Global Environmental Change 53 (2018) 225–232

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

Social cost of carbon under shared socioeconomic pathways

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ARTICLE INFO

Keywords:
Climate change
Integrated assessment model
Social cost of carbon
Shared socioeconomic pathways
C^3IAM
DICE

ABSTRACT

The Social Carbon Cost (SCC) measures present value of future economic damages caused by an additional ton of carbon emissions, and is widely used by governments to design climate policies. Although the use of SCC is very extensive, its predictions are very difficult. Because the SCC is defined by social welfare associated with economic growth and population, its estimation is necessarily dependent on future assumptions that are difficult to project. Many approaches consider the impact of population or economic growth on the SCC, but these socioeconomic factors must be grounded on solid assumptions concerning political, technological and environmental developments. Over the past seven years, the climate change research community has established five plausible socioeconomic narratives, called 'Shared Socioeconomic Pathways' (SSPs), numbered SSP1–SSP5. These scenarios provide descriptions of how the future might unfold in several key areas. To this end, we use the Dynamic Integrated model of Climate and the Economy (DICE) to update the SCC under the five socioeconomic pathways, while also considering alternative damage functions and the social welfare discount rate to address uncertainty. The result of the China Climate Change integrated assessment model (C^3IAM) were used to re-estimate parameters in DICE, therefore characterize the SSPs. The results show that, in a world developing towards regional rivalry (SSP3), the SCC today will likely double compared with other scenarios. If emerged developing countries will follow the same path as previous industrializations (SSP5), the SCC will experience a rapid increase after 2060. Inequality (SSP4) will experience low mitigation pressure under a sustainable development scenario (SSP1), while the historical development pattern (SSP2) will have a moderate SCC with higher uncertainty. The results can provide carbon price benchmarks for policy makers who hold different attitudes towards the future and can help address the need to avoid regional rivalries and fossil-fueled development, which may counteract mitigation efforts.

1. Introduction

After the Paris Agreement, countries have increasingly taken actions to address climate change. Social cost of carbon (SCC), which balances the social costs resulting from emission reductions with the incremental costs of regulation policy has been widely used to provide policy guidance. The US government has relied on the SCC estimates provided by the Interagency Working Group (IWG) as a basis for taxing and implementing regulation policies (Revesz et al., 2017). The IWG SCC estimates started in 2010 and were updated with new scientific developments in 2013 and 2016, resulting in policy benefits of more than $1 trillion (Nordhaus, 2017). The SCC is also increasingly being adopted for regulations at the state level, resulting in regulatory policies in California, New York and Minnesota (California, 2016; Larson, 2016; Minnesota, 2016).

Given the wide range of social and climate interactions included in the calculation, SCC estimation is necessarily complex and highly uncertain (Pindyck, 2013). Damage functions and social welfare discounts are considered the two major contributors to this uncertainty (Cai et al., 2016; Diaz and Moore, 2017; Heal and Millner, 2014; Howarth et al., 2014; Pycroft et al., 2014); however, any discussion of these issues is necessarily based on the underlying socioeconomic assumptions.

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https://doi.org/10.1016/j.gloenvcha.2018.10.001
Received 19 April 2018; Received in revised form 29 September 2018; Accepted 7 October 2018
Available online 16 October 2018

