Estimating the economic cost of sea-level rise

by

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Submitted to the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degree of

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Abstract

To improve the estimate of economic costs of future sea-level rise associated with global climate change, the thesis generalizes the sea-level rise cost function originally proposed by Fankhauser, and applies it to a new database on coastal vulnerability, Dynamic Interactive Vulnerability Assessment (DIVA). With the new cost function, a new estimate of the cost present values over the 21st century is produced.

An analytic expression for the generalized sea-level rise cost function is obtained to explore the effect of various spatial distributions of capital and nonlinear sea-level rise scenarios. With its high spatial resolution, DIVA shows that capital is usually highly spatially concentrated along a nation's coastline, and that previous studies, which assumed linear marginal capital loss for lack of this information, probably overestimated the fraction of a nation's coastline to be protected and protection cost. In addition, the new function can treat a sea-level rise that is nonlinear in time. As a nonlinear sea-level rise causes more costs in the future than an equivalent linear sea-level rise scenario, using the new equation with a nonlinear scenario also reduces the estimated damage and protection fraction through discounting of the costs in later periods.

Numerical calculations are performed, applying the cost function to DIVA and socio-economic scenarios from the MIT Emissions Prediction and Policy Analysis (EPPA) model. In the case of a classical linear sea-level rise of one meter per century, the use of DIVA generally decreases the protection fraction of the coastline, and results in a smaller protection cost because of high spatial concentration of capital. As in past studies, wetland loss continues to be dominant for most regions, and the total cost does not decline appreciably where wetland loss remains about the same. The total cost for the United States is about $320 billion (in 1995 U.S. dollars), an estimate comparable with other studies. Nevertheless, capital loss and protection cost may not be negligible for developing countries, in light of their small gross domestic product.

Using realistic sea-level rise scenarios based on the Integrated Global System Model (IGSM) simulations substantially reduce the cost of sea-level rise for two reasons: a smaller rise of sea level in 2100 and a nonlinear form of the path of sea-level rise.

As in many of the past studies, the thesis employs conventional but rather unrealistic assumptions: perfect information about future sea-level rise and neglect of the stochastic nature of storm surges. The author suggests that future work should tackle uncertain and stochastic sea-level rise damages.

Thesis Supervisor: Henry D. Jacoby
Co-Director, Joint Program on the Science and Policy of Global Change

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Chapter 1. Introduction

1.1. Sea-level rise as a policy issue

It was a single hurricane named Katrina that severely damaged the Gulf Coast region and transformed the City of New Orleans forever. Although much attention has been paid to New Orleans, Katrina also brought an extremely high storm surge in Mississippi (Graumann et al. 2005; Interagency Performance Evaluation Task Force 2006) and caused severe damage in the area. In fact, Katrina broke the record of storm surge set by Hurricane Camille in 1969.

The topic of this thesis is not Katrina or sudden, horrific hurricanes. Rather, it is about a steady, slow rise of the global mean sea level due to human-induced global warming. The Intergovernmental Panel on Climate Change (IPCC) projects that global sea-level rise would be 9–88 cm higher by 2100, relative to the 1990 level (Church et al. 2001). Such a rise of the sea would add to the storm surge levels and exacerbate flooding. Had the sea level been higher when Katrina hit, the damage could have been even larger.

A number of researchers have tackled the question of damage from global sea-level rise, making great advances in understanding its potential impact. Such an exercise is a prerequisite for informed policymaking on climate change and sea-level rise. Estimates have been made of loss of dryland (Fankhauser 1995a (hereafter F95a); Tol 2002a, 2002b; among others), the number of people subject to flooding by storm surge (Nicholls et al. 1999; Nicholls 2004), loss of wetlands (Nicholls 2004), and the number of people who would be forced to emigrate (Tol 2002a, 2002b). Nicholls and Tol (2006) provide new estimates for dryland loss, protection cost, and wetland loss, using the scenarios from the IPCC Special Report on Emissions Scenarios or SRES (Nakicenovic and Swart 2000).

And yet such studies are far from perfect. One remaining issue is the optimal degree of protection. If economies of scale of coastal protection are ignored, the cost of protection is proportional to the fraction of a coastline to be protected. Early studies adopted an arbitrary rule for protection and found high protection levels and huge costs. F95a proposed a formula to obtain optimal protection level, but also found very high protection levels. For example, the United Kingdom should be protecting about 90% of its coastline. A casual observer would wonder why the United Kingdom should become like a neighbor country, the Netherlands.

Another important issue is the impact of capital loss on economic growth. To make an analogy with Katrina, most studies estimated the cost of devastated infrastructures and buildings, but never examined the economic growth that would be diminished by those capital losses. Improving cost studies by incorporating the long-term effects of capital on economic growth is an important component of informed policymaking.

When discussing impact assessment, it is important to distinguish different scales used in the study. In the case of sea-level rise, most decision-making on coastal problems, including adaptation to sea-level rise, takes place on the local level. Indeed, the present research is not intended for informing local decision-making. With global-scale analysis, it rather attempts to stimulate a global-scale policy formulation for climate change. Since effective climate policy requires responses on both local and global scales, impact assessment on various scales are necessary, complementing each other.

1.2. Research contributions

Given the need for better cost studies, this research attempts to provide a way to improve estimates. This thesis constitutes the first part of an effort to calculate the monetary costs of sea-level rise, using the framework of the Integrated Global System Model (IGSM) and Emissions Prediction and Policy Analysis (EPPA) model developed at the Massachusetts Institute of Technology (MIT).

In particular, I have extended the sea-level rise cost function developed by F95a, and produced a new estimate of global sea-level rise, using MIT's IGSM and new datasets on sea-level rise vulnerability, Dynamic Interactive Vulnerability Assessment (DIVA), and geographic distribution of economic outputs, G-Econ (Geographically based Economic data).

The new estimates show lower costs than previous studies, which can be explained by simple analyses with the extended sea-level rise cost function.

The spatial resolution of the new vulnerability database used in this thesis is substantially higher than its predecessor, and the data shows a high degree of capital concentration along the coast. Because of capital concentration, fewer coastal segments should be protected, yielding a lower cost of protection than previous studies. F95a assumed a quadratic function to represent geographic cumulative distribution of capital but the data demonstrates that capital is much more concentrated for a number of countries than F95a assumed. However, the total cost does not decrease appreciably since wetland loss continues to dominate as in the literature. For a one-meter-per-century linear sea-level rise, the total cost for the United States is about $320 billion (in 1995 dollars), which is comparable to other estimates.

Realistic sea-level rise scenarios, which have a lower than one-meter rise in 2100, naturally result in lower costs. However, the reason is not just a lower sea level in 2100. Because the path of sea-level rise is more like a quadratic function than a linear one, a realistic sea-level rise postpones the cost into the future, thereby reducing the present value of the damage by discounting. Though F95a's formula assumed a linear sea-level rise, the present thesis derives a general formula for any sea-level rise scenario. The analysis comparing equivalent linear and quadratic sea-level rise scenarios indicates that many past cost estimates, which relied on linear sea-level rise scenarios in one way or another, have overestimated the cost and/or optimal protection level.

The ultimate goal of the sea-level rise project at MIT is to include the effect in the IGSM framework so that we can represent the accelerated capital depreciation effect which Fankhauser and Tol (2005) pointed out is important, and the interaction between the climate system and socio-economic system. This thesis is a key step in the larger effort.

1.3. Thesis organization

Chapter 2 gives a review of literature to place the present thesis in a larger context. Chapter 3 describes the general methodology used here, especially the datasets I repeatedly use—DIVA, a sea-level rise impact database, G-Econ, a geographic economic database, and EPPA model, a computable general equilibrium economic model, and the IGSM. Chapter 4 is the centerpiece of this thesis, deriving and extending the sea-level rise cost function that was originally developed by F95a, and incorporating it into EPPA. This is followed by the results in Chapter 5. Chapter 6 concludes and explores future research directions.

Chapter 2.
Context: past studies on sea-level rise impact

2.1. General review

The literature on sea-level rise is extensive, and a number of good reviews are available. The most authoritative is, arguably, the reports by the Intergovernmental Panel on Climate Change (IPCC) (Warrick and Orelemans 1990; Tsyban et al. 1990; Warrick et al. 1996; Bijlsma et al. 1996; Church et al. 2001; McLean et al. 2001). Another new report by the IPCC, the Fourth Assessment Report, is expected due in 2007. In addition, there are recent excellent review papers such as Cazenave and Nerem (2004), who reviewed physical science underlying global sea-level rise, and Nicholls (2003), who summarized impact assessment. This chapter gives a brief overview of the issue, and in so doing pays attention to various sources of uncertainty. As Nicholls (2003) points out, global-mean sea-level rise is "one of the more certain impacts of global warming." Nonetheless, the following review gives an unnerving picture that sea-level rise contains considerable uncertainty.

Before embarking on the review of sea-level rise, it would be useful to remind ourselves of the problems coastal areas are currently confronting. Though this thesis is concerned only with sea-level rise, coastal areas are under various kinds of pressure and stress, such as higher-than-national-average population growth, habitat destruction, increased pollution and so forth (Nicholls 2003). Coastal planners will face many kinds of stresses at the same time, and they would have to solve the different problems simultaneously, sea-level rise being only one of them.

A good case in point is the recent increased damage from hurricanes. Pielke and Landsea (1998) clarified that increased coastal population explains the most of a recent hike in the insured damage of hurricanes, which Pielke et al. (2006) reaffirmed. At the same time, Emanuel (2005) and Webster et al. (2005) showed that hurricanes are intensifying globally.[1] Stronger hurricanes have not affected hurricane damage statistics because only a very few hurricanes make landfall.

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[1] Scientific discussions continue to this date. See Chan (2006), Hoyos et al. (2006), Landsea (2005), Landsea et al. (2006), Mann and Emanuel (2006), for example.

And yet, in the future toward the end of the 21st century, coastal planners are expected to deal with increasing coastal population and intensifying hurricanes simultaneously, not to mention sea-level rise.

Commitment of sea-level rise

According to the IPCC, the global mean surface temperature has risen by 0.6 ± 0.2°C degrees Celsius since the late 19th century (Folland et al. 2001). Greenhouse gases emitted by human activity have changed the radiative balance of the earth, leading to warming of the atmosphere-ocean system. Over the 20th century, global sea level has risen by 10–20 cm, mostly through thermal expansion (as opposed to the melting of ice sheets, ice caps, and glaciers) (Church et al. 2001).

Because of the large thermal inertia of the ocean, it will take thousands of years for the entire ocean to adjust to the radiative forcing. Even if the emissions of greenhouse gases were to be cut substantially and the concentration of carbon dioxide to stabilize, the oceans would continue to warm and expand. This implies that we have *committed* ourselves to the future sea level rise already, and that the time span of the global sea-level rise problem is not one hundred years, but several hundred years or longer. Another implication is that the effect of climate change mitigation materializes only after about 2050 because of the oceanic time lag, and that *humans must adapt* to a rising sea level.

