to quantify the indirect impacts of LHPs and simulate post-flood recovery strategies under diverse scenarios. The FLEA integrates a factorial analysis with a dynamic Computable General Equilibrium framework, including a flood module that connects hydraulic initiatives to the economy during floods. The FLEA is applied to the Three Gorges Project (TGP). The results demonstrate that ~$57 billion in GDP and ~12.9 Mt CO_{2eq} reduction would be created annually through supply chains by the TGP. When floods strike, the TGP has the potential to save ~$21 billion in GDP directly and reduce long-term GDP losses by ~50% throughout the reconstruction period. The TGP can have a considerable indirect impact on manufacturing. Furthermore, improved regulations and maintenance for the TGP may be desired for mitigating long-term flood-related losses, which is more crucial than aggressive post-flood fiscal stimuli.

Keywords: the Three Gorges Project, long-term flood-related impacts, factorial analysis.

1. Introduction

Climate change has resulted in an increasing number of natural catastrophes during the last few decades, such as heatwaves (Zhong Li et al., 2018), hurricanes (Weinkle et al., 2018), drought (Trenberth et al., 2014), and especially floods (Mallakpour & Villarini, 2015). Floods have been recognized as the most prevalent natural catastrophe, posing a hazard to the majority of locations worldwide. Floods accounted for 40% of all weather-related disasters, affecting over 1.65 billion people over the previous two decades, while the number of floods around the world has climbed from 1,389 to 3,254 (UN Office for Disaster Risk Reduction, 2020). Thus, although the construction of LHPs is not only time-consuming but also requires numerous human and material resources, many large-scale hydraulic projects (LHPs) have been built in both developed and developing countries to improve river basin flood-resilience and promote flood-risk management. Under such circumstances, it becomes critical to investigate the comprehensive effects of LHPs during and after floods, as well as to develop cost-effective post-flood adaptation and mitigation strategies.

It is preferable to have a solid understanding of how to estimate the flooding losses in order to be aware of LHPs' economic flood-retention impacts. Many recent studies have focused on the direct social and economic impacts of natural catastrophes (e..g, the loss of life and tangible possessions) (Okuyama, 2014). Direct economic losses resulting from natural hazards were typically assessed by government authorities or insurance companies based on first-hand data surveys and interviews, or disaster models. However, the direct losses during a flood event only account for a small portion of total losses whereas indirect losses may impose a much longer and larger impact (Cunado & Ferreira, 2014; Okuyama & Santos, 2014). Some approaches have been developed to analyze such indirect losses. Zeng et al. (2019) distinguished the main approaches for estimating the indirect flood losses of a natural disaster, such as post-disaster economic surveying (Molinari et al., 2014), econometric modeling (Cavallo et al., 2013), input-output (IO) models (Miller & Blair, 2009), and computable general equilibrium (CGE) models (Rose & Liao, 2005). Since the first two methods inevitably require primary data sources and can hardly capture the complex interrelationships in the socio-economic system, academics preferred the IO and CGE models for investigating indirect flood losses (Koks & Thissen, 2016). However, the IO approach has limitations in terms of linearity and rigidity in production relationships and price variations. It also neglects the effects of substitution between production inputs and consumption goods. These have hindered its implementation in the impact assessment of natural disasters (Koks et al., 2016). Although many modifications have been made to the IO approach, such as the development of the adaptive regional IO model (Hallegatte, 2008), the equilibrium has been questioned as the horizon lengthens (Gertz et al., 2019).

Thus, as the effects of LHPs will permeate a variety of elements inside the surrounding territories via industrial links, CGE models have been designed to perform comprehensive evaluations with specified information on multiple industries. For example, Strzepek et al.

(2008) used a single-region CGE model of the Egyptian economy to evaluate the economic impact of the High Aswan Dam, demonstrating that the static effects in 1997 were worth 2.7-4.0% of annual GDP. Liu et al. (2015) applied a static multi-regional CGE model to assess the economic and social impacts of hydropower development in China. They reported that the hydropower project was a win-win solution for both sustainable development and climate change mitigation. To study the direct and indirect consequences of the Grand Ethiopian Renaissance Dam (GERD), Kahsay et al. (2015) developed a multi-regional CGE model and demonstrated that the negative impacts on the Egyptian economy caused by the GERD's construction had begun to reverse during the GERD's operation. The dam's economic value could be further enhanced by implementing a basin-wide power trading scheme. However, Ni et al. (2021) proposed that it was necessary to integrate dynamic linkages and year-by-year adjustments in the CGE model since most of the costs and benefits associated with dam building had a long-time span. Thus, they developed a dynamic multi-regional CGE model, finding that each 10,000 yuan investment in the dam building could generate 1,000 yuan in annual national GDP and the cost was expected to be returned in ten years. Moreover, Siddig et al. (2021) analyzed probable economic implications on Sudan from the GERD's long-term operation using a recursive-dynamic CGE model of Sudan and the outputs of previous studies from biophysical models.

CGE models can consider the market roles for price adjustments more thoroughly, thereby supporting sector-level analysis of indirect impacts resulting from natural disasters (Zhou & Chen, 2021), such as earthquakes (Rose & Guha, 2004), terrorism attacks (Giesecke et al., 2012) and flooding (Pycroft et al., 2016). Static CGE models are suitable for investigating the short-term impacts of minor disasters. For example, Carrera et al. (2015) assessed the direct and indirect economic impacts of flooding in Italy using a regionally-calibrated version of a global CGE model. Both positive and negative effects of the calamity in different parts of the same country were captured. Fung et al. (2021) investigated the resilience impacts by comparing CGE results before and after floods when the initial investment was inputted. They showed that a positive economic shock generated more co-benefits for key economic indicators in 2015 than in 2007. Nevertheless, when considering the long-term impacts of a natural disaster and the ongoing fluctuation of the economy after floods, dynamic modeling approaches would be preferable (Gertz et al., 2019). For instance, Robinson et al. (2012) conducted a dynamic CGE analysis to investigate the economic implications of frequent floods in Ethiopia under climate change scenarios and discovered that aggregate welfare could be restored to pre-flood levels by a specifically designed adaptation investment plan at a cost that is substantially lower than the welfare losses because of climate change. Giesecke et al. (2015) employed a large-scale dynamic regional CGE model of the Los Angeles economy to analyze the economic losses of a terrorist attack. Hoffmann and Stephan (2018) integrated a spatial design into a dynamic CGE model and discovered that local public good adaptation could reduce the welfare and GDP losses caused by floods in vulnerable regions. Such adaptation strategies could also improve the efficiency with which resources are allocated across regions and sectors.

With the serious and long-lasting impacts of floods, LHPs have been playing critical roles in their mitigations. Such occupations have the potential to provide significant direct and indirect socio-economic benefits. However, there has been a paucity of concrete systematic research in terms of indirect socio-economic benefits from LHPs initiatives, although many studies of direct LHPs-related benefits were undertaken (T. Zheng et al., 2016). Indirect benefits may spread to a large number of receptors, such as labor availability, supply chains, market flexibility, trade surplus, etc. Without the reflection of such indirect benefits, the significant positive effects of LHPs on a variety of socio-economic activities that are vulnerable to floods may be substantially underestimated.

To fill this gap, the objective of this study is to develop a factorial CGE-based LHP-effect analysis approach (FLEA) to comprehensively quantify the direct and indirect benefits of LHP initiatives. The FLEA will be applied to the Three Gorges Project (TGP) to reveal its enormous indirect impacts from two perspectives: (1) supply chains; (2) flood-retention capacity. In detail, TGP's indirect impacts on Gross Domestic Product (GDP) and greenhouse gas (GHG) emissions through providing/consuming commodities to/from other industries will be quantified by disaggregating TGP-related socio-economic information into multiple sub-industries/commodities within the social accounting matrix (SAM) of the Yangtze River Economic Belt (YREB). Subsequently, a flood module will be initiated within the FLEA to specify the effects of the TGP on multiple flood-related activities. The indirect impacts related to TGP's flood-retention capacity will be investigated from both short- and long-term viewpoints under multiple scenarios, with a focus on its long-term indirect impacts at a sectoral level. In addition, a factorial analysis will be undertaken to examine the effects of multiple impact factors (related to floods and the TGP) and their interactions in response to short- and long-term GDP losses. Factors (and factorial relationships) with significant effects will be identified. Therefore, both direct and indirect sector-level impacts of the TGP on socio-economic and environmental system components within the YREB will be comprehensively investigated. The indirect multi-dimension, multi-phase and multi-industry impacts of the TGP will be emphasized through comparisons of flooding losses with and without the TGP, aiming to provide new perspectives for decision-makers to seek suitable post-flood fiscal stimuli.

2. Method

2.1. Development of a factorial CGE-based LHP-effect analysis approach.

A factorial CGE-based LHP-effect analysis approach (FLEA) is developed to examine the impacts of LHPs during and after floods on a regional socio-economic system in this study (Figure 1). A single-region dynamic CGE model containing a flood module will be integrated with a two-level factorial analysis. The dynamic CGE model estimates the macroeconomic impacts and detailed sectoral outputs with and without floods under various scenarios. The factorial analysis aims to examine the factors and their interactions with the most significant effects in response to economic changes. The grey textboxes in Figure 1 present the normal components of the FLEA, where dark blue and green colors highlight the locations of the "flood module" and "large-scale hydraulic project". The large arrows represent the relationships among various modules of the FLEA; for example, scenario setting and disaggregation efforts are two important parts of the FLEA. Small arrows represent the relationships within modules; for example, LHP is not only a part of the aggregation and disaggregation module but also that of the flood module. For simplicity, other CGE modules (e.g., production and international transaction) are not included in Figure 1. Industries that are vulnerable to floods are defined as "vulnerable industries" (e.g., agriculture, water-way transportation). Economic indicators that are vulnerable to floods are defined as "vulnerable indicators" (e.g., capital stock, and labor availability). Areas that are vulnerable to floods are defined as "vulnerable areas" which are also the ones protected by LHPs. LHPs normally have various responsibilities and impacts on vulnerable industries, indicators, and areas.