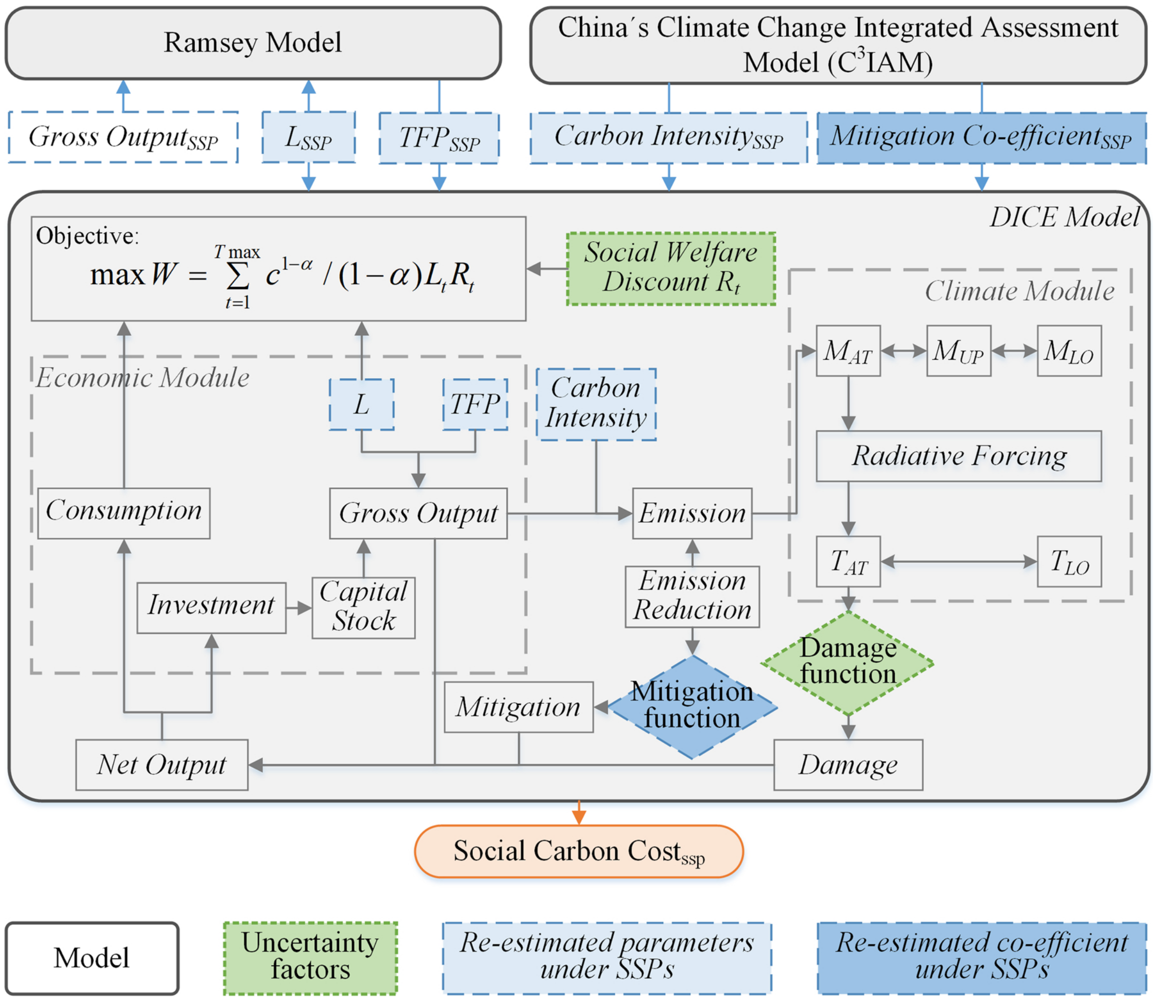

Fig. 1. Research Framework. L: population, TFP: total factor productivity, c: consumption per capita, M_{AT}: atmospheric concentration of CO_2, M_{UP}: upper ocean/biosphere concentration of CO_2, M_{LO}: deep ocean concentration of CO_2, T_{AT}: atmospheric temperature, T_{LO}: lower ocean temperature.

Economic development can alter emission flow patterns (Mi et al., 2017), and—because the SCC is defined by social welfare—population and economic projections are fundamental determinants in its estimation. Scovronick et al. (2017) investigated the influence of future population growth on the SCC, Dietz and Stern (2015) and Moore and Diaz (2015) considered the impacts of climate on economic growth as the drivers of SCC uncertainty. However, the demographic and economic assumptions are only two aspects of the socioeconomic assumption, which may be associated with a wide range of political, technological and environmental contingencies. If the China-US trade war continues developing and becomes a regional rivalry, it may well alter the long-term and global trends, resulting in different SCC patterns.

The SSP framework was initially proposed by Moss et al. (2010) and Van Vuuren et al. (2012), but the quantified and qualified version was published seven years later by Riahi et al. (2017). It include five SSPs which cover the broad spectrum of future challenges to mitigation and adaptation and translate this into consistent narratives of future developments that are quantified for diverse fields like demography, economic growth and convergence, energy, land-use, air pollution, policies, and trading (O'Neill et al., 2017; Riahi et al., 2017). The SSP framework greatly facilitates integrated analyses of mitigation and adaptation. Pizer et al. (2014) revealed the importance of considering the new SSP framework into SCC estimates. However, the current IWG models are too simple to directly quantify the SSP narratives. Therefore, we choose the SSP characteristics quantified by C^{3}IAM (Wei et al., 2018), and use its result to re-estimate the parameters in DICE, in order to characterize the five SSPs. The C^{3}IAM couples CGE with economic growth theory, which result can be used to update the mitigation function in DICE, while match the GDP trajectory with DICE as they both rooted in the economic growth theory.

Our paper estimates the SCC under the five socioeconomic scenarios; we also extend our research by considering the uncertainty caused by damage functions and the social welfare discount rate. The most important innovation of this study is to extent current research by computing the SCC under different socioeconomic pathways (SSPs), rather than considering the demographic and economic separately. The results demonstrate the need to avoid regional rivalries and fossil-fueled development, which can raise the current SCC or induce much heavier mitigation pressures by the end of this century. The SCC value provides a carbon price benchmark for policy makers who hold different attitudes towards the future and is an important reference for future research under the various SSPs.

2. Methodology

2.1. Overview of the methodology

Dynamic Integrated Climate Economy model (DICE) is one of the three models used by the U.S. government to provide latest SCC estimation, and also been widely used for SCC discussion by scholars (Crost and Traeger, 2014; Moore and Diaz, 2015; Scovronick et al., 2017).

Four parameters in DICE are subjected to the socioeconomic assumptions, namely the population, total factor productivity (TFP), carbon intensity, and the mitigation functions. To characterize the SSPs in DICE, these parameters need to be re-estimated according to the SSP narratives.