The popular media often depicts a picture of a catastrophic sea-level rise of several meters with melting of Antarctica and Greenland, but it is usually assumed that such a rise will take more than hundreds of years, if not thousands. Despite its slowness, this is indeed an important problem. But this thesis focuses on the conventional time range of 100 years.

Cascade of uncertainties

Projecting the fate of the global sea level involves various processes. First, it requires emissions of greenhouse agents and aerosols. Second, it is necessary to convert emissions to concentrations in the atmosphere and radiative forcing. The third step is to calculate the warming associated with the estimated radiative forcing and heat penetration into the oceans. Figure 2.1 conceptualizes the so-called cascade of uncertainty. Each step introduces an additional source of uncertainty, and the result is a huge spread of the projected sea-level rise.

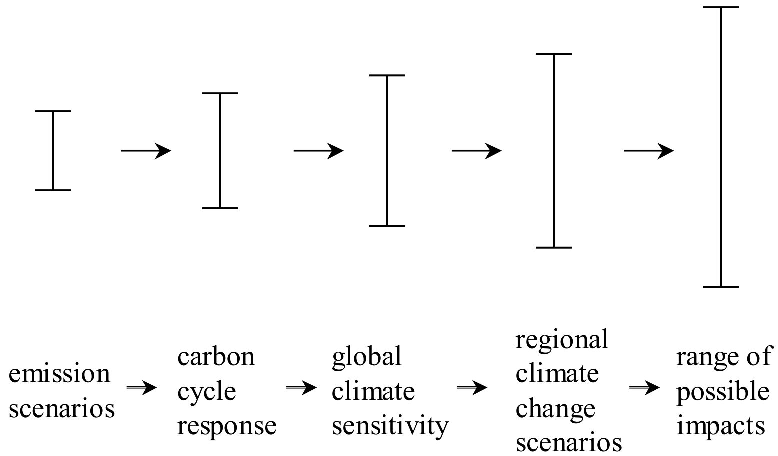

Figure 2.1. Schematic showing the cascade of uncertainty. Each step in impact assessments adds another source of uncertainty, culminating in a huge uncertainty of the final possible impacts. Adapted from Moss and Schneider (2000).

An important source of uncertainty that is often ignored is the regional variation of sea-level rise. Locally, what matters is *relative sea-level rise,* which is a sum of three components: global mean sea-level rise, tectonic uplift or subsidence, and meteorological/oceanographic changes (Nicholls 2003). Global mean sea-level increases by thermal expansion of the oceans and melting of ice sheets, ice caps, and glaciers. A coastline can rise or subside because of a geologic effect, particularly isostatic adjustment since the last glacial period. Local sea levels also reflect meteorological and oceanographic conditions since ocean currents are related to the height of sea surface for geophysical reasons, and wind distributions are a major factor in determining surface ocean currents. Church et al. (2001) report that the spatial standard deviation of sea-level rise can be up to ~35 % of the global mean sea-level rise over a century.

Most studies have focused on global mean sea-level rise and geologic effects, neglecting regional changes due to meteorological and oceanographic factors. In fact, uncertainties of such factors are large as observations and models indicate discrepancies among different analyses (e.g., Church et al. 2001; Cazenave and Nerem 2004). Furthermore, coastal flooding is not only affected by relative sea-level rise but also by the changing pattern of storms. As discussed above, some authors find that hurricanes are indeed intensifying, though such effect has not been included in impact assessment studies. There are, therefore, uncertainties unquantified in the literature.

The IPCC projects a global sea-level rise of 9-88 cm for 2100 relative to the 1990 level (Church et al. 2001). No probability is assigned to this range. Webster et al. (2003) produced another estimate with probability distribution, using the modeling framework developed at MIT. Figure 2.2 shows the probability distribution functions of sea-level rise for 2050 and 2100 for both policy and no-policy cases. It illustrates a significant uncertainty associated with sea-level rise, and reveals that the benefit of mitigation policy will not be felt until the later half of the 21st century because of the prior commitment to sea-level rise. In spite of significant uncertainty, most of the previous impact studies reviewed below do not deal with uncertainty explicitly.

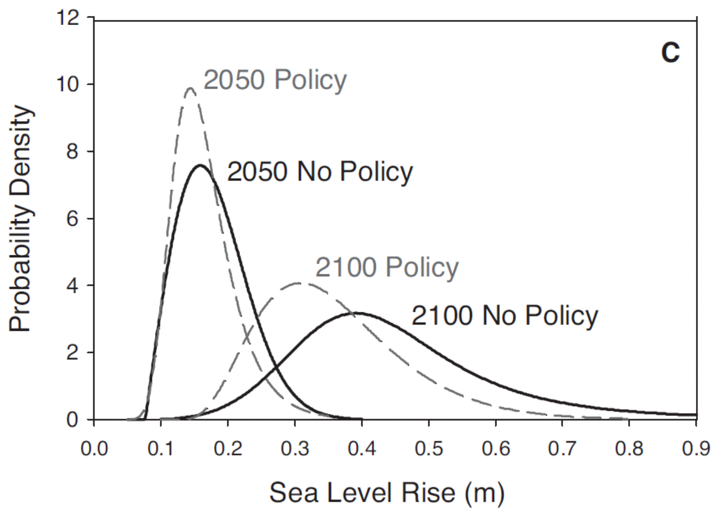

Figure 2.2. Probability distribution functions of sea-level rise estimated by Webster et al. (2002, 2003). Adapted from Figure 2(C) of Webster et al. (2002).

2.2. Cost of sea-level rise

Since the seminal work of Schneider and Chen (1980), numerous researchers tackled the problem of sea-level rise impact, addressing a number of issues such as 1) increased risk of flooding; 2) wetland loss; 3) damage to rice production (due to increased flooding, salinization, and/or poor drainage condition); 4) cost of protection and dryland loss. Some looked at local and national impacts whereas others investigated global impacts. Unfortunately, researchers had to introduce numerous assumptions in the analysis, thereby creating another source of uncertainty (Nicholls 2003).

Among the past works, of particular note is the Global Vulnerability Assessment (GVA) by Hoozemans et al. (1993). GVA has produced vulnerability assessments for 192 coastal polygons that represent the entire global coastline, analyzing increased flooding, wetland loss, and rice production impact for each coastline polygon. It is an internally consistent global dataset, and most global analyses have relied on the dataset provided by GVA in one way or another (Nicholls et al. 1999; Tol 2002a, 2002b; among others). Recently there has been an interest in improving on GVA, which culminated in the creation of the Dynamic Interactive Vulnerability Assessment (DIVA). It is a significant update of GVA, whose details are described in Chapter 3.

Nicholls (2003) gives an excellent review of impact studies, whose subjects range from the number of people flooded to economic cost to wetland loss. This chapter focuses on the monetary cost. Table 2.1 shows an estimate of potential cost of sea-level rise along the developed coastline of the United States. F95a found a significantly lower cost than previous analyses because of his treatment of adaptation, and Yohe et al. (1996) and Yohe and Schlesinger (1998) reduced their cost estimate even further. Earlier studies assumed complete protection for all the coastlines in the U.S., while later papers seek optimal level of protection, reducing the cost substantially.

Table 2.1. Potential cost of sea-level rise along the developed coastline of the United States (billions of 1990 dollars) for a 1-meter global sea-level rise. Adapted from Table 3 of Nicholls (2003), who adapted the table from Neumann et al. (2001).

Source	Measurement	Annualized estimate	Cumulative estimate	Annual estimate in 2065
Yohe (1989)	Property at risk of inundation	N/A	321	1.37
Smith and Tirpak (1989)	Protection	N/A	73-111	N/A
Titus et al. (1991)	Protection	N/A	156	N/A
Nordhaus (1991)	Protection	4.9	N/A	N/A
Fankhauser (1995a, 1995b)	Protection	1.0	62.6	N/A
Yohe et al. (1996)	Protection and abandonment	0.16	36.1	0.33
Yohe and Schlesinger (1998)	Expected protection and abandonment	0.38	N/A	0.4

What is the breakdown of the costs? Interestingly, a great deal of the cost comes from loss of wetland. Table 2.2 lists the results of F95a for a 1-meter sea-level rise. Wetland loss generally accounts for 60% – 90% of the total cost. The reason is two-fold. Global sea-level rise causes substantial loss of wetlands, and wetland value is assumed to be \$5 million per km^2 (F95a), a fairly high value. In addition, most of valuable dryland is protected, preventing potentially expensive damage.

F95a also performed sensitivity calculations for different sea-level rises. He found that the cost increases linearly with sea-level rise. For instance, the cost of a 50-cm per century sea-level rise for the United States is about \$200 billion, half the cost for the 1-meter case. The uncertainty depicted in Figure 2.2 thus directly translates into the uncertainty in the cost.

Table 2.2. Optimal costs of sea-level rise for 5 countries with largest total costs and the OECD total. Adapted from Fankhauser (1995a). Units are billion U.S. dollars.

Country	Cost		Loss		Wetland % of total cost
	Total	Protection	Dryland	Wetland	
OECD total	932.47	174.09	27.49	730.89	78.38%
USA	425.16	62.59	15.96	346.61	81.52%
Japan	141.47	6.83	0.03	134.55	95.11%
United Kingdom	57.26	7.74	0.14	49.38	86.24%
Italy	45.27	7.48	0.30	37.49	82.81%
Australia	34.54	29.55	4.88	N/A	N/A

2.3. What is missing in the past studies

Although impact studies have gone through significant improvement, they still suffer from some deficiencies. One issue concerns the level of optimal protection, which is an important factor for protection cost as Chapter 1 discussed. As shown in Table 2.2, F95a found that more than 90% of the coastal segments in the UK should be protected whereas Turner et al.'s (1995) local-scale analysis concluded that even without acceleration of the rate of sea-level rise, 20% of the coastline in East Anglia is not worth protecting. Nicholls (2003) speculated that the difference is due to the different scales of the two analyses, but there is a need for analysis of such a large discrepancy.

Another issue is about nonlinear sea-level rise. Many past studies assumed a linear sea-level rise although realistic sea-level rises are more like quadratic functions in time, rather than linear. In fact, F95a has assumed a linear sea-level rise. Since a nonlinear sea-level rise would lead to more cost in later periods, it would result in a smaller present value through discounting. It is desirable to extend F95a's formula to nonlinear cases, and make a comparison between linear and nonlinear sea-level rises.

Moreover, there is a bigger issue with economic cost assessment of sea-level rise. To my knowledge, almost all papers used a partial equilibrium analysis. In a partial equilibrium analysis, the cost is calculated on the assumption that costs of sea-level rise do not affect other sectors of the economy, nor other countries. However, sea-level rise impact could affect other sectors by changing economic activity in the coastal areas, and influence other countries through trade effects. The exception is Darwin and Tol (2001), who performed a general equilibrium analysis. They utilized the method of F95a, calculated optimal level of protection, and fed the optimal cost into a computable general equilibrium model by reducing the land endowment. They found that global welfare loss in the general equilibrium analysis was about 13% higher than the direct cost in the partial equilibrium analysis, although some regions incurred less sea-level rise cost by redistributing their costs through international trade.