Place Figure 1 here

2.1.1. The dynamic CGE model with a flood module

The dynamic CGE model is primarily developed to simulate the future socioeconomic system on a basis of a social accounting matrix (SAM). Each industry in the SAM utilizes capital, labor, and intermediate goods from other industries as inputs. Capital and labor are aggregated to value-added based on a constant elasticity of substitution (CES) nested structure. Each industry's value-added is considered to be strictly complementary to the intermediate inputs, without the possibility of any substitution. Indeed, overland floods can substantially affect the transportation and daily lives of residents, leading to significant impacts on labor availability. In this study, the overall labor availability would be shocked by floods instead of direct mobility. This means that labor can still flow freely across various industries in the aftermath of floods, as long as it is available. The consumption, saving, and investment of the household and government are also defined as endogenous variables. Trades with other counties (international trades) and those with the rest of China are aggregated as "Trades outside YREB" (Supplementary Information, S1.1 and Figure S2). The model is calibrated to a balanced growth path. The nested structures are employed to reflect the substitution relationships in both the production process and value-added. The key parameters (e.g., elasticity and marginal propensity parameters) are firstly calibrated based on the information of the benchmark year (i.e., 2015). The economic data of 2015 are employed to certify that the model will reproduce the initial data as an equilibrium solution. After the calibration of these key parameters, the developed model is used to simulate the shocks caused by floods under a number of scenarios. The detailed modeling procedures are further explained in Supplementary Information, S1.

A flood module is developed and implemented into the CGE model. The flood module is used to reflect the flood-related information, which would contain *n* specific aspects of the system in time period *t*:

$$A_t^n = f(A^{*n}_t, L_t^{nms}, C_t^{nms}) \tag{1a}$$

where A^{*n}_t represents the value of variable *n* affected by floods (vulnerable indicators) under a no-flood scenario in time period *t*. Such aspects can contain capital stock, labor availability, total factor productivity of vulnerable industries, etc. A_t^n represents the value of vulnerable indicators *n* under a flood-related scenario in time period *t*. L_t^{ms} is the direct loss proportion of industry *m* at flood water depth *s* and C_t^{ms} is the flood-retention capacity of the studied LHP.

This equation will be used to update related vulnerable indicators in the CGE model where flood events happen. For example, if capital stock (KD_t) and labor availability (LS_t) are investigated during floods, then, $KD_t = A_t^1, LS_t = A_t^2$. They would be updated using equation (1a). Since floods of various scales can impose different direct impacts on various industries, the direct loss proportion (L_t^{nms}) is used to reflect such impacts, which can be obtained from equation (1b):

$$L_t^{nms} = f(E_t^{nms}, D_t^{nms}) \tag{1b}$$

where E_t^{nms} represents the share of industry *m* being prone to floods at flood water depth *s*; D_t^{nms} represent the damage rates of industry *m*; E_t^{nms} captures the idea that for a specific aspect of an industry, taking capital stock as an example, once there is a flood event, only parts of the capital stock are threatened, a proportion of which will suffer physical damage. Thus, L_t^{nms} can be calculated by a function consisting of E_t^{nms} and D_t^{nms} (Gertz et al., 2019).

2.1.2. Factorial analysis

The indirect impacts of LHPs on the socio-economic systems, particularly GDP, are in relation to multiple factors as well as their interactions. Factorial analysis (FLA) is powerful to examine the effects of multiple factors and their interactions on a particular response (Montgomery, 2017; X. Zheng et al., 2021). FLA includes five steps: 1) select target factors; 2) identify the fluctuating range of each factor; 3) collect the responses in sequence; 4) perform the analysis of the variance (ANOVA); 5) identify significant factors and interactions. For example, a two-level (2^k) FLA denotes *k* factors with each of them having two different levels (e.g., lower and upper bounds). If there are five factors to be considered, 32 (2^5) experiments are needed. The detailed FLA approach is introduced in Supplementary Information, S2. The main advantage of FLA is that it can accurately assess the main effect of each factor and the interactive effects among multiple factors under a given significance level (Y. Fu et al., 2021). Therefore, in association with the developed CGE model, the FLA is introduced to investigate the indirect socioeconomic effects of LHP initiatives, which may be derived from multiple factors and their interactions.

2.2. The case study of the Three Gorges Project

2.2.1. Overview of the Three Gorges Project

The TGP is a large-scale hydraulic project in the upper reaches of the Yangtze River in the People's Republic of China, located in Sandouping, Yiling District, Yichang City, within the Xiling Gorges. It is the world's largest hydroelectric power station and China's largest dam ever built. The dam is 2335 meters long and 185 meters high, keeping a water level between 135 to 175m during its normal operation. It has functions of flood retention, electricity generation, waterway navigation, and freshwater supply (B. J. Fu et al., 2010). Thus, the impacts of the TGP can be classified as: non-flood-retention and flood-retention ones

In terms of non-flood-retention impacts, the direct ones (obtained from the "2016 Annual Report of China Three Gorges Corporation" (Corporation, 2016)) included the generation of hydropower (111.8 billion kWh in 2021), leading to more than 80 Mt GHG reduction per year due to the reduced fossil fuel consumption for power generation. It also improved waterborne cargo volume (110.6 billion tonnes in 2015) and water supply (29.1 billion m^3 in 2015). Furthermore, the TGP helped increase the revenue of tourism by more than 20% (over two million tourists) and over $6 billion was consumed for its maintenance each year (Corporation, 2016). Thus, the TGP altered the supply chains within the YREB dramatically by providing/consuming various commodities to/from a number of sectors, leading to enormous indirect impacts.

Since millions of people live downstream of the dam and several of China's most important industrial areas (e.g., Wuhan, Nanjing, and Shanghai) are located alongside the Yangtze River (Chau et al., 2005), flood retention has been regarded as the most important function for the TGP (Venture, 1988). TGP's flood-retention capacity will be beneficial for substantially mitigating the flooding risk of the Jingjiang River (the tributary of the Yangtze River flowing across Hubei Province and Hunan Province) with its river basin being highly populated and at the same time, being extremely vulnerable to the floods of the Yangtze River. Besides, the TGP can also help mitigate the flooding risk of its lower reaches in wet seasons, and thus extend its impacts to the entire YREB. For example, in 2016, a serious flood event struck the middle and lower reaches of the Yangtze River. The flood peak (over 50,00 m3 /s) was reduced by 38% when passing through the TGP, which avoided the superposition of the second-largest flood peak in the middle and lower reaches of the Yangtze River. Thus, the downstream flood risks were greatly relieved. Moreover, the TGP also played a critical role in controlling floods in July 2019 and June 2020, reducing flow peaks by more than one-third. Thousands of square kilometers of land and billions of physical assets were thus protected from flooding disasters. The inundation period was greatly reduced, resulting in rapid recoveries in labor provision, supply chain re-establishment, and asset reconstruction (Teng, 2020). These effects were further spread to a large number of receptors, leading to enormous indirect benefits.

Therefore, the TGP can benefit the YREB from both flood-retention and non-flood-retention perspectives. It is thus crucial to comprehensively analyze and then fully demonstrate TGP's contribution.

2.2.2. Estimation of TGP's indirect impacts

As the TGP is the largest hydraulic water-resource project around the world, it can play multiple roles such as hydropower generation, navigability increment and water supplement. While providing many kinds of commodities to industries, it also consumes a number of products from them. These lead to close relationships between the TGP and other industries, forming important links in supply chains. From this perspective, the GDP of each industry may be affected by the TGP. In fact, the GHG emissions of each industry are related to its GDP contribution. Thus, the TGP may affect the GHG emissions of each industry through its impacts on GDP contribution. These demonstrate TGP's indirect impacts through supply chains, defined as TGP's non-flood-retention indirect impacts. In this study, these impacts on other industries by providing six kinds of commodities are investigated in terms of GDPs and GHG emissions (Corporation, 2016; T. Zheng et al., 2016); they include commodities of agriculture (TAG), energy (TE), water (TW), transportation (TTR), tourism (TTO), and water conservancy management (TWC). These six commodities related to the TGP are disaggregated individually for estimating the TGP's indirect impacts on GDP by the FLEA. The details of the aggregation and disaggregation approach are described in Supplementary Information, S3 and S4, respectively. Then, TGP's indirect effects on GHG mitigation can be evaluated by multiplying time-evolving GHG emission intensity (GEI), as illustrated in equations 2a and 2b(Su et al., 2019).

$$\mathrm{GEI}_{\mathrm{m}}^{\mathrm{t}} = \mathrm{GEI}_{\mathrm{m}}^{0} \times \exp(a_m \times T) \tag{2a}$$

$$\mathrm{GE}_{m}^{\mathrm{t}} = GDP_m^t / GEI_m^t \tag{2b}$$

where t is the time; $\mathrm{GEI}_{\mathrm{m}}^{0}$ is the GDP per unit GHG emission of industry m in the initial year; $\mathrm{GEI}_{\mathrm{m}}^{\mathrm{t}}$ is the GHG emission per unit GDP of industry m in time t; T is the number of years since the initial year; a_m is the exponential parameter of GHG emission intensity of industry m; $\mathrm{GE}_{m}^{\mathrm{t}}$ is the GHG emission of industry m in time t. The e^{a} is named the change rate of GHG emission intensity (GR).