Population and GDP can be found in the SSP database, using the two, the TFP under each SSP can be re-estimated using the Ramsey model. Carbon intensity and mitigation policy cost is underlining in the SSP descriptions, and the value could be varied under different model structure. With many IAMs quantification of SSPs, only a few can calculate mitigation policy cost. Based on the DICE definition for the mitigation function and its economic structure, we choose the C^{3}IAM quantification (Wei et al., 2018), because it provides the policy cost under the economic growth theory (Detailed description in Supplementary Information). As they use the model to calculate three to five policy scenarios under each SSPs, every policy scenario has its emission reduction amount compared with BAU and related policy cost. We use these results to re-estimate the mitigation functions in the DICE model, therefore characterize the difference of mitigation cost under different socioeconomic pathways.

In Section 2.2, we describe our work to characterize SSPs in DICE. Then we demonstrate the calculation of SCC in Section 2.3. Because the SCC is also sensitive to alternative damage functions and to social welfare discounts, we extend our research by considering the uncertainty that arises from these two aspects. The damage functions and alternative social welfare discounts selected in this study are discussed in Section 2.4. An outline of our method is shown in Fig. 1.

2.2. Characterizing the SSPs in the DICE model

2.2.1. Characteristics of the five SSPs

The SSPs consist of a set of quantitative projections and qualitative descriptions. The quantitative projections include population and economic growth. These parameters are exogenous drivers to most integrated assessment models that form the fundamental characteristics of each SSP. The qualitative narratives are thoroughly described in O'Neill et al. (2017), including the aspects that are difficult to project quantitatively. To summarize, SSP1 represents the sustainable development path (van Vuuren et al., 2017), SSP2 implies a development pathway consistent with typical historical patterns (Fricko et al., 2017), and SSP3 is characterized by international fragmentation and regional rivalry (Fujimori et al., 2017). Low challenges to mitigation but high challenges to adaptation are observed in SSP4 (Calvin et al., 2017), which emphasizes extreme inequality. In contrast, SSP5 represents high challenges to mitigation and low challenges to adaptation (Kriegler et al., 2017), forecasting economic successes for both industrialized and emerging economies.

2.2.2. Qualify the SSPs in the DICE model

For the two quantitative factors, population can be directly set as exogenous in the DICE model, and the growth rate of GDP is reflecting by the total factor productivity in the growth model of DICE. Although these two factors are the fundamental inputs to characterize the five SSPs, the projections were varied under different projection methodologies. Among the two versions of population and three versions of GDP in SSP database, we choose the estimation from IIASA and PIK (Leimbach et al., 2017; Samir and Lutz, 2017), which is more in accord with the theoretical basis of DICE. While the DICE model has its own economic growth model known as the Ramsey model (Ramsey, 1928), the GDP cannot be directly exogenous to the model. Therefore, we use the TFP to reflect different growth rates under different SSPs. The process to derive the TFP can be seen in the Supplementary Information.

The qualitative factors are highly related to the energy and sectoral assumptions, which cannot be directly reflected in DICE. The carbon intensity and the mitigation function are two differentiating factors of DICE that can altered under different SSPs. Carbon intensity is exogenous as parameters, which measures the CO_2 intensity before any climate policies from all sectors. Mitigation function describes the policy cost as fraction of output, which is best described in the CGE model. The DICE model was built on economic optimum growth theory, while most CGE model endogenous saving rate without considering welfare, we need an IAM which can couple both CGE and economic growth model. The China Climate Change integrated assessment model (C^{3}IAM) is the model which fit the demand most. Therefore, we choose the China Climate Change integrated assessment model (C^{3}IAM), which is described in (Wei et al., 2018) to re-estimate the two factors in DICE.

C^{3}IAM divides the world into 12 regions and include 27 sectors for each region. As the DICE model is a global model, we aggregate the sectoral emissions of all regions from C^{3}IAM under each SSP baseline scenarios, and calculate the carbon intensity under five SSPs as follow:

$$\sigma_{ssp,t} = \frac{\sum_{n=1}^{12}\sum_{s=1}^{27} E_{ssp,n,s,t}}{GDP_{ssp,t}} \tag{1}$$

where $E_{ssp,n,s,t}$ is the CO_2 emission from region n and sector s at term t under each SSP, $GDP_{ssp,t}$ is the global GDP at term t under each SSP.

The socioeconomic assumptions (e.g., the level of regional rivalry, inequality and the development of sustainable technologies) will also result in different mitigation policy costs. In Wei et al. (2018), they combine the Representative Concentration Pathways (RCPs) with the SSPs, result in three to five policy scenarios under each SSPs. Each policy scenarios may result in a mitigation policy cost with the amount of emission reduction. In DICE model, the mitigation function is defined as follows:

$$\Lambda_t = a\mu_t^b \tag{2}$$

where μ_t is the emission reduction rate in each term, Λ_t presents the mitigation policy costs of the emission reduction policies. While Wei et al. (2018) had provide the two parameters under five SSPs, we use their results to re-estimated the parameter a and b. The regression result can be seen in the Supplementary Information.

2.3. Estimate the social cost of carbon

We estimate the SCC by DICE, following Nordhaus (2017). The DICE model optimizes a social welfare function, which is the discounted sum of the population weighted utility of per capita consumption:

$$\max W = \sum_{t=1}^{T\max} c^{1-\alpha}/(1-\alpha)L_tR_t \tag{3}$$

W is the global welfare, c is the per capita consumption, α is interpreted as generational inequality aversion, L_t is the population, R_t is the social welfare discount rate.