Furthermore, the loss of capital due to sea-level rise can change the course of economic growth. In a theoretical paper, Fankhauser and Tol (2005) employed standard neoclassical growth models and explored the implication of capital loss due to climate impacts, finding that the forgone economic growth could be larger than the cost calculated in a partial equilibrium framework. More work with a general equilibrium framework is necessary to fully explore these economic effects on the cost of sea-level rise.

The last problem concerns the climate-economy feedback. A sea-level rise would cause an economic cost, which would reduce the future economic growth, which in turn could reduce emissions slightly and affect the rate of sea-level rise. Such an effect would be small since the sea-level rise cost is generally small relative to the economic output of the entire world. Nonetheless, it should be incorporated in the integrated assessment exercise for completeness.

2.4. Problem Statement

This thesis addresses the issues with previous studies: Why did F95a find such high protection level, and could we apply a more realistic sea-level rise scenario to determine the protection fraction? I answer these two questions by extending the F95a sea-level rise cost function.

After mathematical analysis, I provide a new cost estimate of sea-level rise. To do so, I use the Emissions Prediction and Policy Analysis (EPPA) model, a computable general equilibrium model developed at MIT, and include the F95a sea-level cost function in it. I apply a simple statistical equation based on a climate system model (Integrated Global System Model) to estimate sea-level rise, and combine it with a sea-level vulnerability database, the Dynamic Interactive Vulnerability Assessment (DIVA), and a geographically based economic dataset (G-Econ).

The next chapter details the models and databases along with methodology.

Chapter 3. Methodology

3.1. Outline of the methodology

This thesis utilizes various tools: One economic model (EPPA), a set of climate model (IGSM) outputs, and two databases (DIVA and G-Econ). First, EPPA calculates economic activity and associated greenhouse gas and other emissions. The sea-level rise function based on IGSM simulations then converts emissions to a sea-level rise. The cost function calculates three kinds of costs, using sea-level rise and inputs from DIVA and G-Econ databases.

Figure 3.1 outlines the overall methodology. The economic model EPPA calculates emissions of greenhouse gases such as CO_2, which a function based on IGSM simulations converts into sea-level rise. The sea-level rise cost function then uses sea-level rise and calculates three components of cost: protection cost, capital loss, and wetland loss. In the future, the cost will be fed back into EPPA but this is outside the scope of the present thesis.

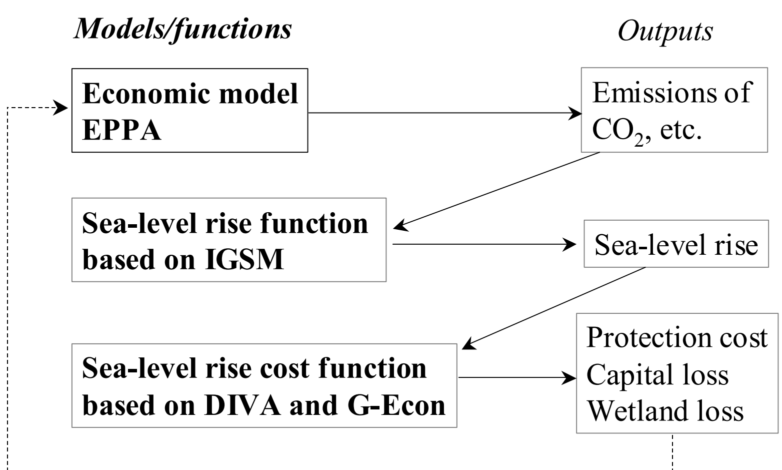

Figure 3.1. Schematic outlining how different models and databases are utilized. The dotted line represents the feature to be included in the future, not implemented in the current study.

The need for a sea-level rise function deserves elaboration. Ideally one would like to couple the IGSM's climate component and the EPPA directly. However, although the climate component and the EPPA have been utilized together, the models are coded separately and the interaction has been primarily one-way from EPPA to IGSM's natural system component. That is, the climate model of the IGSM utilizes the outputs of EPPA as its input, and no two-way coupling has been conducted yet. Coupling different models is a serious business, and requires substantial model development efforts. A way to circumvent such issue is to construct a reduced form of sea-level rise function to be embedded in the EPPA code.

At this stage of research where we ignore dotted lines in Figure 3.1, we do not need such a simple sea-level rise function within EPPA. Nonetheless, it is advantageous to have such a function since it would make calculations very efficient. For the purposes of future preparation and computation efficiency, I thus develop a simple sea-level rise function for use in EPPA.

3.2. Dynamic Interactive Vulnerability Assessment (DIVA)

Dynamic Interactive Vulnerability Assessment (DIVA) (Hinkel and Klein 2003; Vafeidis et al. 2004; Vafiedis et al. 2006, submitted manuscript) is a geographic information system (GIS)-based dataset of vulnerability to sea-level rise. It is unique in that it is not a raster dataset, a preferred format for various datasets, but rather its fundamental element is a coastal segment (a polygon). The world's coast is divided into 12,148 segments with an average coastal segment length of 70km. For each of the segments, DIVA provides a multitude of parameters, including population density, frequency and height of storm surges, and areas of wetland. These will be used as inputs for the extended sea-level rise cost function as described in Chapter 4. DIVA also contains various data for countries, major rivers, tidal basins, and administrative units (states, prefectures, etc.). Table 3.1 summarizes DIVA's characteristics.

DIVA is considered to be the successor of the Global Vulnerability Assessment (GVA), which was compiled by Hoozemans et al. (1993). GVA has only 192 coastal segments while DIVA comes with 12,148 segments. With two orders of magnitude more segments, DIVA should provide a good basis for substantial improvement of impact studies. As GVA was a cornerstone for previous impact studies, DIVA serves as the foundation for the present thesis.

Table 3.1. DIVA characteristics.

Data categories (GIS features)	Coastal segment, administrative unit (such as 50 states in the United States), country, river, tidal basin
Number of coastal segments	12,148
Number of parameters for each coastal segment	> 30
Sample parameters	LENGTH (length of coastal segment) UPLIFT (geological uplift/subsidence) SLOPECST (slope of the coast) TOTALWETAR (total wetland area, excluding mangrove) MANGS_KM2 (mangrove area)
Number of countries	207
Number of parameters for each country	> 20
Sample parameters	SDIKECOST (cost of sea dike) GDPC (gross domestic product (GDP) per capita in 1995 in market exchange rate)

3.3. Geographically based Economic data (G-Econ)

The Geographically based Economic data (G-Econ) (Nordhaus 2006; Nordhaus et al. 2006) is a geographic database of economic output for 1-by-1-degree grid cell, which the authors call *gross cell product* (GCP). The novelty of this database is that it provides economic information for each geographic cell, rather than for each country as covered by conventional economic statistics. It thus expands the number of economic observations from about 200, the number of countries, to 27,079, the number of cells in G-Econ.

To arrive at gross cell product, the authors exploit a detailed geographic database on population. The authors calculate gross cell product as

(GCP by grid cell) = (population by grid cell) × (per capita GCP by grid cell).

They estimate per capita GCP by combining national (e.g., GDP), state (e.g., gross state product), and province/county data (e.g., regional income by industry).

Figure 3.2 shows a logarithmic plot of GCP for the entire globe. Developed economies and emerging economic countries show up in the figure. Because the scale is logarithmic, we see that the distribution is quite skewed. This is also apparent in Figure 1 of Nordhaus (2006).

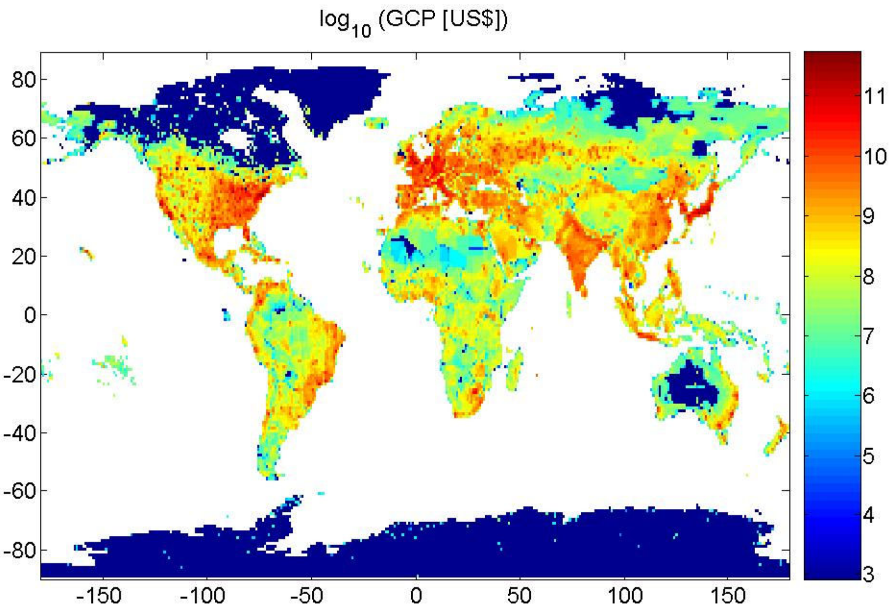

Figure 3.2. A graphic representation of gross cell product. Non-terrestrial cells are indicated by white. Note that some cells contain zero values, whose logarithm is undefined. They are thus also represented by white.

3.4. MIT Emissions Prediction and Policy Analysis (EPPA) model

The MIT Emissions Prediction and Policy Analysis (EPPA) model Version 4 (Paltsev et al. 2005) is a computable general equilibrium model of the world economy, which calculates economic activity and associated emissions of greenhouse gas and urban gas emissions. It is recursive-dynamic and has 16 regions, and is built on the Global Trade Analysis Project (GTAP) (Hertel 1997; Dimaranan and McDougall 2002) and other datasets. It has detailed breakdown of the energy sector. Table 3.2 summarizes key outputs that are utilized as inputs for the sea-level rise cost function.

Table 3.2. Output variables of EPPA that are used in the calculation.

Variable	Description	Variable	Description
Y	Gross national product	E_{CH_4}	Methane emission
E_{CO_2}	Total carbon dioxide emission	E_{N_2O}	Nitrous oxide emission
E_{SO_2}	Sulfur dioxide emission		

3.5. MIT Integrated Global System Model simulations

The MIT Integrated Global System Model Version 2 (IGSM) (Sokolov et al. 2005) is a model of the climate-economy system. Its components include atmosphere and ocean circulations, atmospheric and oceanic chemistry, ecosystem, and the economic model, EPPA. It is designed for efficient calculations with simplified configurations. In particular, by changing key parameters, it can reproduce the transient responses of various atmosphere-ocean general circulation models. Such flexibility and relative efficiency allow for numerous runs of the model and uncertainty analysis of climate change.