As for the flood-retention one, direct capital stock losses and business interruption (BI) are considered as the main damage and economic losses caused by floods, respectively. This indicates that TGP's flood-retention capacity can be reflected from two perspectives: 1) reduce direct capital losses; 2) reduce business interruption. In terms of direct capital losses, many industries can be directly affected by floods. However, among 43 industries considered in this study, the losses of some industries are significantly less as compared to the losses of AGR (Agricultural, forestry, animal husbandry and fishery products and services), CON (Construction), Transportation, warehousing and postal (TSM), AMI (Accommodation and catering), ECN (Financial), WEM (Water conservancy, environment, and public facilities management) industries (Kang et al., 2006). Thus, direct capital losses of vulnerable industries (i.e., industry-AGR, -CON, -TSM, -AMI, -ECN, and -WEM) are estimated according to equation 2c in this study and the rest are neglected:

$$direct\ capital\ losses^{m} = KD^{*m} \times AF^{m} \times E^{m,s} \times D^{m,s} \times I^{s} \times (1 - FRC \times AFT^{m}\ )(2c)$$

where KD^{*m} is the capital stock of industry *m* without floods; FRC is the flood-retention capacity of the TGP for reducing the loss of capital stock; AF^{m} is the share of industry *m* located in vulnerable areas within the YREB; AFT^{m} is the share of industry *m* protected by the TGP. $I_{m,s}^{t}$: the binary indicator of flood water depth *s*.

Besides, during the inundation period, output production would be reduced by 100% or close to it due to interruption of supply chains, the inability of workers, and a range of other issues. Labor loss has been considered as a useful indicator for BI to describe that productive activity cannot resume as normal and workers have not been reallocated to work with undamaged capital (Gertz et al., 2019). However, such BI would be not of long duration since cleaning activities and emergency measures are undertaken. Herein, the recovery parameter (RPL) is employed to estimate the labor loss during floods and a linear function of labor recovery (Figure S1) is assumed (Tanoue et al., 2020). Since the TGP can help reduce the severity of flooding disasters, the labor loss considering TGP's impacts can be described as:

$$\text{Labor loss} = \left(1 + \frac{RPL}{2}\right) \times \text{IP} \times (1 - FCTD) \times P \times (1 - FCTL) \times LAF^{s} \qquad (2d)$$

where IP is the inundation period; FCTD is the flood-retention capacity of the TGP to reduce the inundation period; P is the labor supplies per day without floods; LAF^{s} is the loss of labor availability at flood water depth *s*; FTCL is the flood-retention capacity of the TGP to reduce LAF. FCTD and FCTL are assumed to be the same value in this study (Supplementary Information, S5.3).

Thus, a flood module that links the TGP's flood-retention capacity and flood water depth to other modules can be established. The direct flood-retention impacts (DFI) of the TGP will be firstly estimated by investigating the direct capital losses under scenarios with and without the TGP. To calculate the indirect flood-retention impacts of the TGP, the concept of "flooding year" and "reconstruction period" should be first defined. The flooding year refers to the time nodes at which the flood shock is applied and the reconstruction period is defined as the time interval between the nodes where the flooding year begins and the nodes where the economy returns to the balanced growth path. Thus, short-term indirect flood-retention impacts (SIF) of the TGP are estimated by investigating the GDP variations of the flooding year under scenarios with and without the TGP; long-term indirect flood-retention impacts (LIF) of the TGP on a particular indicator are estimated by investigating the changes of indirect "flood footprint" (IFF) under scenarios with and without the TGP. "Flood footprint" is a new concept proposed by Mendoza-Tinoco et al (2017) to quantify both direct and indirect cumulative losses caused by a flood, until the GDP has returned to its level without floods. The direct flood footprint refers to the short-term impacts on natural resources, human lives and tangible assets, while the indirect one is about the impacts resulting from flood-induced effects (e.g., delays and disruption of economic activities, destruction of industrial infrastructure, the costs of physical capital reconstruction) (Zeng et al., 2019). In this study, the IFF is investigated from multiple angles, including the expenditure for investing in industrial products (INV), the investment for forming new capital (IND), and the balance of trade surplus (EX-IM).

2.2.3. Data description

The YREB-SAM is developed based on two types of data: a)"2015 Inter-Regional Input-Output Table for 31 Provinces" (National Bureau of Statistics (NBS), 2015); 2) basic economic data (e.g., income tax, tariffs, commodity tax, and government subsidies to enterprises) (National Bureau of Statistics (NBS), 2015). The YREB-SAM is a single-region table where all industries and commodities of 11 provinces (i.e., Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hunan, Hubei, Chongqing, Sichuan, Yunnan, Guizhou) are aggregated into contains 43 industries and 48 commodities (Table S6). International trades were highlighted (international trades provide one of the most important revenues for local government), although the economic interactions between YREB provinces and the rest of China are also considered in the FLEA. The structure of YREB-SAM is shown in Figure S2. The RAS method is used to balance the matrix row and column sums (He et al., 2010). Socio-economic parameters include the elasticity substitution coefficients of CES functions, Armington functions and CET functions shown in the "Supplementary Data-Key parameters.xlsx", which are obtained from previous studies (Y. Fu et al., 2021; X. Zheng et al., 2021). The GHG emissions from 2005 to 2015 at a sectoral level are obtained from the Carbon Emission Accounts & Datasets (CEADs) which are used to estimate the parameter of sectoral GHG emission intensity (Table S1 to S4) (Guan et al., 2021; Shan et al., 2016, 2018, 2020). Due to the data limitation, the percentage of sectoral capital stocks exposed to floods in Vancouver (Gertz et al., 2019) is used to estimate the share of capital stocks prone to floods within the YREB in this study (Table 1). Because the potential of TGP's flood-retention capacity can be realized to different extents under various flood-retention operations. Thus, FRC is estimated according to the information on the TGP's performance from 2011 to 2020 (obtained from the "Record of Operation the Three Gorges Project" published by China Three Gorges Corporation (Corporation, 2019)). The information on the population vulnerable to flood disasters (Table S5) is obtained from the "Yearbook of Meteorological Disasters in China" which is used to estimate LAF, FCTL and FCTD (China Meteorological Disaster Yearbook Committee, 2017). The RPL and IP are obtained from Tanoue et al (2020). AF is obtained by dividing its total outputs in the entire YREB into its total outputs in the middle and lower reaches of the YRB (Table 1). Damage rates of various industries are obtained from Kang et al. (2006).

2.2.4 Scenario designs

The business-as-usual (BAU) case in the absence of a flood event is considered as the baseline. A series of scenarios related to flood water depth is designed to simulate the complexities of damage rate (Table 1), motivated by the theory that floods with varying scales can lead target areas to be flooded to various depths, which corresponds to different damage rates of vulnerable industries (Kang et al., 2006). There are three scenarios related to flood water depth in this research (FWD1 for 0 to 0.5 m, FWD2 for 0.5 to 1.0 m, FWD3 for 1.0 to 2.0 m). They emphasize different consequences of flood events in the flooding year instead of the exact scale of floods. For example, the damage rate of industry-AGR under the FWD1 scenario means 33% of industry-AGR's capital stock within the YREB except for industry-AGR in Sichuan, Chongqing, Yunnan and Guizhou province, would suffer from the asset damages because its capital stocks are flooded below 0.5 m by a flood event in this year. The post-flood fiscal stimuli will be achieved through an endowment of "foreign savings" received by industrial proprietors. The majority of such stimuli consist of both insurance money and government financial assistance. It captures the idea that the local economy is physically constrained by available capital and labor but allows for increases in investment and import. It also implies that these new funds may flow into the local investment market to promote economic recovery. Multi-year payments, proportional to the disaster-related losses of the affected proprietors, will be provided for economic recovery until the GDP recovers to the level without floods at the same time node (Supplementary Information, S1.4 and S1.7). Due to the scarcity of information on fiscal stimuli (for the public disaster assistance and insurance compensation) in the YREB, an interval value of 20 to 40% is considered (Table 2) as the proportion of the post-disaster multi-year payments to direct capital losses, where 10% of stimuli is paid by insurance money and 20~30% is paid by governmental financial assistance (Lin Wang, 2021; The Economic Observer, 2020). All cases consist of three kinds of scenarios "flood-retention capacity (NT, LT, HT)- flood water depth (FWD1, FWD2, FWD3)- fiscal stimuli (20, 40)". For example, HT-FWD2-40 represents the case where the flood water depth ranges from 0.5 to 1.0m with an additional investment that is 40% of direct flood-related capital losses after the flooding year, and upper bound of TGP's flood-retention capacity (FRC: 38.0%; FCTL and FCTD: 60.9%). The same case without the TGP (FRC, FCTL and FCTD equal zero) is coded as "NT-FWD2-40". The mean value of LAF is used under each flood water depth scenario (i.e., FWD1: 6.4%, FWD2: 9.7%, FWD3:15.3%). Some provinces (i.e., Shanghai, Jiangsu, Zhejiang, Anhui, Hunan, Hubei, Jiangxi) are considered "vulnerable areas" which are also the areas protected by the TGP.

This study involves the following assumptions:1) For a specific industry, the TGP has consistent flood-retention effects in the middle and lower reaches of the Yangtze River (excluding Sichuan, Chongqing, Yunnan and Guizhou province, positioned in the upper reach of the Yangtze River), which indicates AFT is assumed to 1 in this paper. 2) In a flooding year, a specific industry in vulnerable areas will suffer consistently from flood-related losses, implying that variations in the industry's losses are insignificant among regions. 3) The fiscal stimuli will come into force in the year following the flooding year. 4) Siting of a specific industry would follow similar principles, i.e., the share of capital stocks that are sensitive to floods (in flood-sensitive cities of the YREB) can be obtained based on Gertz et al. (2019).