Output available for investment and consumption is the gross output reduced by mitigation costs and climate damage:

$$Y_t = TFP_tK_t^{0.3}L_t^{0.7}(1-D_t)(1-\Lambda_t) \tag{4}$$

Gross output is a Cobb-Douglas function of technology, capital and labor. Damage D_t and mitigation cost Λ_t are fraction of gross output. Y_t denotes net output of climate damage and mitigation costs.

Following a standard neoclassical optimal growth model known as the Ramsey model, society reduce consumption today to invest in capital goods, thereby increase consumption in the future:

$$C_t = Y_t - I_t \tag{5}$$

C_t is total consumption, I_t is the total investment.

The capital formation is guided as:

$$K_t = (1\text{-}\delta_K)K_{t\text{-}1} + I_t \tag{6}$$

K_t is the capital stock in term t, δ_K is the depreciation rate of capital stock.

$$E_t = \sigma_t(1 - \mu_t)TFP_t K_t^{0.3} L_t^{0.7} + LU_t \quad (7)$$

CO_2 emission E_t is the sum of industrial emissions and land use emissions LU_t. Industrial emissions without policy are given by carbon intensity σ_t times gross output, and μ_t is emission reduction rate. The emission then input to the three-reservoir carbon cycle in DICE, which details can be seen in (Nordhaus, 2018, 2017).

Under the structure of DICE, SCC can be calculated in discrete approximation to:

$$SCC_t = \frac{\partial W}{\partial E_t} / \frac{\partial W}{\partial C_t} \quad (8)$$

2.4. Alternative damage functions and social welfare discount rate

The SCC is very sensitive to the damage function and social welfare discount rate. However, with our limited knowledge about the mechanisms of climate change, the accuracy of damage functions is unknown. The social welfare discount rate is valued not only as an economic term but also considered as an ethical primitive. Therefore, we provide the social carbon cost under nine damage functions and discuss the SCC under six alternative social welfare discount rates.

The damage function in DICE-2016R has been used to provide SCC estimations for the U.S. government. To consider the uncertainty of damage functions, we tested eight additional functions based on the meta-analysis by Richard Tol (Tol, 2018), which includes 27 published estimates of the economic impact of climate change. The piecewise linear function provides the best fit with the lowest standard error; however, Tol also used seven other forms to fit the data. Although some functions have a higher standard error of regression, we still include the results as possibilities. Together with the damage function in DICE-2016R, we estimate the SCC under 9 damage functions to consider all the possibilities (as shown in Table 1).

h the social welfare discount rate can be defined as an economic concept, many argue that the choice of discount rate is also an ethical primitive. Stern recommended a value of 0.1% (Stern, 2006). Nordhaus valued it in the Ramsey equation, resulting in an estimate of 1.5% (Nordhaus, 2017). The IWG provided evaluations using the social discount rates on dollars of 2.5%, 3% and 5%. Thus far, however, the social welfare discount concept has not converged to a single value in the literature. The SCC is highly sensitive to the discount rate(Heal and Millner, 2014). To better illustrate the uncertainty caused by socioeconomic assumptions and damage functions, we chose the 1.5% economic discount rate for discussion. The alternative discounts, ranging from 0% to 5%), are discussed in Section 3.2.3 Alternative Social Welfare Discounts.

3. Results

3.1. Evaluating the SSP outcomes in DICE

As shown in Fig. 1, the socioeconomic assumption is accompanied by a particular emission trajectory. The emission patterns differentiate under each SSP, leading to increases in atmospheric concentrations, which indicate the long-term temperature trends. Temperature is the direct indicator of climate change and produces different degrees of climate damage, which further determine the SCC. Therefore, we chose emission, concentration and temperature to illustrate the major outcome of SSP in the DICE model (Fig. 2). Compared with the five SSP marker scenarios(Calvin et al., 2017; Fricko et al., 2017; Fujimori et al., 2017; Kriegler et al., 2017; van Vuuren et al., 2017), the DICE model considers the optimal emission reduction strategy under a cost-benefit analysis and generate temperature using its own climate module. Compared with the marker scenarios, the results from DICE are slightly lower than their baseline scenarios, but the relationships accord with the general narratives.

Under SSP5, industrial emissions are markedly higher than other scenarios because of industry's reliance on fossil fuels. Thus, SSP5 results in 130 $GtCO_2$ emissions in 2100. The emission trajectories of SSP1 to SSP4 diverge after 2050. SSP2 and SSP3 exhibit an increasing emissions trend until the end of this century; in 2100, their values are 65 $GtCO_2$ and 70 $GtCO_2$, respectively. With low challenges to mitigation, SSP1 and SSP4 both reach their emissions peaks in the middle of the century. Under SSP1, emissions reach 47 $GtCO_2$ in 2050 but decrease to 42 $GtCO_2$ by 2100. Under SSP4, the peak emission is higher at 48 $GtCO_2$ in 2055 and decreases more slowly to 45 $GtCO_2$ at the end of this century. Under SSP5, higher emissions will magnify the uncertainty of climate damage, resulting in a wider range of emissions trajectories. Under some damage functions, the optimal emission control rate results in an emissions decrease in SSP5, but under most scenarios, the emissions generally increase.