The MIT Joint Program on the Science and Policy of Global Change has performed 1000 runs of the IGSM by perturbing key socio-economic parameters and climate parameters. Table 3.3 lists the perturbed climate parameters in the IGSM. The stored outputs include the time series of sea-level rise (thermal expansion and glacier melting separately) for every year for each run along with greenhouse gas emissions from EPPA. Note that five-year averages of the simulation outputs are used throughout the thesis.

Table 3.3. Key climate-related parameters that affect sea-level rise.

Variable	Description
C_s	Climate sensitivity (note that this is different from the standard IGSM notation)
K_v	Effective ocean diffusivity
F_{aer}	Aerosol forcing parameter

In the next section, I use these outputs to construct a reduced form of the IGSM by statistical regression.

3.6. Sea-level rise function for EPPA based on IGSM simulations

This section constructs a simple sea-level rise function of emissions for use in EPPA. There are a multitude of ways to create such a function, including developing a box model, an upwelling-diffusion-type model, and a simple statistical function. Here the simplest one is chosen: linear multiple regression equation. Although such a function would have no physical basis, it should suffice for the present purposes. The objective here is not to calculate a very precise sea-level rise but rather to simply represent sea-level rise and, in the future, to include a climate-economy feedback. Hence the present approach, though crude, would be a useful starting point.

In what follows, I perform linear multiple regressions on results from 1000 runs of IGSM, as described in the previous section. In so doing, I use three specifications of the sea-level rise functions.

Multiple linear regression

First, I briefly review the method of linear multiple regression. The linear model can be written as $\mathbf{s} = \mathbf{Xb} + \boldsymbol{\varepsilon}$ or $S_i = X_{ij} b_j + \varepsilon_i$ where summation over the common index is assumed. Here $\mathbf{s} = (S_i)$ is a $M \times 1$ vector of the dependent variable, sea-level rise, $\mathbf{X} = (X_{ij})$ is a $M \times N$ matrix of independent variables, $\mathbf{b} = (b_j)$ is a $N \times 1$ vector of coefficients, and $\boldsymbol{\varepsilon} = (\varepsilon_i)$ is an error term $M \times 1$ vector. Note that $X_{i,1} = 1$.

The least-square estimator for $\mathbf{b}$ is $\hat{\mathbf{b}} = \left(\mathbf{X}^T \mathbf{X}\right)^{-1} \mathbf{X}^T \mathbf{s}$ whereas the estimator of the variance of b_i is $\hat{V}(b_i) = Z_{ii}$, where $\mathbf{Z} = (\mathbf{X}^T \mathbf{X})^{-1} \cdot (\mathbf{s} - \mathbf{Xb})^T (\mathbf{s} - \mathbf{Xb}) / (M - N)$.

The significance of multiple regressions is tested ("$\beta_j = 0$ for all $j > 1$" against "$b_j \neq 0$ for all $j > 1$"), using F statistic, which is estimated as

$$\widetilde{F} = \frac{(T_0 - T_1)/(N-1)}{T_1/(M-N)} \quad \text{where} \quad T_0 = \sum_{i=1}^{M} \left(S_i - \overline{S}\right)^2, \quad T_1 = (\mathbf{s} - \mathbf{Xb})^T (\mathbf{s} - \mathbf{Xb}) = \left\|\mathbf{s} - \mathbf{Xb}\right\|^2 .$$

This quantity follows the F distribution, $F(N-1, M-N)$. It is more convenient to frame the test in terms of the multiple regression coefficient, R^2, which is

$$R^2 = \frac{\Sigma\left(\hat{S}_i - \overline{S}\right)^2}{\Sigma\left(S_i - \overline{S}\right)^2} = 1 - \frac{\Sigma\left(S_i - \hat{S}_i\right)^2}{\Sigma\left(S_i - \overline{S}\right)^2} = 1 - \frac{\Sigma\left(S_i - X_{ij} b_j\right)^2}{\Sigma\left(S_i - \overline{S}\right)^2} = 1 - \frac{T_1}{T_0} = \frac{\widetilde{F} \cdot (N-1)/(M-N)}{\widetilde{F} \cdot (N-1)/(M-N) + 1} .$$

The significance of each coefficient is tested against the null hypothesis $\beta_i = 0$ by assessing Student's t statistic, $t_i = \hat{b}_i / \sqrt{\hat{V}(b_i)}$ with the degree of freedom $M - N$. Two-sided tests are applied.

Specification 1

In this specification, the sea level in each period is regressed on the previous period's level and various independent variables. After taking an average of all the climate variables every 5 years, the following multiple regression is applied to t = 1995, 2000, 2005, 2010, …, 2095:

$$S(t + \Delta t) = b_1 + b_2 S(t) + \sum_{j=3}^{N} X_j b_j .$$

Here each 5-year period is represented by the last year in that period (i.e., the period 1995 indicates 1991-1995). Because *the same, single equation is applied to all* the periods, the sample size is 1000 × 21 = 21,000.

Note that this equation cannot calculate sea-level rise in 1995. For 1995, Chapter 5 uses Specification 3, which is described below.

Three alternative specifications of independent variables are considered:

$$S(t+\Delta t) = b_1 + b_2 S(t) + b_3 C_s + b_4 \sqrt{K_v} + b_5 F_{aer} + b_6 E_{\mathrm{CO_2}} + b_7 E_{\mathrm{N_2O}}, \tag{3.1}$$

$$S(t+\Delta t) = b_1 + b_2 S(t) + b_3 C_s + b_4 \sqrt{K_v} + b_5 F_{aer} + b_6 E_{\mathrm{CO_2}} + b_7 E_{\mathrm{SO_2}} + b_8 E_{\mathrm{CH_4}} + b_9 E_{\mathrm{N_2O}}, \tag{3.2}$$

$$\begin{aligned} S(t+\Delta t) = b_1 + b_2 S(t) + b_3 C_s + b_4 C_s^{\,2} + b_5 \sqrt{K_v} + b_6 K_v \\ + b_7 C_s \sqrt{K_v} + b_8 F_{aer} + b_9 E_{\mathrm{CO_2}} + b_{10} E_{\mathrm{N_2O}} \end{aligned}. \tag{3.3}$$

Tables of regression results are presented in Appendix A, showing R^2, b_i, and t_i. The appendix actually lists results for Equations (3.4), (3.5), and (3.6) but they are identical to those from (3.1), (3.2), and (3.3), except for R^2 as discussed below. All regressions (R^2 and b_i) are statistically significant. Probably the reason is the large sample size (M = 21,000). A closer look reveals that there are some unexpected results. For example, the coefficient for methane ($E_{\mathrm{CH_4}}$) is negative in (3.2), which is inconsistent with physical reasoning. Moreover, cross-correlation tables demonstrate that some independent parameters exhibit high correlations (e.g., ~0.7 for S and $E_{\mathrm{CO_2}}$). Even with all these caveats, the overall results appear reasonable.

However, standard statistical measures are not useful metrics for our purposes. Since Equations (3.1), (3.2), and (3.3) are supposed to be used repeatedly for multiple time periods, examining errors for a single period is not sufficient. An alternative is to look at errors that accumulate over time periods.

Figures 3.3, 3.4, and 3.5 summarize regression results along with single-period and cumulative errors. The top left panel shows scatterplots of the IGSM simulations and statistical fits. As is clear in the scatterplots, multiple regression coefficients R^2 are extremely high. The issue of high R^2 is addressed in the next subsection. The top right panel displays errors for each period, which appear Gaussian. Comparison of R^2 in the top panels of these figures suggests the difference among (3.1), (3.2), and (3.3) is negligible.

What about cumulative errors rather than errors at each time period? The bottom panels of Figures 3.3, 3.4, and 3.5 show absolute and relative errors that accumulate over time. Unlike errors at each period, there is a clear difference in the cumulative errors between (3.2) and (3.1)/(3.3). There are a few outliers in both absolute and relative errors in the bottom panels of

Figures 3.3 and 3.5, but they are absent in Figure 3.4 (note that the horizontal scales are different).

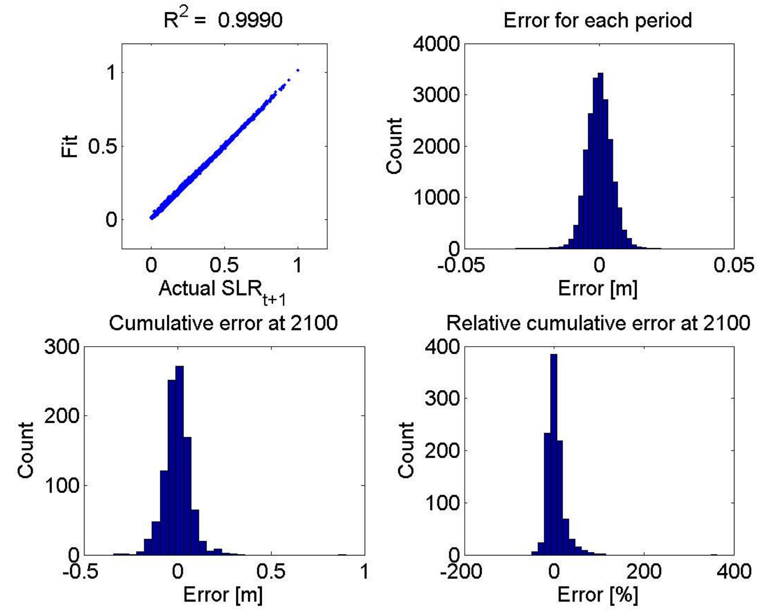

Figure 3.3. A summary graph for the regression equation (3.1). (Top left) Scatterplot of the IGSM simulations and statistical fits. (Top right) Error distributions for each time step. (Bottom left) A cumulative error distribution that would result if (3.1) is used repeatedly for all the time steps. (Bottom right) Same as the bottom left panel but in relative error terms.

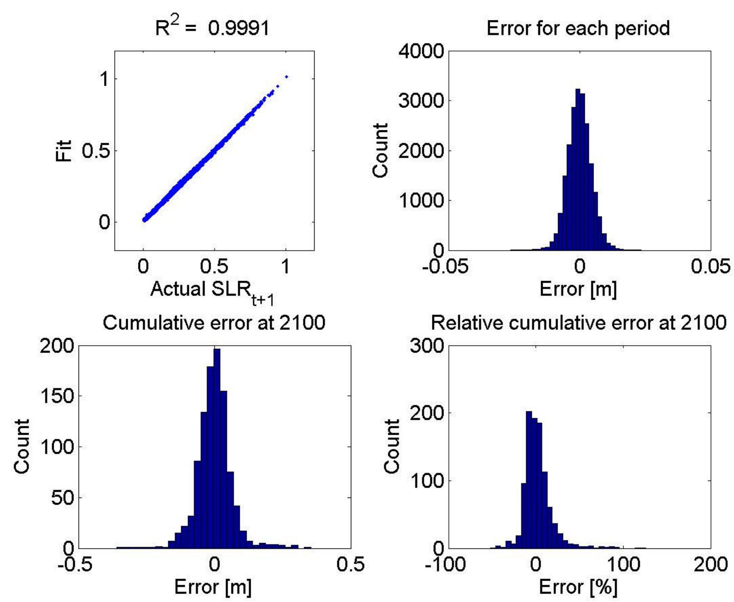

Figure 3.4. As in Figure 3.3. but for (3.2).