Place Table 1 here

Place Table 2 here

3. Results

3.1. Indirect impacts of the TGP through supply chains

TGP's disaggregation yields a new industry called industry-TGP, which can be used to analyze the TGP's non-flood-retention indirect impacts on other industries under the BAU scenario (Figure 2). The results of the 43 industries are further aggregated into six categories for exhibition (Table S6). During the simulation period (2015-2024), ~\$57 billion in GDP would be created (Figure 2a) annually (~9.8% of total YREB's GDP) due to the erection of the TGP, which provides extra water and electricity commodities and increases waterway shipping quantities, as well as attracts tourists, etc. Especially, industry-AGR would benefit most from the TGP (Figure S3a), with GDP increasing by ~9.7% (i.e., ~\$41 billion annually). Since TGP's direct impacts on the agriculture industry have been disaggregated from industry-AGR into industry-TGP, such increases may result from the requirement of the rest of industry-AGR for multiple commodities and services supported by the TGP. Industry-CON would get the most negative indirect impacts (~2.8%), followed by industry-MIN (~2.0%) and industry-MAN (~1.4%), while the annual mean of GDP losses of industry-SER would be the highest (~\$35billion). Thus, the TGP would lead to a ~\$23 billion net increase in GDP through the supply chains annually. Sectoral variations imply that those capital-intensive industries (e.g., MAN, CON, ECN and REI) would be more affected by the TGP. The capital and labor investment that should have been devoted to these industries might be shared by other industries (e.g., AGR) which are strongly supported by the TGP (Figure S3b). Industry-SER has a significant reliance on other industries' production because it needs many products supplied from other industries. Since other aggregated industries (MIN, MAN, MET, CON) are negatively affected by the TGP, the decreased capital and labor inputs, and reduced intermediate consumptions from those industries might result in the severest GDP losses of industry-SER.

Place Figure 2 here

On the other hand, the same changes in GDP can correspond to different GHG-mitigation amounts due to various GEIs of industries. Through the estimation of each industry's GEI from 2015 to 2024 (Table S4), the TGP's impacts on GHG mitigation through supply chains can be analyzed (Figure 2b). During this decade, the TGP can help to reduce ~129 Mt GHG emissions (CO_{2eq}) through the supply chains from 2015 to 2024, despite a slight increase in GHG emission in industry-AGR. Industry-MAN and -MET are ranked in the first and second position, respectively, with an emission reduction of ~75.9 and ~39.1 Mt. These results imply that the TGP can reduce GHG emissions overall without obvious economic losses. On the contrary, there might be an additional GDP increase within the YREB by the virtue of the TGP.

3.2. Economic indirect impacts of the TGP's flood-retention capacity

Figure 3a and 3b depict that TGP's DFI resulting from reducing direct capital losses during floods can range from ~\$3.0 billion (FWD1) to ~\$24.0 billion (FWD3) while BI losses can be mitigated by ~0.1% (FWD1) and ~0.8% (FWD3). Under the FWD1 scenario, the SIF of the TGP are estimated as \$[1.2, 2.7] billion, which can be extended to \$[3.7, 8.6] and \$[9.3, 21.1] billion under FWD2 and FWD3 scenarios, respectively. Since anthropogenic factors interfere with the TGP's flood-retention schemes, TGP's flood-retention potentials cannot be fully realized in the absence of appropriate flood-retention schemes. When vulnerable industries are not seriously damaged by floods (under FWD1 scenario), the TGP can easily meet the flood prevention demand because of its extradentary flood-retention capacity. Moreover, as the damages increase due to the increased flood water depth (under FWD2 and FWD3 scenarios), TGP's flood-retention capacity will dramatically benefit the entire socio-economic system. The variations in Figure 3a and 3b indicates the great flood-retention potentials of the TGP from both direct and indirect perspectives.

Place Figure 3 here

As for TGP's LIF, GDP is considered as the criteria for determining the reconstruction period to calculate related IFFs. The dynamic GDP changes are obtained by comparing GDP in cases with flooding shocks to that in the BAU case (Figure 3). The reconstruction period ranges from four to seven years (Figure S3c) with a decrease in the compensation proportion under various fiscal stimuli scenarios. The 2nd year is the flooding year where the flooding shocks are applied. The lagging effects of the investment for economic recovery can be observed. The additional investment injected into the economy in the 3rd year will come on-line to support the recovery in the 4th year while the GDP increase in the 3rd year under various fiscal stimuli shows minor differences. Such lagging time reflects that the transformation of the investment to new capital stocks is time-consuming. Neither the compensation from the government nor the indemnity covered by the insurance cannot promote productivity immediately. This can explain why the GDP after the recovery can surpass its level without floods slightly. Taking HT-FWD2-20 case as an example (Figure 3c), the reconstruction period starts in the 2nd year and ends in the 8th year but at the end of the 7th year, GDP is a little lower than that under the BAU scenario. Thus, the additional investment would still be injected in the 7th year, resulting in the continuous increase of GDP in the 8th year. Doubling the compensation proportion can reduce the reconstruction period by ~28%, creating more than a two-fold increment in GDP (Figure 3c). Figure 3d indeed denotes that a situation without the TGP (Figure 3d) or with severe flood events (Figure 3e) would result in a higher GDP as compared to the other scenarios. However, it does not mean that such a situation is desired. This is because: 1) Severe destruction of physical assets and injury/loss of human lives due to severe flood events can impose irreparable damages on socio-economic systems (Gertz et al., 2019); 2) Such higher GDP levels would be subject to a significantly raised risk of flooding disaster; 3) To achieve a more advanced GDP than its level without floods would require an unacceptable reconstruction cost. As denoted in Table S7, the total cost for post-flood recovery under FWD3 scenario is over eight times that under FWD1 scenario (Table S7). It violates the goal of post-disaster fiscal stimuli: complete the reconstruction with minimum money and time. Moreover, the TGP can help reduce such costs by ~48%. Thus, a situation with the TGP (and thus reduced flood severities) (Figure 3e) would be more beneficial for improving the safety of the YREB. Whereas, such a pattern is an important characteristic of investment-oriented fiscal stimuli after floods, which should not be neglected in investigating the LIF of the TGP (Xie et al., 2018).

The differences in GDP changes under the cases with and without the TGP ([HT, LT]-FWD2-20 and NT-FWD2-20) over time can be observed in Figure 3d, where the GDP losses are considerably reduced by the TGP. The GDP changes under different flood water depth scenarios are also significant (Figure 3e). Even though the compensation proportion is the same (20%), the socio-economic system will require more investment for the recovery owing to the increased direct losses. Based on the dynamic results under various scenarios, TGP's LIF on the GDP is obtained by analyzing the related IFFs (Figure 3f). With various fiscal stimuli, the IFFs of the GDP without the TGP are $[4.6, 7.5] billion under FWD1 scenario, $[18.5, 26.8] billion under FWD2 scenario, and $[35.7, 58.2] billion under FWD3 scenario. The TGP can help reduce as much as ~50% IFFs on GDP (IFFG) and the detailed TGP's LIF on the GDP losses are shown in Table 3. The increase of flood water depth can affect the uncertainties of TGP's LIF as the interval width expands nearly eight times (from FWD1 to FWD3 scenarios). It reveals that the TGP's flood-retention potentials can protect $[2.1, 4.9], $[7.6, 27.4], and $[16.4, 38.3] billion GDP annually from being destroyed by floods indirectly in the long run under FWD1, FWD2, FWD3 scenarios when post-flood fiscal stimuli vary.

Place Table 3 here

3.3. Multi-angle indirect impacts of the TGP's flood-retention capacity

The TGP can affect the macroeconomy from various aspects. For example, the capital stocks of different industries suffer from direct losses under different flood water depths and rebound alongside varied paths (Figure S4a). Industry-AGR, -CON, -SER suffer from direct capital losses significantly in the 2nd year. The reconstruction of damaged industries may demand more investments for new capital accumulation in the following year, leading to capital losses of industry-MAN and -MET in the 3rd year. The situation of industry-MAN becomes even worse as the additional investment is injected (4th year). Since industry-MAN is the pillar industry in the YREB, it would suffer from great indirect losses after floods due to the destruction of the supply chains and investment transformation. The investment that should be allocated to manufacturing might be reallocated to those seriously damaged industries (Figure S4b), particularly industry-AGR and -SER. The investment in industry-AGR for new capital formation reaches its peak in the 2nd year, which gradually decreases in the next few years because agriculture is the base industry of the economic development within the YREB once disasters occur. On the contrary, after the fundamental needs are satisfied after floods, the investment will flow into industry-CON from the 3rd year for the post-flood reconstruction of commercial buildings, industrial buildings, infrastructure and transportation, and decrease as the reconstruction is completed gradually. At the same time, industry-SER and -MAN begin to demand more investment to form new capital stocks. Such demands increase continuously until reconstruction ends because they are core engines to support the economic recovery within the YREB.