The difference in emissions is directly reflected by the atmospheric concentration trend, which determines the long-term growth of temperature. Under SSP 1 and SSP4, the concentration nearly stabilizes by the end of this century, reaching average levels of approximately 720 ppm. The concentrations in SSP2 and SSP3 continue increasing to 760 ppm and 799 ppm, respectively, by the end of this century. With high dependence on fossil fuels, in SSP5, the concentration rises to 1019 ppm by 2100. According to the IPCC Fifth Assessment Report (Pachauri et al., 2014), the concentration is likely ($> 66\%$) to cause temperature increases of up to 4 °C by 2100 under SSP1–SSP4. At concentrations above 1000 ppm, the SSP5 temperture is unlikely ($< 33\%$) to remain at 4 °Cin 2100 and will continue to rise according to the concentration trend.

The result from the DICE model agrees with the IPCC result. Because the climate cycle is a long-term process, the temperature increases are

Table 1
Damage Function Based on Meta-analysis by Richard Tol (Tol, 2018).

Specification	Proposer	Standard Error of Regression
$0.236\ T^2$	DICE-2016R	
$(-0.74\ T)\ I_{T < 1.01} + (1.41\ T\text{-}2.18)\ I_{T \geq 1.01}$	Meta-analysis	1.12
$0.12\ T + 0.16\ T^2$	Tol (2009)	1.17
$0.19\ T^2$	Nordhaus	1.25
$0.71\ T$	Hope	1.34
$0.02\ \exp(T) - 0.02$	Karp; Van der Ploeg	1.71
$4.2{*}10^{-175}\ \exp(\exp(T)) - 1.1{*}10^{-174}$	Golosov	2.10
$1.6{*}10^{-4}\ T^2\text{-}0.36\ T^2$	Weitzman	2.69
$2.6{*}10^{-5}\ T^2\text{-}0.35\ T^2$	Weitzman	2.73

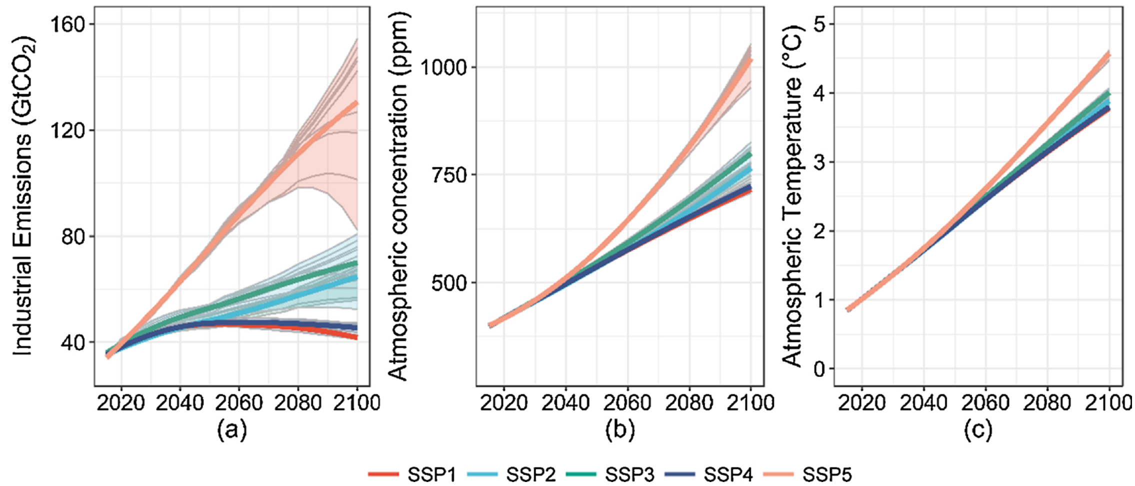

Fig. 2. Industrial emissions and their influences on atmosphere concentration and temperature under the five SSPs: (a) industrial emissions, (b) atmospheric concentration, (c) atmospheric temperature. The gray lines indicate the results from nine different damage functions; the colored lines show the smoothed conditional means of the results under the five SSPs.

quite similar among the scenarios. SSP5 has the largest temperature increase—4.6 °C compared to the preindustral level. In SSP1 to SSP4, temperatures increase by approximately 4 °C, to 3.8 °C, 3.9 °C, 4.0 °C and 3.9 °C, respectively.

3.2. Estimate the social carbon cost with uncertainty

3.2.1. Impact of socioeconomic assumptions on social carbon cost

Socioeconomic assumptions greatly affect the levels and trends of the SCC. Under the five SSP narratives, the SCC calculated under nine