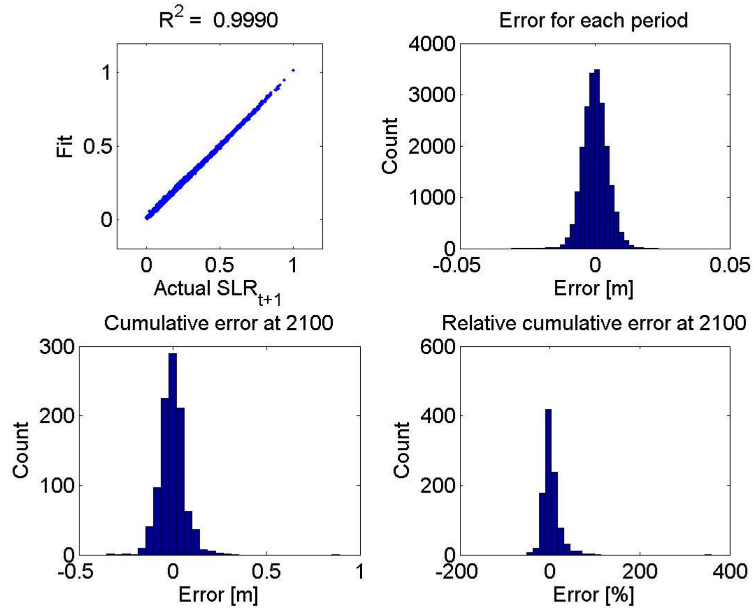

Figure 3.5. As in Figure 3.3. but for (3.3).

Specification 2

In the second specification, the dependent variable is taken as the change of sea level, rather than sea level itself:

$$S(t+\Delta t) - S(t) = b_1 + b_2 S(t) + \sum_{j=3}^{N} X_j b_j \ .$$

The extremely high multiple regression coefficients R^2 in the first specification motivate this formulation. We would expect that the resulting values of b_i ($i \neq 2$) are identical because moving the $S(t - \Delta t)$ to the right-hand side yields the same equation as the specification 1. However, this may not hold true for R^2. As before, three sets of independent variables are considered:

$$S(t+\Delta t) - S(t) = b_1 + b_2 S(t) + b_3 C_s + b_4 \sqrt{K_v} + b_5 F_{aer} + b_6 E_{\mathrm{CO_2}} + b_7 E_{\mathrm{N_2O}} \,, \tag{3.4}$$

$$\begin{aligned} S(t+\Delta t) - S(t) = b_1 + b_2 S(t) + b_3 C_s + b_4 \sqrt{K_v} + b_5 F_{aer} \\ + b_6 E_{\mathrm{CO_2}} + b_7 E_{\mathrm{SO_2}} + b_8 E_{\mathrm{CH_4}} + b_9 E_{\mathrm{N_2O}} \end{aligned} \,, \tag{3.5}$$

$$\begin{aligned} S(t+\Delta t) - S(t) = b_1 + b_2 S(t) + b_3 C_s + b_4 {C_s}^2 + b_5 \sqrt{K_v} + b_6 K_v \\ + b_7 C_s \sqrt{K_v} + b_8 F_{aer} + b_9 E_{\mathrm{CO_2}} + b_{10} E_{\mathrm{N_2O}} \end{aligned} \,. \tag{3.6}$$

Statistical results for b_i and t_i ($i \neq 2$) are identical to those of Specification 1, and we see the expected changes for b_2 because of the rearrangement of the equation. Hence they are not presented here. However, multiple regression coefficients are different. Figure 3.6 shows scatterplots for Equations (3.4), (3.5), and (3.6). Multiple regression coefficients R^2 are ~ 0.84, which can be contrasted with R^2 = ~ 0.999 for Equations (3.1), (3.2), and (3.3). Very high R^2 found for Specification 1 is therefore an artifact of choosing the sea level itself as the dependent variable.

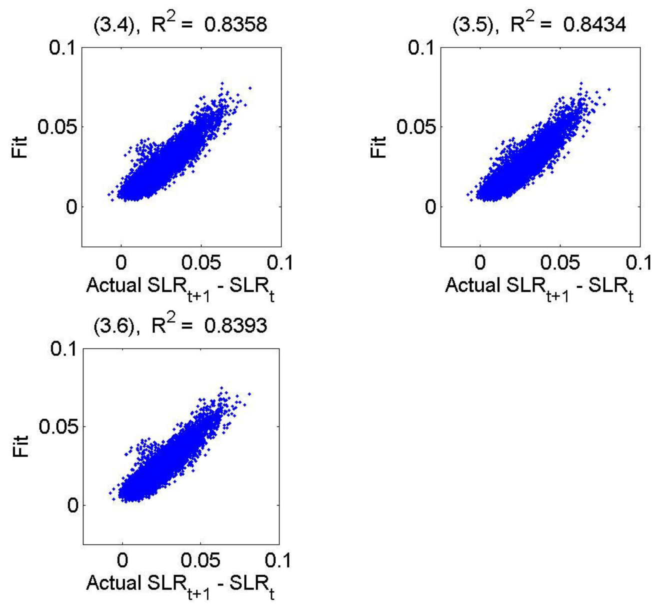

Figure 3.6. Scatterplots for (3.4) (top left), (3.5) (top right), and (3.6) (bottom) along with multiple regression coefficients.

Specification 3

Now we turn to another specification, where we construct separate regression equations for different time periods. After taking the time average as in the previous specification, we apply the following regression equations:

$$S(t) = b_1 + \sum_{j=2}^{N} X_j(t) b_j \quad \text{for} \quad t = 1995,\ 2000, ..., 2100$$

This yields 22 equations in total since there are 22 periods. The sample size is substantially reduced from 21,000 in the previous two specifications to 1,000.

As before, 3 sets of independent variables are tested:

$$S(t) = b_1 + b_2 C_s + b_3 \sqrt{K_v} + b_4 F_{aer} + b_5 E_{\mathrm{CO_2}} + b_6 E_{\mathrm{N_2O}}, \tag{3.7}$$

$$S(t) = b_1 + b_2 C_s + b_3 \sqrt{K_v} + b_4 F_{aer} + b_5 E_{\mathrm{CO_2}} + b_6 E_{\mathrm{SO_2}} + b_7 E_{\mathrm{CH_4}} + b_8 E_{\mathrm{N_2O}}, \tag{3.8}$$

$$S(t) = b_1 + b_2 C_s + b_3 C_s^{\ 2} + b_4 \sqrt{K_v} + b_5 K_v + b_6 C_s \sqrt{K_v} + b_7 F_{aer} + b_8 E_{\mathrm{CO_2}} + b_9 E_{\mathrm{N_2O}} \,. \quad (3.9)$$

Appendix A contains the full results of regressions. Here again, all regressions are statistically significant (for R^2 and b_i). Figures 3.7, 3.8, and 3.9 summarize the results. The top and bottom right panels exhibit multiple regression coefficients R^2 and t statistics for each period, respectively. Figures 3.7 and 3.8 show that R^2 is larger for (3.8) than for (3.7), and comparing Figures 3.7 and 3.9 shows that (3.9) improves R^2 relative to (3.7). The t statistics are all significant (different colors correspond to different i's).

In Specifications 1 and 2, standard statistics are not good metrics as indicated by the cumulative errors. Here each equation is used for one time and there is no worry about accumulation of error over time. It is still useful, nevertheless, to examine error distributions in light of a much smaller sample size.

The top left and middle panels of Figures 3.7, 3.8, and 3.9 depict absolute errors for each fitting equation. The top left panel represents error distribution for each period, with more blue colors indicating earlier periods and more red colors later periods. Absolute errors spread with time, which is also confirmed by the top middle panel that displays the maximum and minimum of errors.

It is also instructive to have a look at relative errors. The bottom left panels show relative error distributions for each period whereas the bottom middle panels describe the maximum and minimum relative errors. Note that we have not taken the absolute value of errors. In the first period (1995), the relative minimum error is extremely large as indicated by the bottom left and middle panels. The sea-level rise is very small and small absolute errors yield large relative errors. Nonetheless, the statistical fitting equations (3.7), (3.8), and (3.9) appear as reasonable as Specifications 1 and 2, aside from the problem with the first period (1995).

Summary of regression exercise

Linear multiple regressions have yielded statistically significant fitting equations for all cases considered, even for very stringent statistical tests. However, standard statistical tests turned out not to be sufficient. Especially for Specifications 1 and 2, which produce a single equation for all the periods, errors accumulate over time. The cumulative errors cannot be understood by a standard statistical test. Also it is important to note that some of independent variables are highly correlated with each other, degrading the robustness of regression results.

Although errors were analyzed for each fitting equation, I have not compared how differently these statistical fits behave under realistic emissions scenarios such as the EPPA reference case scenario. To this I turn in Chapter 5, when discussing results.

Having developed the sea-level rise function, the next chapter derives the cost function.

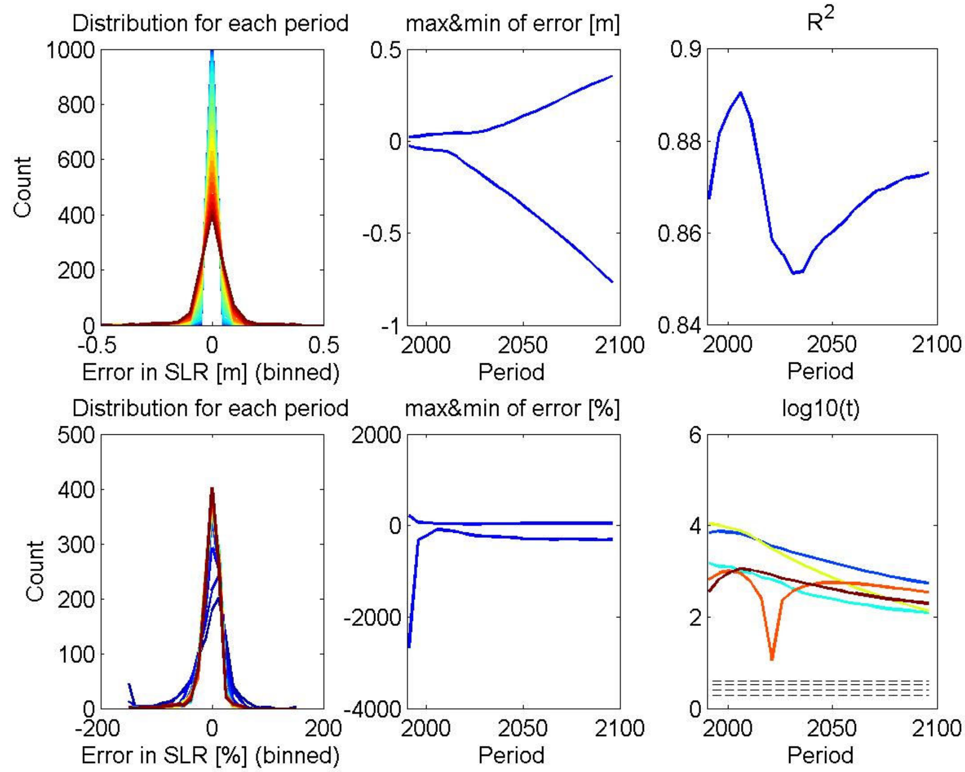

Figure 3.7. A summary graph for the regression equation (3.7). (Top left) Errors for each period. Colors become more red for later periods, with blue indicating 1991 and brown 2095. The bin size is 0.05 m. (Top middle) Maximum and minimum of errors for each period. (Top right) multiple regression coefficients for each period. (Bottom left) Relative errors for each period. The color convention is the same as for the top left panel. The bin size is 12.5%. (Bottom middle) Maximum and minimum relative errors in percent for each period. (Bottom right) logarithm of *t* statistic for each period and each independent variable. The larger the index of the variable, the more red the color is. Dotted lines represent *t* statistics corresponding to the 95%, 99%, 99.9%, and 99.999% confidence levels against the "zero" null hypothesis.