Based on those dynamic patterns, the related IFFs during the reconstruction period of various industries in different aspects can be analyzed (Figure 4). The overall IFFs on the KD of industry-CON under scenarios with deeper flood water depth are positive (Figure 4a), which can be further advanced by the TGP. Industry-CON will be more important under severe flood-related scenarios than under slight ones since the IFFs on KD under FWD1 are below 0 because less reconstruction work is needed as the flood water depth is below 0.5 m. Industry-MAN may suffer from heavy capital losses indirectly because the TGP can protect the direct capital losses during floods, indicating that less additional investment would be required after floods (Figure 4b). TGP's LIF on industry-CON and -SER can help them make room for industry-MAN in the investment market, contributing to avoiding severe indirect capital losses. This also reveals how the following fiscal stimuli work to promote economic recovery. The sectoral variations in KD and IND imply that the erection of the TGP weighs much more than the fiscal stimuli in industry-AGR and -MAN where significant variations can be seen in Figure 4a. Since the TGP can help protect part of capital stocks during floods, i.e., the TGP-induced incremental flood-retention capacity can help reduce flood-related losses, leading to less post-flood investment injected into the YREB, the IND of industry-SER can be reduced. Thus, flooding is both a disaster for the economy and a chance for resource reallocation (to allow industrial transformation and renovation). Further analysis might be desired for the interactions between

TGP's flood-retention capacity and the degree of post-flood fiscal stimuli.

Place Figure 4 here

The final demands for investment purposes (INV) and international trade surplus (EX-IM) of different industries depict the most significant changes in terms of commodities. As shown in Figures S4c, S4d and S4e, dramatic fluctuations in these two aspects can be seen in industry-CON and -MAN. Detailed results of INV and EX-IM are shown in Figure S5 and Table S8, respectively. Severe flood water depth always requires industry-CON to consume more investment commodities (Figure 4c), which replace depreciated capital and produce new capital needed for growth. As for trade surplus, since the productivity of the domestic industries is influenced by floods, the imports can increase accompanied by the descending exports during the reconstruction period, leading to considerable losses of the trade surplus, particularly in industry-MAN. However, the TGP can help to reduce such disadvantageous situations (Figure 4d). Under various fiscal stimuli, the TGP can reduce the trade surplus losses of the industry-MAN by $[1.7, 6.3] billion under FWD1 scenario, and $[5.6, 18.3] billion under FWD2 scenario and $[13.8, 51.6] billion under FWD3 scenario. The extension of the interval width under varied flood water depth scenarios suggests that the TGP can play a more essential role in disastrous floods. Besides, the TGP can impose enormous indirect impacts on some industries positively while affecting others negatively from particular economic perspectives. It reveals TGP's abilities to assist some particular industries (e.g., industry-CON, -SER) in grabbing opportunities arising from suitable post-flood fiscal stimuli for further development.

3.4. Factorial analysis of TGP's indirect flood-retention impacts

There are five impact factors (i.e., FS, FCT, FWD, LAF, RPL (Table 4)) considered in this study, which can affect the direct and indirect flood-related losses. Thus, a 2^4 and 2^5 FLA is employed to examine the effects of these impact factors and their interactions on direct GDP losses (DGL) and IFFG, respectively. Because the fiscal stimuli are assumed to take effect in the year after the flooding year, there is no need to consider FS in response to DGL. The high- and low-level of each factor are displayed in Table 4. The logarithm transformation (i.e., ln(DGL) and ln(IFFG)) is employed to make the errors closer to the normal distribution because of the dramatic variations in the simulation results of both DGL and IFFG. Only the main factors and second-order interactions are considered in the FLA because they can explain 99% of the variations in the model simulation.

Place Table 4 here

ANOVA table of ln(DGL) and ln(IFFG) are offered in Table S9 and S10. As shown in Figures S6b and S6d, all residuals are positioned near a straight line, demonstrating a normal distribution. In Figure S6a, the effects of FCT, FWD, LAF and RPL, as well as their interactions are significant to the ln(DGL) except the interaction between FWD and RPL (P-value > 0.05, Table S9), where the effect of FWD is the largest. The effects of FWD, LAF, and RPL are positive with their contribution being 85.6%, 0.6% and 5.6% to ln(DGL). In Figure 5a, the increase of LAF, and RPL can intensify GDL slightly while FWD is the main reason for the enormous GDL. The effect of FCT on ln(DGL) is statistically significant but only accounts for 8.10%. The patterns of interactions are depicted in Figure 5b, where the interactions related to FCT are all negatively significant to ln(DGL) and a similar uptrend can be seen in the rest interaction plots. These results reveal that improving the resistance of those vulnerable industries to floods (which can reduce the damage rate of vulnerable industries) and regulations of the TGP (which can improve TGP's flood-retention capacity) might be the most effective measures to mitigate direct flood-related GDP losses.

Place Figure 5 here

As for long-term GDP losses, FWD is still the one with the most significant effects (Figure S6c), contributing 85.8% to ln(IFFG). The effects of FS can be seen in Figure 5c, where IFFG would be decreased by ~$6 billion as FS rises from the lower to the upper bound. FCT contributes 7.2% of IFFG negatively, slightly higher than FS. This implies that measures (e.g., suitable flood-control scheduling and regular maintenance of the TGP) to guarantee the full realization of TGP's flood-retention capacity may contribute more to reducing long-term GDP losses than aggressive fiscal stimuli. Besides, FS and FCT have similar trends in their interactions with the other factors (Figure 5d), where FCT*LAF is the only interaction with significant effects (Figure S6c). It reveals that promoting the post-disaster recovery of labor availability would be more necessary in some areas which benefit a little from the TGP's flood-retention capacity during floods (i.e., areas far away from the TGP). The pattern of FWD*FCT depicts that in the lower level of FWD, the TGP can only exhibit ~$3.3 billion flood-retention impacts from a long-term view, which would be extensively expanded to ~$25.4 billion as FWD increases to the upper bound. Moreover, to make the fiscal stimuli more effective, lower-level RPL and upper-level FCT can both be supportive. It is interesting to notice that with lower-level FCT, the increase of FS can reduce ~$8.1 billion in IFFG on average. Once FCT improves, this value drops to ~$4.5 billion. It indicates that improving investment after floods might not always be effective because of decreasing marginal returns resulting from improved regulations and maintenance of the TGP. This also indicates the important trade-offs between the investment in pre-floods infrastructure construction and post-flood reconstruction. The regression equation which contains significant factors and interactions can be obtained from FLA:

$$\ln(\mathrm{IFFG}) = 6.9454 - 0.2030\mathrm{FS} - 0.2908\mathrm{FCT} + 1.0074\mathrm{FWD} + 0.0587\mathrm{LAF} + 0.1878\mathrm{RPL} - 0.0238\mathrm{FCT} * \mathrm{LAF} \qquad (3a)$$

This equation can be used to estimate the long-term GDP losses resulting from floods within the

YREB roughly. The coefficient of determination (R^2) between the simulated and observed value of ln(IFFG) can reach up to 0.9955.

4. Discussion

4.1 Policy implication

The concept of "flood footprint" is useful to quantify the long-term indirect impacts of natural disasters from various perspectives, especially from a sectoral view. The comparison of IFF under scenarios with and without the TGP offers quantification of TGP's LIF on multiple economic losses. However, controversies still exist regarding the contributions of the TGP to GHG emission mitigation and economic contributions within the YREB. This is because more negative and long-term impacts led by dam construction have been widely investigated (Campo & Sancholuz, 1998; Fujikura & Nakayama, 2013), including reservoir-triggered seismicity, landslides, saltation, water pollution, and many ecological problems (B. J. Fu et al., 2010; K. Li et al., 2013). Zheng et al. (2016) reported the negative externalities of the TGP in 2010, i.e., the values of the hydropower resources ($0.96 billion), intergenerational land loss ($0.13 billion), and invisible losses ($0.35 billion). Nevertheless, the impacts of the TGP should not be confined to the consequences of dam construction, because more links between the TGP and other industries showed up in the past decade, leading to a number of indirect impacts through supply chains within the YREB. These indirect impacts can lead to a net increase in GDP (in the YREB) by ~$23 billion and reduced GHG emissions by ~12.9 Mt CO_{2eq} annually from 2015 to 2024. Indeed, TGP's construction led to losses of villages and forests, accounting for 46.9% and 5.1% of total land use, respectively. The pre-construction GHG emissions of this area were estimated as 5.1×10^5 t $CO_{2eq} \cdot yr^{-1}$ (Zhe Li et al., 2020), demonstrating that the forest losses because of TGP's construction would not increase GHG emissions. Thus, considering that the building cost of the TGP is approximately $33 billion, the positive impacts of the TGP might overweigh its negative impacts from both economic and environmental perspectives.

The post-flood fiscal stimuli in this study are designed as an undifferentiated investment that will be allocated according to market-based mechanisms. Both positive and negative impacts during the reconstruction period are investigated. The legging time resulting from the construction cycle of new capital stocks indicates that some industries could have chances to reach a higher or more advanced level. For example, the TGP can help tertiary industries benefit more from the post-flood financial aid to surpass the level without floods while agriculture can basically recover to its level without floods. Since no specific policy is available for post-flood fiscal stimuli within the YREB, investment-oriented financial assistance can be a potential option compared to financial support with explicitly targeted industries. Because the free allocation of additional investment under the market mechanism can allocate resources after floods more efficiently to accelerate the economic recovery in meeting the requirements of those fundamental industries so as to avoid the inefficiency of direct financial aid (Zeng et al., 2019). Under this circumstance, even though the disasters bring about destructive outcomes to the socioeconomic system, they also provide opportunities for the transition of the industrial structures, which should not be neglected by the government and stakeholders. These results can support policy-makers to seek an optimal way to recover from the disruption or imbalance of the socioeconomic system after floods.

Based on the calculation of IFFs on different macroeconomic indicators, the policy-makers can have a thorough understanding of TGP's comprehensive short-term/long-term impacts, in order to make better use of the largest hydraulic project around the world. Industry-level outcomes show comprehensive patterns to stakeholders in different industries of when the economic losses would come from, and which aspects would suffer the severest losses directly or indirectly. From this perspective, the government can allocate the financial responsibility of improved maintenance and regulations of the TGP, and flood risk mitigation interventions to the stakeholders of specific industries based on the 'who benefits, who pays' principle. This approach can not only ease the government's financial burden but also spread the related cost among major stakeholders alongside the supply chains.