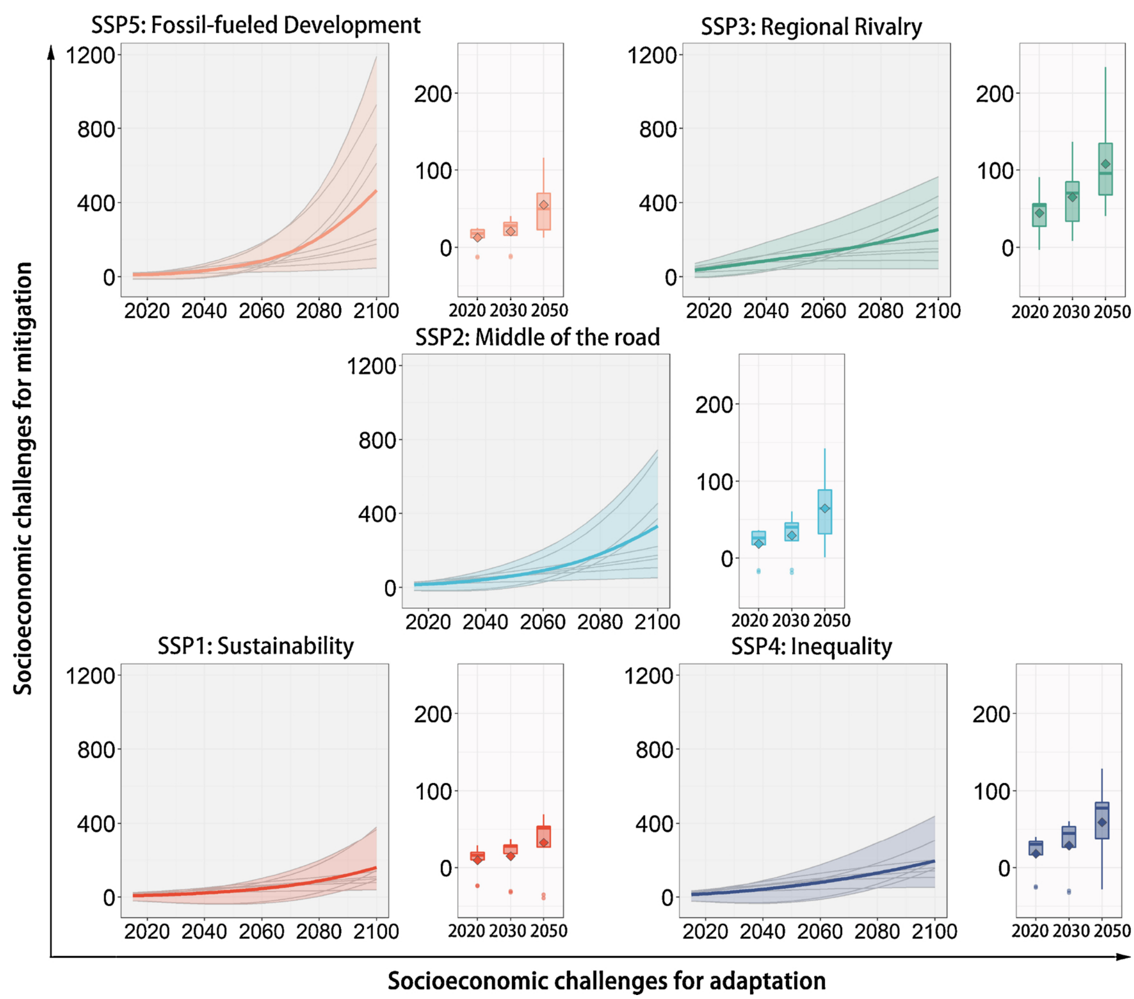

Fig. 3. Social carbon cost ($/tCO$_2$) under five SSPs. The gray lines show the SCC calculated under nine damage functions; the colored lines show the smoothed conditional means of the SCC.

damage functions result in different uncertainty extents as shown in Fig. 3.

In 2020, the average SCC estimations under SSP1, SSP2, SSP4 and SSP5 are 10 $/t$CO_2$, 19 $/t$CO_2$, 18 $/t$CO_2$ and 12 $/t$CO_2$, respectively. The SSP3, which represents high mitigation and adaptation challenges, has the highest SCC early in this century, reaching 45 $/t$CO_2$ in 2020 and increasing to 108 $/t$CO_2$ by 2050. This level is remarkably high compared with other scenarios, and it suggests that if the world socioeconomic conditions increasingly develop into regional rivalries, the SCC will undergo a significant increase. Under the benefit-cost framework, the SCC equals the carbon price under a tax or trade instrument (Nordhaus, 2013). In 2017, 19 carbon trading markets were in place with an average price of 9.1 $/t$CO_2$, and 22 nations/sectors have implemented a carbon tax, which averages 29.9 $/t$CO_2$ (World Bank, 2017). Under all the scenarios, the SCC is higher than the quota price but quite similar to the carbon tax. This result indicates that, thus far, the carbon trading system need more mechanism perfection to reflect the SCC. However, as carbon taxes are implemented by governments, they can be targeted to maximize public welfare. Therefore, a carbon tax can better reflect the social costs of additional emissions.

Different socioeconomic assumptions can also alter the SCC trend, especially after 2050. SSP3 features a slow growth of SCC at high levels; its annual growth rate is 3% from 2015 to 2050 but the level is the highest among all scenarios. Social costs undergo rapid growth in SSP5, with an annual growth rate of 5% from 2015 to 2050 and continued increases thereafter at 4% annually until the end of this century. SSP1, SSP2 and SSP4 are characterized by medium growth throughout the century, with annual growth rates of 4% from 2015 to 2050. The SCC trend can be an important indicator of policy section among price and quantity instruments(Weitzman, 1974). Therefore, different socioeconomic developments may affect the choice of policy instruments.