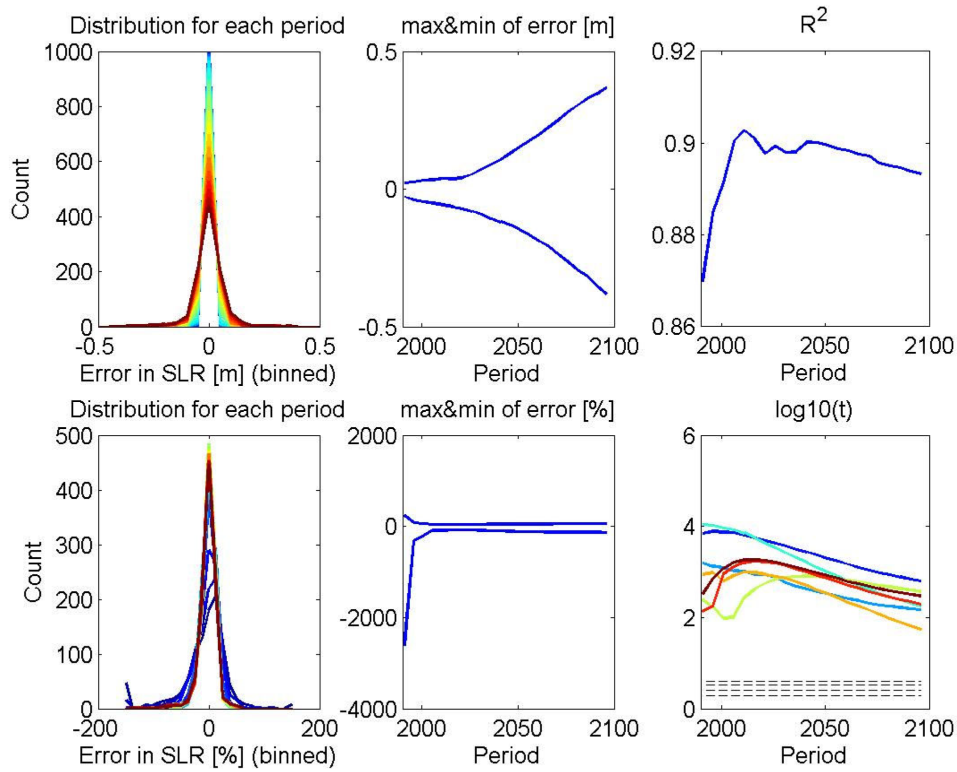

Figure 3.8. As in Figure 3.7 but for (3.8).

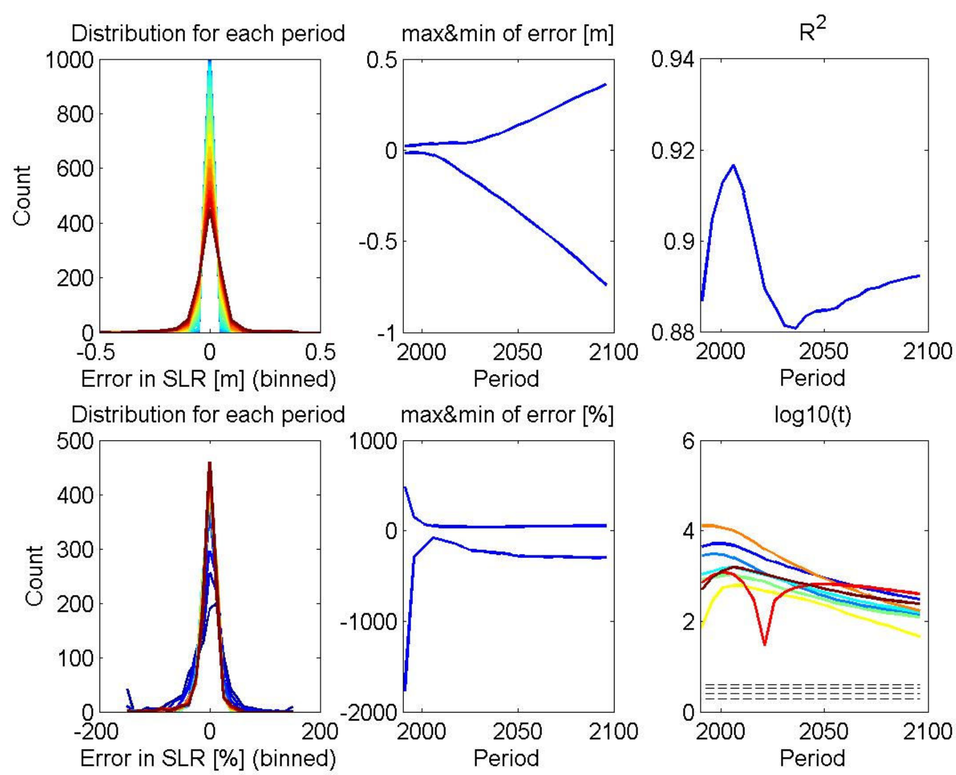

Figure 3.9. As in Figure 3.7 but for (3.9).

Chapter 4. Sea-level rise cost function

This chapter derives and extends the cost function originally developed by F95a. The essential purpose of this cost function is to capture the trade-off between protection and retreat. While protecting a coastline avoids the loss of capital and land, it requires building a sea dike, and hence protection cost. Presumably it could decrease the wetland area since with human intervention, wetlands would be squeezed between a sea dike and the rising sea. On the other hand, abandoning a coastline saves the cost of protection and allows wetland to migrate inland, but leads to capital loss. F95a formulated this trade-off in a fairly tractable manner, and this chapter builds on his work.

As pointed in Chapter 2, two important issues with F95a's approach have not been addressed: discrepancy of optimal protection fraction between local-level and national-level studies, and inclusion of nonlinear sea-level rise. In what follows, the F95a's method is extended such that it can resolve both issues.

4.1. The cost minimization problem

For a given scenario of sea-level rise $S = S(t)$, the F95a's cost minimization problem for each coastal segment is

$$\min_{L,h} \; Z = p^{(pv)}(L,h) + d^{(pv)}(L,S) + w^{(pv)} - g^{(pv)}(L,S)$$

$$s.t. \quad \int_0^t h(t')\,dt' \geq S(t)\,, \quad h(t) \geq 0\,, \quad 0 \leq L \leq 1\,. \tag{4.1}$$

With an assumption of perfect information about the future sea-level rise, the total cost to be minimized is the present value (as denoted by $^{(pv)}$) of a sum of protection cost *p*, dryland/capital loss *d*, and wetland loss *w*, less wetland *gain g*. Figure 4.1 graphically illustrates the cost trade-off. The control variables are the protection fraction of a coastal segment *L* and additional sea dike height h=$h(t)$. The sea dike height must be always above the level of sea, and be increasing. The protection fraction, by definition, takes a value between 0 and 1. As the total cost is a sum of four components, it captures the trade-off of protection and retreat.

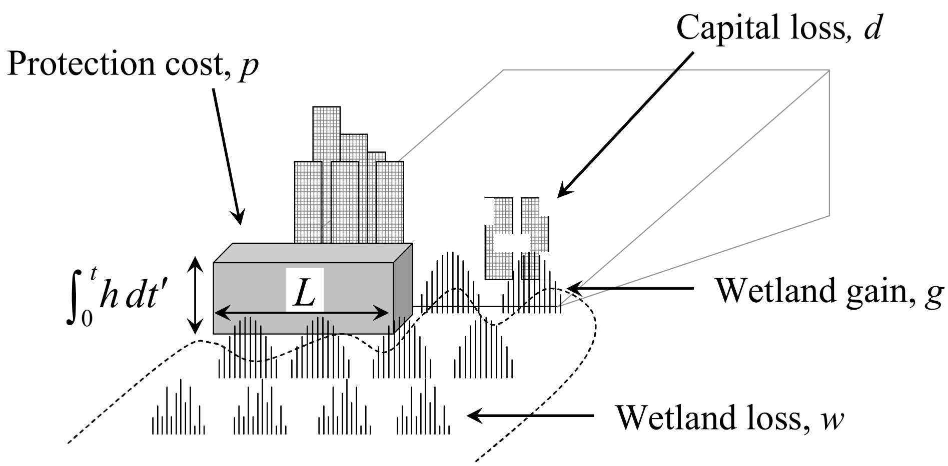

Figure 4.1. Schematic illustrating the cost minimization problem. The choice variables are the fraction of the coastal segment to be protected L, and incremental sea dike height h. Since h is an additional dike height, the height of sea dike is its integral. There are four cost items: protection cost p, capital (dryland) loss d, wetland gain g, and wetland loss w. A sea dike protects capital but prevents wetland from migrating inland. A decision not to build protection allows wetland to migrate, but leads to capital loss. Regardless of the decision to protect or not, wetland on the seaside is lost by submergence.

Some of the terms depend implicitly on the sea-level rise, $S = S(t)$. For convenience, Table 4.1 gives definitions of all the symbols used throughout this chapter. Note that the symbols are different from those of F95a and Tol (2002a, 2002b).

Since the total cost depends on the path of $h(t)$, or in other words, Z is a functional of $h(t)$, (4.1) is a dynamic optimization problem. The problem is framed in terms of continuous time but it is straightforward to rewrite the equation in terms of discrete time periods.

Equation (4.1) assumes that protection is only in the form of sea dikes, although there are other protection forms such as beach nourishment. Including other protection measures is left to future research. Also, the constraint in (4.1) implies that initial dike height is zero. It is possible to include non-zero initial dike height by changing the constraint to

$$\int_0^t h(t')\,dt' + H_0 \geq S(t)\,.$$

This thesis restricts itself to the case of $H_0 = 0$ for simplicity.