The increase of flood water depth can considerably raise the uncertainties in the achievements of TGP's flood-retention potentials since the TGP is designed for coping with floods of 10,000 year return period (Venture, 1988) which implies that the TGP can help potentially mitigate the impacts of severe flood events. It indicates that TGP's flood-retention impacts can vary from case to case. More field data and systematic approaches are desired. On the other hand, the improvement of TGP's flood-retention capacity and aggressive fiscal stimuli can promote the economy to recovery within a short period but such plans also require intensive investment which may aggravate the burden on the local government after floods. Thus, the trade-offs between long-term indirect GDP losses and the cost of fiscal stimuli should be balanced.

The FLA technique reveals the effects of FS, FCT, FWD, LAF and RPL and their interactions on short- and long-term GDP losses resulting from floods. It is found that the effects of these factors on IFFG are significant, demonstrating that reducing the flood water depth and increasing the TGP's flood-retention capacity might be effective ways to minimize indirect economic losses. These can be accomplished through improved maintenance and regulation of the TGP. Although these improvements may involve extensive financial and human-resource inputs, they are worthwhile due to the enormous TGP's indirect economic contribution (section 3.1) and flood-retention benefits (sections 3.2 and 3.3). The significant effects of FS responding to ln(IFFG) indicate the necessity of post-flood financial assistance for activating fundamental industries, which can help improve economic recovery. When the GDP approaches its normal level (i.e., conditions without floods), such assistance might not be necessary (Figure 3). Thus, a post-flood fiscal stimulus with a gradually decreasing subsidization level over time might be suitable for the YREB. Furthermore, such investment-oriented financial assistance follows the market allocation mechanism (Shell & Stiglitz, 1967) such that industries may get investments differently. Thus, the TGP may contribute to industrial upgrading and transformation after floods, particularly for manufacturing, tertiary, and construction industries (Figure 4). On the other hand, the energy and mining industries can hardly acquire financial assistance from the investment market after floods. Targeted financial assistance and reconstruction plans, therefore, would be vital for flood-sensitive regions that rely heavily on energy and mining industries. Moreover, the results of the FLA reveal that the effects of RPL are significant in response to the IFFG. RPL is related to the duration of inundation and the time required for post-flood remediation. Thus, reducing the inundation period and accelerating remediation activities may help mitigate the long-term economic losses of floods.

4.2 Limitations

Although the FLEA provides many new insights for the research related to direct and indirect impact assessment of the TGP and post-flood decision-making, some limitations still exist: 1) TGP's impacts are classified as non-flood-retention impacts and flood-retention ones based on the government's policies as follows: a) Flood-retention function is the dominating priority of the TGP as defined by the governmental authorities (Venture, 1988). In flood seasons, all other functions must give way to controlling floods. b) In each year, the water level of the TGP must be reduced to 145-155 m in June to cope with floods afterward and return to 175 m after the flood season for electricity and water replenishment (Corporation, 2019). Such information can help us to disaggregate the TGP as an individual industry providing multiple commodities to analyze its indirect impacts on the socioeconomic system through the supply chains. Nevertheless, we cannot deny that the interactions among TGP's various functions have been neglected in this study. 2) In Assumption 1, we assume that "TGP has consistent flood-retention effects in the middle and lower reaches of the Yangtze River". In fact, the impacts of TGP's flood-retention capacity can decrease with the distance from it. Thus, Assumption 1 can lead to the overestimation of TGP's flood-retention impacts. 3) The hydrologic process during a flood event where the TGP handles the flows using its huge water storage capacity, and the political process related to post-flood fiscal stimuli are extremely complex. Thus, a large number of uncertainties exist in the estimation of TGP's flood-retention capacity, post-flood compensation, etc., resulting in challenges in relevant modeling and assessment efforts. Interval values and scenario designs are used to deal with these uncertainties in this study due to the scarcity of related information. The proportions of capital stocks being prone to floods (proposed by Gertz et al. (2019)) are used for approaching direct flooding losses. These can lead to over- or under-estimations of not only the direct losses but also the indirect ones. For alleviating the impacts of these uncertainties on parameter estimation, we may consider integrating hydrological and political models with the developed FLEA in our future studies. 4) In this study, a specific industry in vulnerable areas is assumed to suffer consistently from flood-related losses, implying that variations in the industry's losses among regions are insignificant. Indeed, these industries are distributed over YREB, with the data on the exact locations for production capacities of each affected sector being available from the background information of regional input-output tables (Han et al., 2021; Tan & Bi, 2018; Zhai et al., 2021). Neglection of regional differences in approaching flood-related losses can lead to an overestimation of TGP's impact in this study. A multi-regional CGE model would help identify sites that are significantly sensitive to TGP's flood-retention impacts. If so, more regionally-specific industries vulnerable to floods can be considered. 5) It is hard to validate TGP's indirect impacts on various macroeconomic indicators since there is no official corresponding report. The Chinese Ministry of Water Resources announced a flood-retention benefit of $4.01 billion from the TGP in 2010 (T. Zheng et al., 2016). This lies within the estimated range of TGP's SIF ($[3.7, 8.6]) in this study. In general, our estimation is somewhat over-optimistic due to the limitations in estimating the losses of direct capital-stock damage and business interruption. 6) In this study, GDP is a key indicator for assessing TGP's indirect impacts. However, it indeed has some limitations as a global measure. For example, it cannot reflect the improvements in the quality of life or technological progress, as well as the ecological environment. Thus, multiple indicators from various perspectives (e.g., social welfare, consumer price index, environmental quality index) will be desired to reveal the comprehensive impacts of LHPs.

5. Conclusions

The FLEA provides a systematic approach to estimate both direct and indirect impacts of the LHPs on the socioeconomic system from multiple perspectives. The case study of the TGP demonstrates that the proposed model can facilitate the identification of the essential industries affected by the TGP through the supply chains and is capable of analyzing the socioeconomic impacts of TGP's flood-retention capacity at a sectoral level from short- and long-term views. In detail, the TGP would create ~$57 billion in GDP and ~12.9 Mt CO_{2eq} reduction annually through supply chains, and protect short-term GDP losses led by floods up to ~$21 billion. It can also reduce ~50% of long-term GDP losses during the reconstruction period after floods. Different industries could benefit from the TGP in different ways. Those investment-intensive industries might have opportunities to a more advanced level with the help of investment-oriented fiscal stimuli. Moreover, increased maintenance and regulations of the TGP might be the optimal way for mitigating long-term flood-related losses in a wide region, superior to enlarging investment for aggressive post-flood fiscal stimuli.

Although several assumptions are employed in the study for demonstrating the indirect impacts of the TGP through the FLEA, it still provides a new perspective for future research on both direct and indirect impact assessment of LHPs and many new insights into the decision-making related to post-flood reconstruction strategies. The FLEA is capable of being integrated with a hydrological and political module, improved to a multi-regional one, adapted to other LHPs around the world with adequate information, and further applied to consecutive flood events over many years in future research.

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Availability Statement

The FLEA model is solved by the PATH solver of the General Algebraic Modeling System (GAMS) software. The China Statistical Yearbook can be downloaded from the National Bureau of Statistics China http://www.stats.gov.cn/tjsj/ndsj/. Some basic economic socioeconomic data are collected from data.stats.gov.cn/easyquery.htm?cn=C01. Other key parameters are collected from the previous research (Y. Fu et al., 2022; X. Zheng et al., 2021). The YREB-SAM table is displayed in Supplementary Data Key parameters.xlsx. The Yearbook of Meteorological Disasters in China can be downloaded from the China National Knowledge Infrastructure: https://data.cnki.net/yearBook?type=type&code=A. The GHG emissions from 2005-2015 are obtained from the Carbon Emission Accounts & Datasets: https://www.ceads.net/data/province/. The information about the TGP can be obtained from the Annual Report and the Record of Operation of the Three Gorges Project from the China Three Gorges Corporation: https://www.ctg.com.cn/sxjt/xzzx37/jtnb/index.html#index0.

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Figure captions

Figure 1 The framework of the FLEA. Notes: DGL represents direct GDP losses and IFFG represents indirect flood footprints on GDP.

Figure 2 (a) The annual mean of GDP changes in various industries. (b) The total changes in GHG emissions in various industries induced by the TGP from 2015 to 2024. Note: the TGP is not contained in industry-SER in Figure 2.

Figure 3 The direct capital losses (a) and the GDP changes (b) under scenarios with (Y-TGP) and without the TGP (N-TGP). The dynamic GDP changes: (c) under various fiscal stimuli scenarios (upper and lower lines of grey areas are LT-FWD2-40 and LT-FWD2-20 cases); (d) under scenarios with and without the TGP (upper and lower line of grey area are HT-FWD2-20 and LT-FWD2-20 cases); (e) under various flood water depth scenarios (LT-FWD1, FWD2, and FWD3-20 cases). (f): The IFFs on GDP during the reconstruction period under various fiscal stimuli and TGP's flood-retention capacity scenarios. Note: FWD1, 2, 3, represents scenarios with flood water depth below 0.5 m, from 0.5 to 1.0 m, and from 1.0 to 2.0 m, respectively.

Figure 4 The IFFs of various industries under different flood water depth scenarios with and without the TGP: (a) capital stock (KD); (b) investment demand for capital formation (IND). (c) The IFFs of industry-CON on investment commodities (INV) under scenarios with and without the TGP. (d) The IFFs of industry-MAN on international trade surplus balance (EX-IM) under scenarios with and without the TGP. Note: Yes and No represents scenarios with and without the TGP.