Varying levels of uncertainty can be witnessed within the socioeconomic scenarios due to the impact of damage functions. Higher emissions magnify the uncertainty from climate damage, thereby resulting in a wider SCC range in SSP2, SSP3 and SSP5.

3.2.2. Impacts of damage functions on social carbon costs

The SCC values under the nine damage functions can be divided into two groups, indicating different expectations for climate change. However, the choice of damage function will not reverse the SCC relationships under the five SSPs.

As shown in Fig. 4, the SCC under the nine damage functions can be classified into ‘moderate’ estimation and ‘sharp change’ estimation. Moderate estimations include the five functions proposed by Hope, Tol and Nordhaus. Using these, the estimated SCC never exceeds 300 $/t$CO_2$ in this century, and it reaches an average level of 157 $/t$CO_2$ by 2100 under the five SSPs. In contrast, applying the damage functions provided by Weitzman, Karp and Golosov results in a sharp increase of SCC by the end of this century, reaching an extremely high average level of 864 $/t$CO_2$ by 2100. The moderate estimation is mainly extrapolated from observation, while the sharp change group suggests that several of the climate system elements could be tipped into a different state by the temperature increase. According to the two damage functions from Weitzman, a modest increase of temperature will initially benefit the economics but then abruptly decrease after the tipping point. These functions result in an initially negative SCC, which indicates that the additional emissions will provide positive effects and a social welfare gain under a moderate temperature increase. Under SSP1 and SSP4, with low mitigation challenges, the negative SCC will continue until 2060 to 2075, while under SSP3, with high mitigation challenges, the SCC becomes positive between 2015 and 2020. Under the damage function from Golosov, the SCC increases from 13 $/t$CO_2$ in 2015 to 1192 $/t$CO_2$ in 2100, leading to enormous mitigation and adaptation pressures by the end of this century.

Regardless of the damage function used, the SCC relationships under the five SSPs are not reversed. The sustainable development scenario (SSP1) always ranks the lowest under all damage functions. SSP5 is characterized as a rapid increase of SCC by the end of this century. SCC under SSP3 is initially high but has a low growth rate over the century. Moderate growth is also observed in SSP2, but the initial level is lower than in SSP3.

3.2.3. Alternative social welfare discount

The social cost of carbon is also highly sensitive to the social welfare discount rate. Because climate damage mainly accrues over the long term, the discount rate affects how the prospect of future damage should be addressed today. A high discount rate will significantly reduce the present perception of future climate damage, which results in a low SCC. In contrast, when the climate damage has no future discount, so that people today are as concerned with their descendants' welfare as with their own well-being, ambitious climate actions should be taken immediately under high SCC. A near-zero discount rate highlights the ethical issues of climate policy, while the Ramsey discount emphasizes the economic benefits of adaptation. This section provides alternative SCC estimations under discounts of 0%–5% and compares them with the carbon tax and quota price in 2017 to reflect the present policy intensity.

Average SCC decrease exponentially from 0% to 5% (as shown in

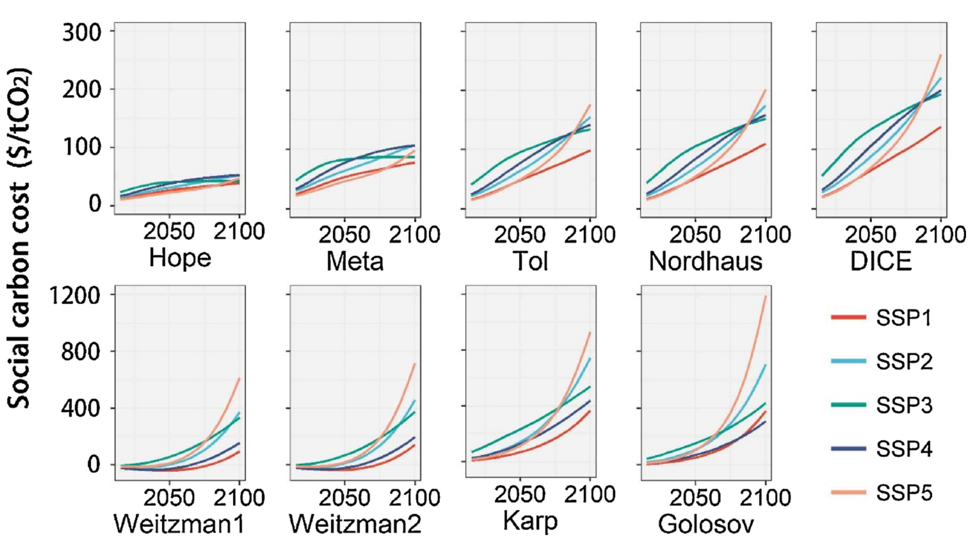

Fig. 4. Social carbon cost ($/t$CO_2$) under nine damage functions.