Table 4.1. Variables and parameters in the sea-level rise cost function.

Symbol	Description
Z	Total cost
p	Protection cost
d	Dryland loss or capital loss
g	Wetland *gain* due to decision not to build coastal protection
w	Wetland loss that takes place regardless of coastal protection
π	Unit protection cost
δ	Unit capital loss (dryland value)
γ	Unit wetland loss/gain (wetland value)
$p_1(h)$	$\equiv p(h, L=1)$
$d_0(h)$	$\equiv d(h, L=0)$
$g_0(h)$	$\equiv p(h, L=0)$
P	Normalized protection cost, $P(L) = p^{(pv)}(L) / p^{(pv)}(L=1)$
D	Normalized capital loss, $D(L) = d^{(pv)}(L) / d^{(pv)}(L=0)$
G	Normalized wetland gain, $G(L) = g^{(pv)}(L) / g^{(pv)}(L=0)$
L	*Fraction* of a coastline that is to be protected
h	Additional height of sea dike (or protection in general)
S	Relative sea-level rise at the coastline
F	Sea dike height resulting from the change in design frequency
Λ	Length of a coastal segment
Ω	Length of the portion of a coastal segment with wetland
α	Wetland migration speed
ψ	Slope of the coastline
r	Discount rate
ε	Economic growth rate
t	Time
τ	The end time
$(\ )^{(pv)}$	Present value operator, $(\ )^{(pv)} \equiv \int_0^\tau (\ ) e^{-rt} dt$ or $(\ )^{(pv)} \equiv \sum_{t=0}^{\tau} (\ ) \left(\frac{1}{1+r}\right)^t$
*	Superscript denoting optimality

4.2. Separability assumption and optimization with regard to *h*

The biggest and most important assumption is separability between incremental dike height h and protection fraction L. The model assumes that L is determined once initially and L does not change with time. This allows us to solve the model in a straightforward way.

Now let us solve for incremental dike height h. As F95a pointed out, if there is no economy of scale in dike construction, which I assume below, the constraint in (4.1) always binds. The optimal solution is therefore

$$h^*(t) = \frac{dS}{dt}(t), \tag{4.2}$$

where the asterisk denotes an optimal solution.

This solution actually assumes that a design frequency, which refers to the frequency of storms against which a coastline is protected, remains constant. However, this may not be a realistic assumption since developing countries would become wealthier and desire a safer level of coastal protection. They might prefer to avoid flooding from storms that occur every 1000 years in the late 21st century, although they might tolerate 100-year storms as of today. Indeed, Nicholls et al. (1999), Nicholls (2004), and Nicholls and Tol (2006) incorporated this effect in their models of inundation of population.

In the present model, it is actually easy to include the changing design frequency. The only change to make is to replace the constraint with

$$\int_0^t h(t')\,dt' \geq S(t) + F(t),$$

where $F(t)$ represents the sea dike height resulting from the changing design frequency. The optimal solution is then

$$h^*(t) = \frac{dS}{dt}(t) + \frac{dF}{dt}(t).$$

Nonetheless, there is an issue of how to decompose the total cost into the change in preference and the damage of sea-level rise. For simplicity, I neglect this effect in the calculations below.

It is straightforward to incorporate the effect of economies of scale of protection construction or the nonlinear cost of sea dikes (doubling the height of protection costs more than double). In such case, it is only necessary to write down a standard dynamic optimization problem with respect to h. For instance, dropping dependence on L (which is a different problem), the problem may be written as

$$\min_{h(t)} \int_0^\tau p(h(t))e^{-rt}dt \quad s.t. \quad \frac{dx}{dt} = h, \;\; x(t) \geq S(t), \;\; h(t) \geq 0.$$

Following Bryson and Ho (1975), the Hamiltonian is defined as

$$\widetilde{H} = p(h)e^{-rt} + \lambda h + \mu_1(-h) + \mu_2(S-x).$$

The necessary conditions for optimality are

$$\frac{dx}{dt} = h, \quad \frac{d\lambda}{dt} = -\frac{\partial \widetilde{H}}{\partial x} = \mu_2, \qquad \frac{\partial \widetilde{H}}{\partial h} = 0 = \frac{\partial p}{\partial h}(h)e^{-rt} + \lambda - \mu_1,$$
$$\mu_1(-h) = 0, \quad \mu_1 \geq 0, \quad \mu_2(S-x) = 0, \quad \mu_2 \geq 0.$$

4.3. Optimization with regard to *L*

The next question is how to determine the optimal protection fraction L. Dropping the dependence on h and the constant term $w^{(pv)}$, the optimization problem (4.1) becomes

$$\min_L \widetilde{Z} = p^{(pv)}(L) + d^{(pv)}(L) - g^{(pv)}(L). \tag{4.3}$$

I further rewrite the cost function as

$$\min_L \widetilde{Z} = p_1^{(pv)} \cdot P(L) + d_0^{(pv)} \cdot D(L) - g_0^{(pv)} \cdot G(L) \tag{4.4}$$

where $p_1(h) = p(h, L=1)$ and $P(L) = p^{(pv)}(L)/p^{(pv)}(L=1)$, and so forth. Note that

$$0 \leq P(L), D(L), G(L) \leq 1,$$
$$P(0) = 0, \quad P(1) = 1, \quad D(0) = 1, \quad D(1) = 0, \quad G(0) = 1, \quad G(1) = 0,$$
$$\partial P/\partial L \geq 0, \quad \partial D/\partial L \leq 0, \text{ and } \partial G/\partial L \leq 0. \tag{4.5}$$

What are the interpretations of $P(L)$, $D(L)$, and $G(L)$? First, they are normalized cost functions since $P(L) = p^{(pv)}(L)/p^{(pv)}(L=1)$, etc. Second, their derivatives $\partial P/\partial L$, $\partial D/\partial L$, and $\partial G/\partial L$, represent marginal costs and gain (as the cost minimization problem equates these terms). They thus represent normalized cumulative cost distribution functions.

So far I have not specified the functional forms of $P(L)$, $D(L)$, and $G(L)$ yet. Since $P(L)$ is determined by engineering considerations, it would be reasonable to approximate $P(L)$ with a linear function if the variation within a coastal segment is negligible. It may be difficult to get a handle on $G(L)$ because of variations of ecological factors, and we adopt a simple assumption of a linear function. My choice is thus $P(L) = L$ and $G(L) = 1–L$. The form of D is discussed below.

It is useful to notice that P, G, and D can be defined at multiple scales. For instance, it is possible to define D for a country like the entire United States. Then D describes the capital distribution in that country. On the other hand, one can define D for Greater Boston, in which case D represents the capital distribution in the Greater Boston area. What F95a had in mind was D at the national level. Later in this chapter, I address the difference between the D at the country scale and that at the coastline scale.

For the interior solution, the first-order condition for optimization of (4.4) is

$$\partial\widetilde{Z} / \partial L(L = L^*) = 0 = p_1^{(pv)} + d_0^{(pv)} D'(L^*) + g_0^{(pv)}.$$

By defining

$$C \equiv \frac{p_1^{(pv)} + g_0^{(pv)}}{d_0^{(pv)}}, \tag{4.6}$$

I can concisely write the optimal solution as

$$L^* = (D')^{-1}(-C), \tag{4.7}$$

where the asterisk indicates optimality. The case of corner solutions depends on the choice of D and should be treated appropriately. L^* in (4.7) represents the protection fraction that equates marginal benefit from wetland gain with marginal costs from protection and dryland loss. Equation (4.7) shows that we can obtain the closed form of the optimal value of L as long as the derivative of D is invertible. Table 4.2 lists solutions for some analytic forms of D. F95a chose $D(L) = (1 - L)^\beta$ with β = 2 since he assumed that the marginal dryland loss is linear: $\partial D/\partial L = -2(1-L)$ for $\beta = 2$.

Interestingly the optimal level of protection is determined by only the functional form of D and the ratio C, which is a ratio of capital loss in the case of no protection to a sum of full protection cost and maximum possible wetland gain. Although C is a key parameter, there is no straightforward interpretation of C, unfortunately.

Table 4.2. Solutions for some forms of D. C is given by (4.6).

$D(L) = 1 - L$	$L^* = \begin{cases} 0 & C > 1 \\ 1 & C < 1 \end{cases}$
$D(L) = (1 - L)^\beta \quad (\beta > 1)$	$L^* = \max\left[1 - \left(\dfrac{C}{\beta}\right)^{\frac{1}{\beta-1}},\ 0\right]$
$D(L) = \dfrac{e^{-\lambda L} - e^{-\lambda}}{1 - e^{-\lambda}} \quad (\lambda > 0)$	$L^* = \max\{0, \min(1, \widetilde{L})\}$ where $\widetilde{L} = \dfrac{1}{\lambda}\ln\left[\dfrac{\lambda}{1 - e^{-\lambda}}\left(\dfrac{1}{C}\right)\right]$

How sensitive are the total cost and optimal protection fraction to the choice of the capital loss distribution function $D(L)$? Especially, how do these variables change with the degree of capital concentration? A simple choice of $D(L) = (1 - L)^\beta$ helps illustrate the sensitivity. Since D represents the normalized cumulative capital loss, the higher β, the more concentrated capital is. Figure 4.2 depicts $D(L) = (1 - L)^\beta$ for β = 2, 5, and 15. If β is higher and capital is

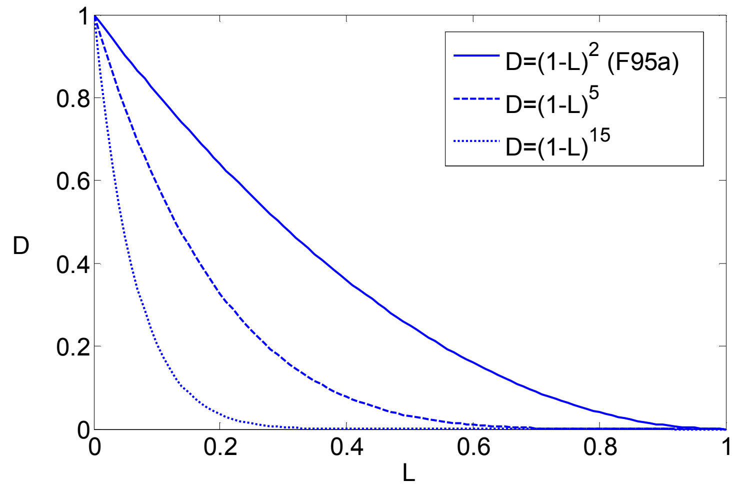

Figure 4.2. $D = (1 - L)^{\beta}$ for β = 2, 5, and 15. Note that F95a chose β = 2.

concentrated, a lower protection fraction L is required to achieve the same level of capital loss.