Figure 5 The main effect plots (a, c) of significant factors and interactive plots of significant interactions (b, d) in response to ln(DGL) and ln(IFFG), respectively.

Tables captions

Table 1. The parameters related to floods of various industries.

Industry	Damage rate by flood water depth (D)			Share of capital stocks prone to floods (E)	Share of industry's capital stocks in vulnerable areas (AF)
	FWD1	FWD2	FWD3		
AGR	0.33	0.58	0.78	0.20	0.6680
CON	0.03	0.05	0.07	0.16	0.7329
TSM	0	0.07	0.15	0.16	0.8103
AMI	0.05	0.1	0.15	0.2	0.7197
ECN	0	0.07	0.15	0.15	0.8130
WEM	0.05	0.1	0.15	0.20	0.7621

Table 2. Other key parameters used in this study.

Terms	FWD1	FWD2	FWD3
Loss of labor availability caused by floods (LAF)	5.7-6.9%	9.3-10.2%	13.2-17.2%
Inundation period (IP)	6.65 days	13.05 days	21.2 days
TGP's flood-retention capacity to reduce capital stock losses (FRC)	11.5-38.0%	11.5-38.0%	11.5-38.0%
TGP's flood-retention capacity to	20.6-60.9%	20.6-60.9%	20.6-60.9%

reduce labor loss (FCTD, FCTL)			
Proportion of fiscal stimuli	20-40%	20-40%	20-40%

*Note: "Proportion of fiscal stimuli" represents the proportion of the post-disaster multi-year payments to direct capital losses. The details of this parameter used in FLEA can be seen in Supplementary Information, S1.7.

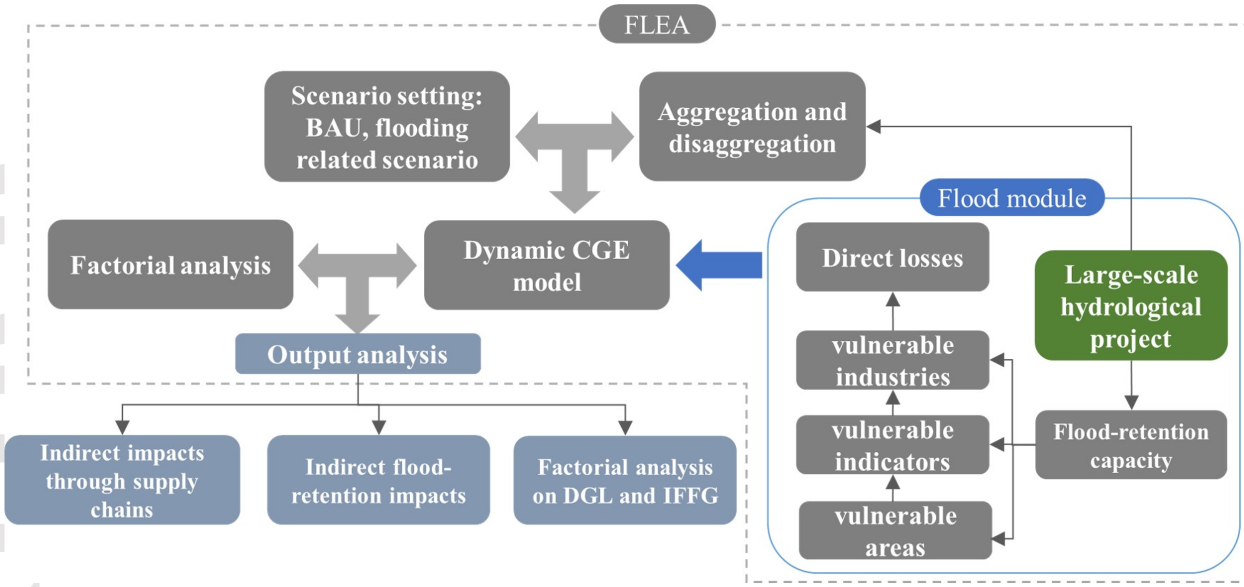
Table 3. The estimation of TGP's long-term indirect flood-retention impacts on the GDP. Note: IFFG represents the indirect flood footprints on GDP.

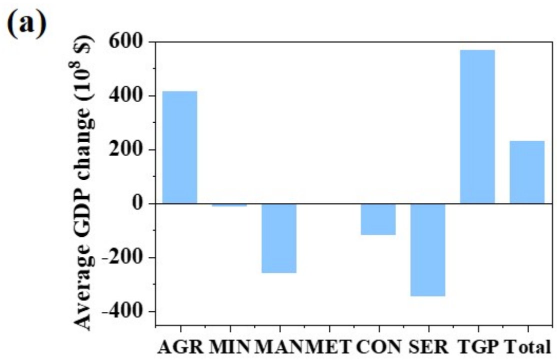
Flood water depth	Fiscal stimuli (%)	LIF ($ billion)	Reduced proportion of IFFG(%)
FWD1	20	[1.29, 3.89]	[14.42, 52.13]
	40	[0.92, 6.23]	[20.00, 47.08]
FWD2	20	[4.21, 14.18]	[15.72, 52.13]
	40	[3.11, 10.31]	[16.77, 55.70]
FWD3	20	[10.20, 30.21]	[17.54, 51.95]
	40	[7.25, 16.70]	[20.30, 46.77]

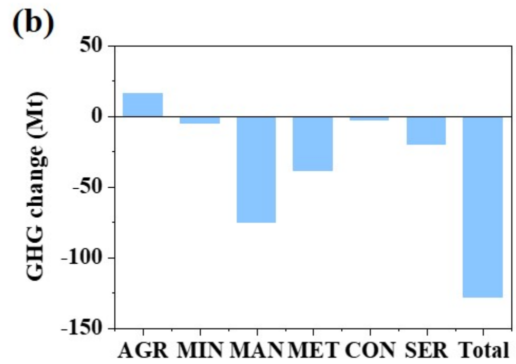
Table 4 The selected factors for factorial analysis.

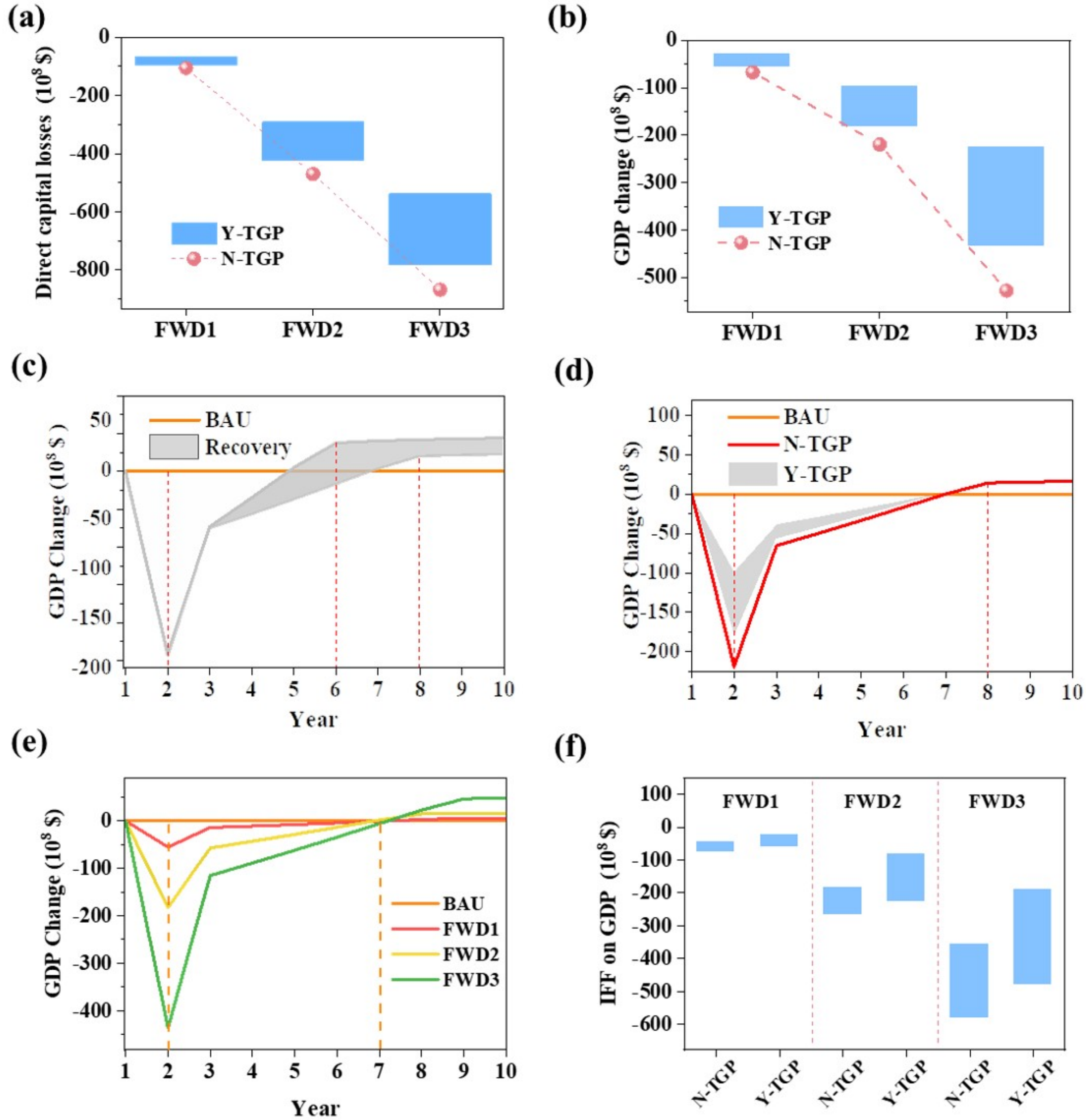
Factors	FS	FCT	FWD	LAF	RPL
Upper bound (+1)	40%	FRC: 38.0%; FCTL and FCTD: 60.9%	FWD3	FWD1: 6.9%; FWD3: 17.2%	2.5
Lower bound (-1)	20%	FRC: 11.5%; FCTL and FCTD: 20.6%	FWD1	FWD1: 5.7%; FWD3: 13.2%	2

*Note: FS represents proportion of fiscal stimuli, whose upper and lower bounds are the proportion of post-flood multi-year payments; FCT represents TGP's flood-retention capacity; FWD represents flood water depth; LAF represents the loss of labor availability because of floods; RPL represents the recovery parameter of labor.