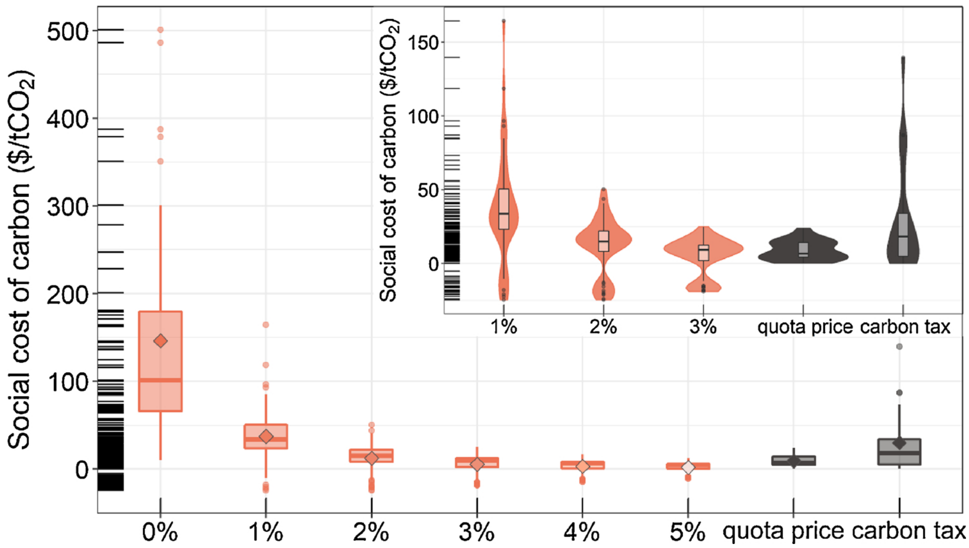

Fig. 5. The social cost of carbon in 2020 under a 0%–5% social welfare discount compared with the carbon price in 2017.

Fig. 5). In 2020, the average SCC values under discounts from 0% to 5% SI are 146 $/tCO_2$, 37 $/tCO_2$, 12 $/tCO_2$, 5 $/tCO_2$, 3 $/tCO_2$ and 2 $/tCO_2$, respectively. A low discount rate substantially magnifies the uncertainty of impacts from emissions, temperature and climate, resulting in a wide range of SCC estimations—from -25 $/tCO_2$ to 501 $/tCO_2$ in 2020 under a 0% discount. When the discount rate exceeds 3%, the wellbeing of future generations has less influence on today's policy decisions, resulting in SCC values below 5 $/tCO_2$.

The SCC provides a basis for pricing carbon; in 2017, the average quota price was 9.1 $/tCO_2$, while the carbon tax averaged 29.9 $/tCO_2$. Comparing these figures with our SCC estimates, the carbon tax indicates a discount rate preference of 1%, and the carbon quota price indicates a discount rate of 2%–3%. However, although the average carbon tax can be as high as 139.58 $/tCO_2$ in Sweden, the mean distribution of the tax is still quite low.

4. Conclusions

Paris Agreement had promoted more countries to implement climate policy, and the cost-benefit of climate policy is a good point for nations to start. As the SCC internalize the CO_2 externality, its value will be helpful to provide regulatory policy guidance. The term has been used for carbon tax, tradable obligations or renewable portfolio standards (Burke, 2016). However, SCC estimation relies heavily on future assumptions (e.g., mitigation and adaptation challenges, population growth and economic development), a reliance that has not previously been recognized. Previous studies have discussed the population and economic impacts separately; however, these factors have a synergistic effect on all aspects. This paper is based on the five plausible future descriptions established by the climate change research community, and it provides the future social costs of emissions under different development pathways.

We found that the scenario representing extreme regional rivalry (SSP3) will cause substantial increases in the SCC in the near term, indicating that if more trade tariffs are implemented due to increasing regional conflicts, the social carbon cost today will be underestimated. Under SSP5, where developing countries emerge by exploiting abundant fossil fuels, the pressures for mitigation will become unbearable by the end of this century. The SCC is initially at a relatively low level. Then, it undergoes a rapid increase after 2060 and reaches an average level of 471 $/tCO_2$ by 2100. The damage this growing trend will cause is unstoppable, according to the atmospheric concentration; thus, it demands an increase in attention to the clean development of emerging economies. SCC under increasing inequality (SSP4) is similar to the sustainable development pathway (SSP1) and maintains a low growth rate at a moderate level. The scenario that follows the historical development patterns (SSP2) experiences the same annual growth rate as SSP1 but at a higher social cost and with more uncertainty. The results of this study highlight the importance of avoiding regional rivalries and expending efforts to ensure the green development of emerging economies to deal with climate change. Our results also provide a breakeven carbon price for policy makers who hold different attitudes concerning the future and they facilitate mitigation and adaptation analysis under the SSPs. However, the original form of mitigation function in DICE cannot describe the extreme sustainable development under SSP1, which made one of the co-efficient not significant in this study. This weakness needs to be overcome in the future work. Also, because the regional SCC is still under discussion and difficult to explain even at the domestic level (Fraas et al., 2016; Guivarch et al., 2016), we defer a discussion of regional SCC for the future.

Acknowledgements

The authors gratefully acknowledge the support from the National Key R & D Program (Grant No. 2016YFA0602603), the National Natural Science Foundation of China (Grant Nos. 71521002, 71642004, 71673026). The paper also benefitted from the participants at a seminar at Beijing Institute of Technology.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.gloenvcha.2018.10.001.

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