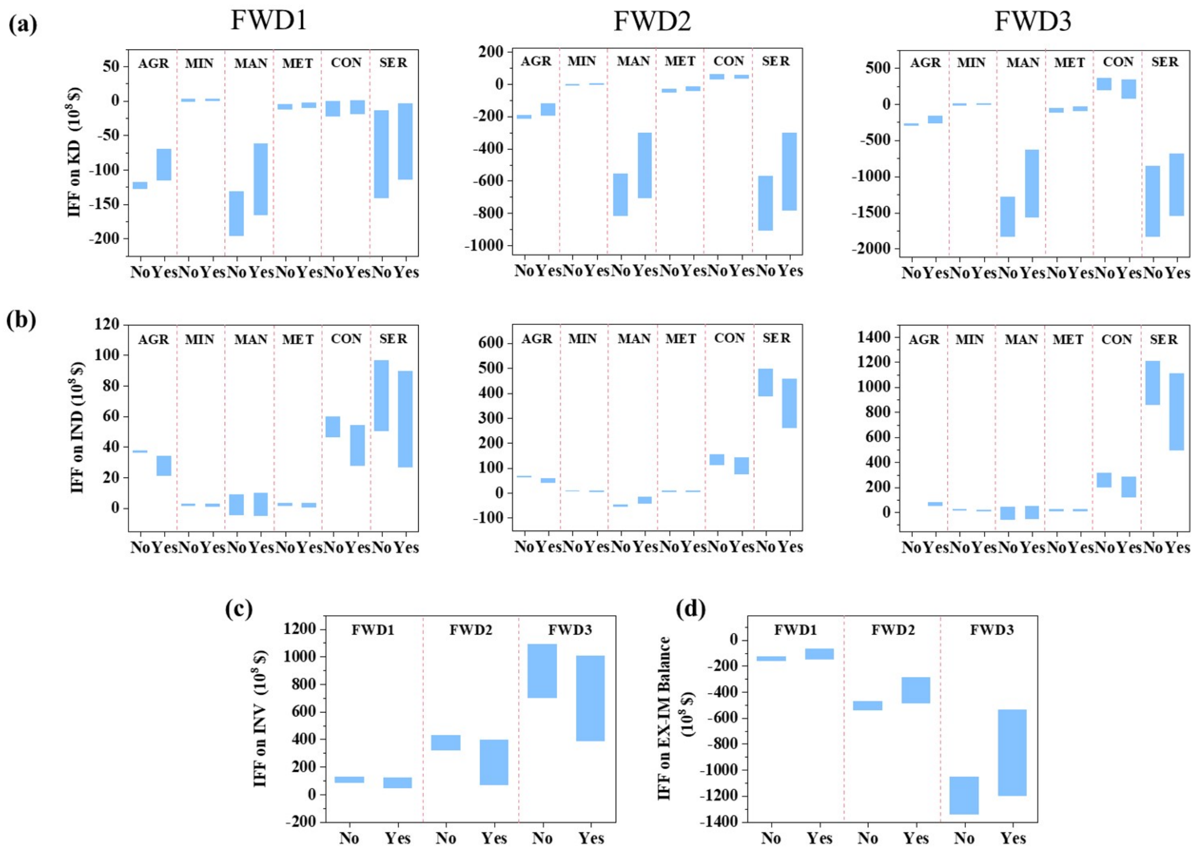

FLEA
Scenario setting: BAU, flooding related scenario
Aggregation and disaggregation
Factorial analysis
Dynamic CGE model
Output analysis
Flood module
Direct losses
Large-scale hydrological project
vulnerable industries
vulnerable indicators
vulnerable areas
Flood-retention capacity
Indirect impacts through supply chains
Indirect flood-retention impacts
Factorial analysis on DGL and IFFG

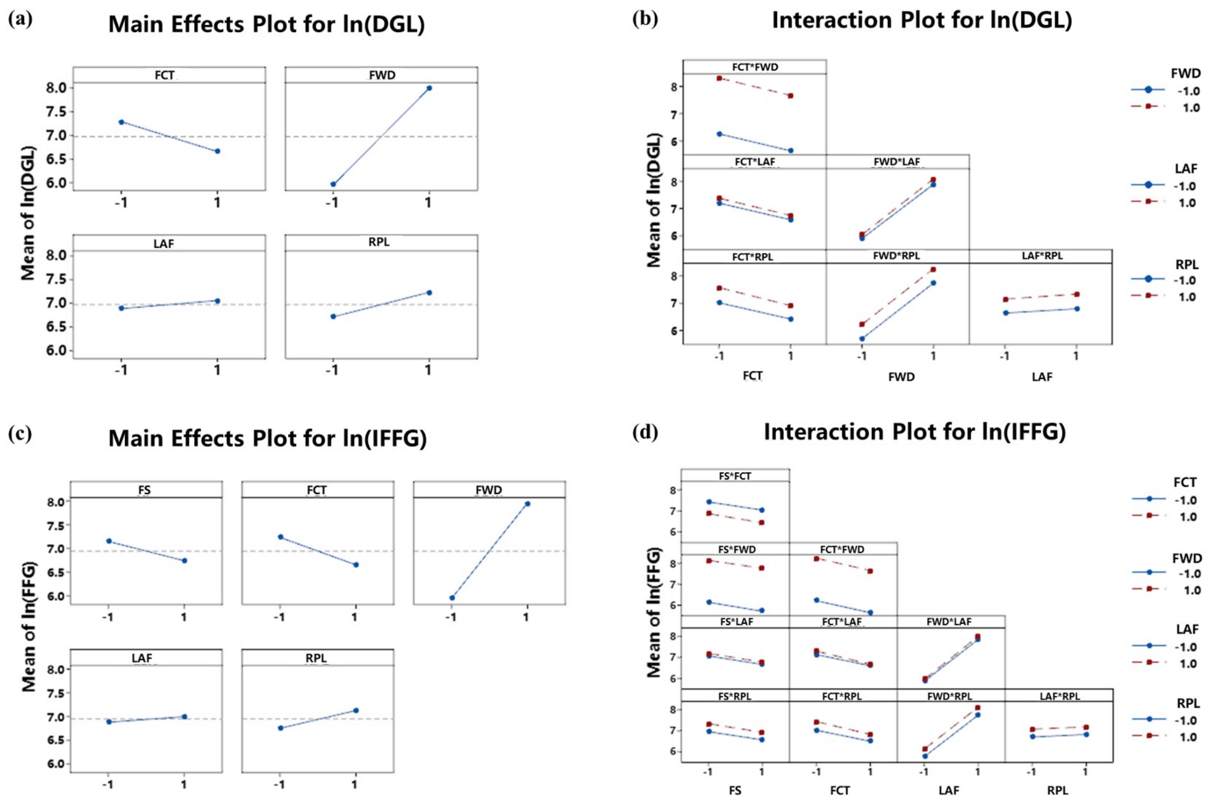

(a)
Average GDP change (10^8 \$)
600
400
200
0
-200
-400
AGR MIN MAN MET CON SER TGP Total


(b)
GHG change (Mt)
50
0
-50
-100
-150
AGR MIN MAN MET CON SER Total



(a)
Direct capital losses (10^8 $)
0
-200
-400
-600
-800
Y-TGP
N-TGP
FWD1
FWD2
FWD3
(b)
GDP change (10^8 $)
0
-100
-200
-300
-400
-500
Y-TGP
N-TGP
FWD1
FWD2
FWD3
(c)
GDP Change (10^8 $)
BAU
Recovery
Year
(d)
GDP Change (10^8 $)
BAU
N-TGP
Y-TGP
Year
(e)
GDP Change (10^8 $)
BAU
FWD1
FWD2
FWD3
Year
(f)
IFF on GDP (10^8 $)
FWD1
FWD2
FWD3
N-TGP
Y-TGP


(a)
FWD1
FWD2
FWD3
AGR MIN MAN MET CON SER
IFF on KD (10^8 \$)
No Yes No Yes No Yes No Yes No Yes No Yes
(b)
IFF on IND (10^8 \$)
(c)
IFF on INV (10^8 \$)
(d)
IFF on EX-IM Balance (10^8 \$)
No Yes No Yes No Yes


(a)
Main Effects Plot for ln(DGL)
Mean of ln(DGL)
FCT
FWD
LAF
RPL
(b)
Interaction Plot for ln(DGL)
Mean of ln(DGL)
FCT*FWD
FCT*LAF
FWD*LAF
FCT*RPL
FWD*RPL
LAF*RPL
FWD
LAF
RPL
(c)
Main Effects Plot for ln(IFFG)
Mean of ln(IFFG)
FS
FCT
FWD
LAF
RPL
(d)
Interaction Plot for ln(IFFG)
Mean of ln(IFFG)
FS*FCT
FS*FWD
FCT*FWD
FS*LAF
FCT*LAF
FWD*LAF
FS*RPL
FCT*RPL
FWD*RPL
LAF*RPL
FS
FCT
FWD
LAF
RPL