Interestingly Figure 4.2 hints at an alternative interpretation of D: a Lorenz curve for spatial distribution of capital along the coastline, with the horizontal axis reversed. The Lorenz curve is often utilized to describe income inequality, but Asadoorian (2005) constructed Lorenz curves for geographic distribution of population, which inspired this alternative interpretation of D.

To gain insight into the sensitivity to the degree of capital distribution, it is helpful to rearrange the cost equation in (4.4). The cost function in (4.4) can be rewritten as

$$\widetilde{Z} = \left(p_1^{(pv)} + g_0^{(pv)}\right)L^* + d_0^{(pv)}(1 - L^*)^{\beta} - g_0^{(pv)}.$$

Moving $g_0^{(pv)}$ to the left-hand side and dividing through $d_0^{(pv)}$, I arrive at

$$\frac{\widetilde{Z} + g_0^{(pv)}}{d_0^{(pv)}} = \frac{p_0^{(pv)} + g_0^{(pv)}}{d_0^{(pv)}} L^* + (1 - L^*)^{\beta}.$$

With the definition of C in (4.6), this becomes

$$\zeta(\beta) \equiv \frac{\widetilde{Z} + g_0^{(pv)}}{d_0^{(pv)}} = CL^* + (1 - L^*)^{\beta}. \tag{4.8}$$

ζ is the total cost plus the wetland gain normalized by the present value of capital loss, and can be considered as a measure of the total cost.

Figure 4.3 describes two variables, the optimal protection fraction $L^*(\beta)$ and a measure of normalized total cost $\zeta(\beta)$ for three different values of C: C = 0.01, 0.1, and 1. $L^*(\beta)$ is given in Table 4.2 and $\zeta(\beta)$ in (4.8). The top three panels indicate that for all cases considered here, the optimal protection fraction decreases with β. The more concentrated the capital is, the smaller

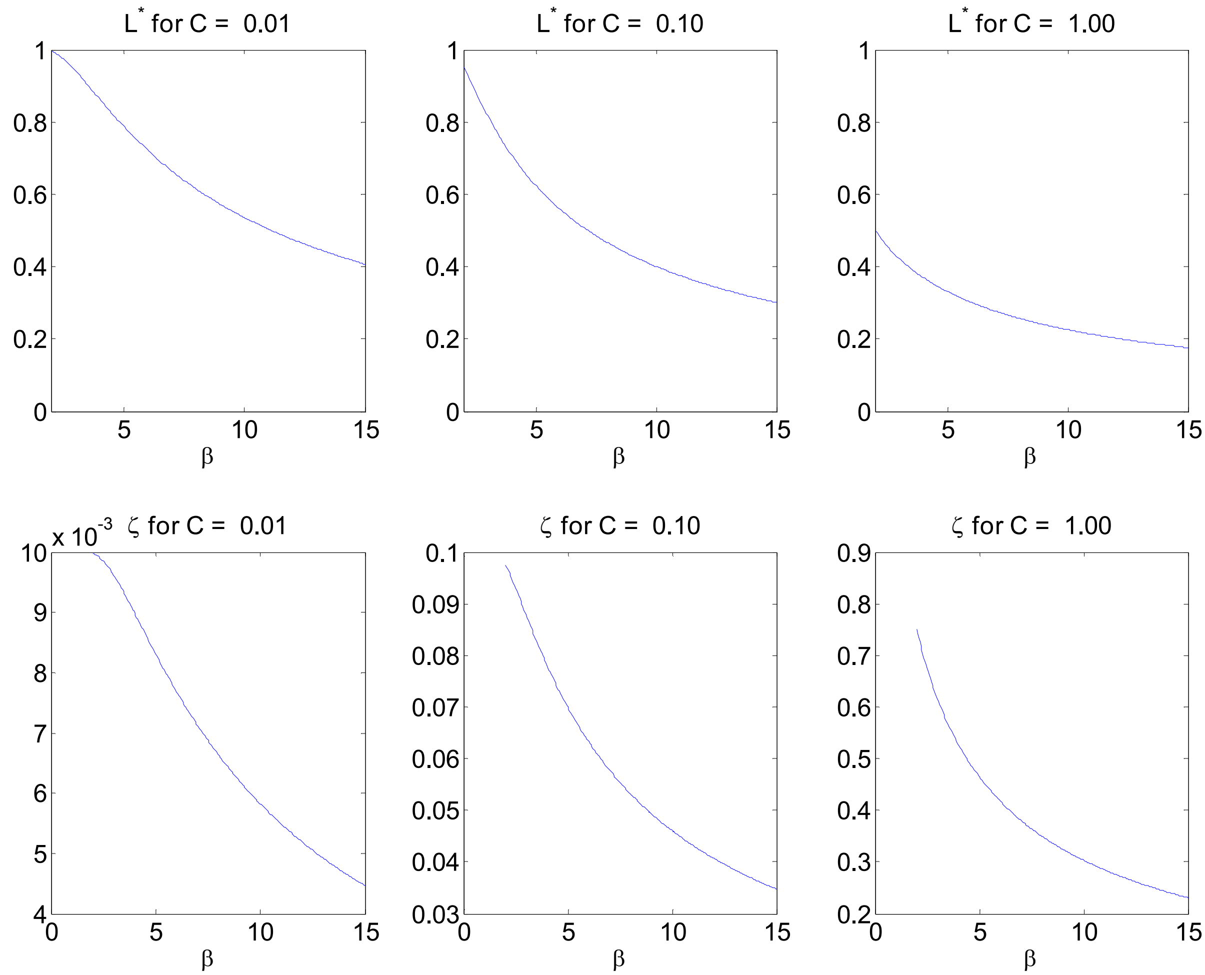

Figure 4.3. (Top 3 panels) Optimal protection fraction L^* as a function of β for (left) $C = 0.01$, (middle) $C = 0.1$, and (right) $C = 1$. (Bottom 3 panels) A measure of the total cost ζ as a function of β for (left) $C = 0.01$, (middle) $C = 0.1$, and (right) $C = 1$.

the optimal protection fraction. Similarly, the bottom 3 panels display that the measure of the total cost ζ declines with β. For example, the bottom left panel shows that changing β from 2 to 10 reduces ζ by about half.

In general, whether the optimal protection fraction L^* and the total cost (as measured by ζ) decrease or not with β depends on C, because for interior solutions,

$$\frac{\partial L^*}{\partial \beta} = \left\{ \frac{1}{\beta - 1} \ln\left(\frac{C}{\beta}\right) + \frac{1}{\beta} \right\} \frac{1}{\beta - 1} \left(\frac{C}{\beta}\right)^{1/(\beta-1)},$$

$$\frac{\partial \zeta}{\partial \beta} = \frac{1}{\beta - 1} \ln\left(\frac{C}{\beta}\right) \cdot \left(\frac{C}{\beta}\right)^{\beta/(\beta-1)}. \qquad (4.9)$$

Here the envelope theorem facilitates the calculation of $\partial\zeta/\partial\beta$. From the results in Table 4.2, the interior solution implies $C/\beta < 1$, and hence $\partial\zeta/\partial\beta < 0$ as $\ln(C/\beta) < 0$ in (4.9). The sign of $\partial L^*/\partial\beta$ cannot be determined algebraically.

Figure 4.4 describes $\partial L^*/\partial\beta$ and $\partial\zeta/\partial\beta$ as given in (4.9). The right panel shows $\partial\zeta/\partial\beta$, which is always negative as shown above. On the other hand, $\partial L^*/\partial\beta$, which is shown in the left panel, can be positive. An intuitive result holds for ζ but not L^*: more concentrated capital leads to a smaller total cost (as measured by ζ), but not necessarily a smaller protection fraction L^*.

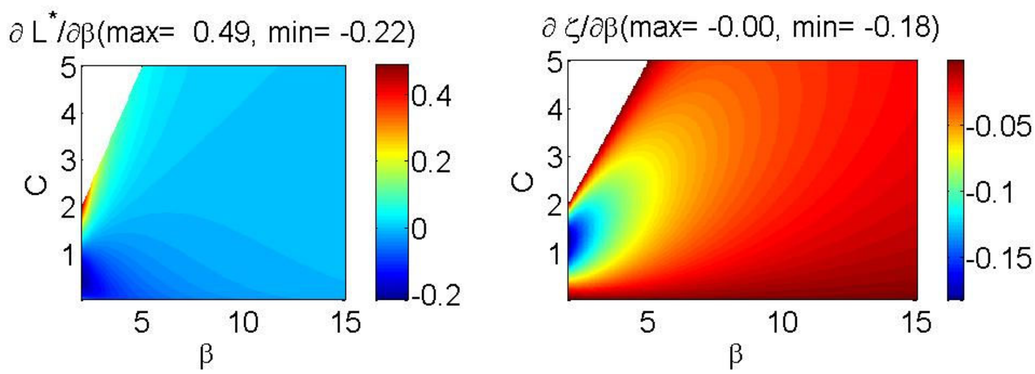

Figure 4.4. (left) $\partial L^*/\partial\beta$ and (right) $\partial\zeta/\partial\beta$ as a function of β and C, as given in (4.9). The maximum and minimum values are also shown in the parentheses. Corner solutions are indicated by white.

What is a realistic functional form of $D(L)$? Nicholls and Small (2002) calculated how population is distributed along the coastline for the entire globe. Such an estimate is illuminating but ideally we would like to know the capital distribution *within a country* since F95a used GVA-type data, where each country is represented by about one polygon. Here the new database, DIVA, is useful. DIVA has two orders of magnitude more coastal segments than its predecessor GVA, and it can give us some insight into the nature of distribution.

To estimate the distribution function D, population is chosen as a surrogate for the dryland value. Let Λ_j be the length of the j-th coastal segment, and q_j be the population density per length. Λ_j is indexed such that q_j decreases monotonically (more precisely, $q_{j+1} \leq q_j$). The discrete form of the function D can be defined as

$$D(L_i) = 1 - \frac{\sum_{j=1}^{i} q_j \Lambda_j}{\sum_{j=1}^{N} q_j \Lambda_j} \quad \text{where} \quad L_i = \frac{\sum_{j=1}^{i} \Lambda_j}{\sum_{j=1}^{N} \Lambda_j}. \tag{4.10}$$

Figure 4.5. conceptualizes how to formulate this function.

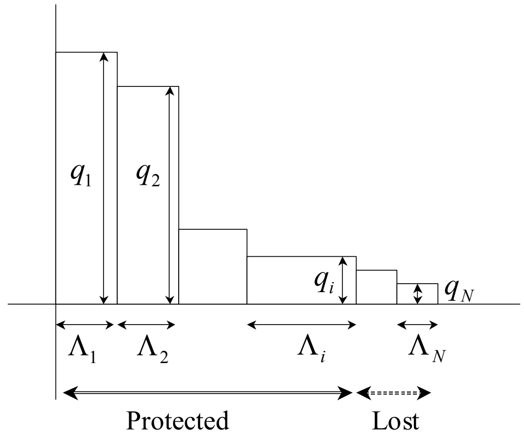

Figure 4.5. Schematic explaining how to calculate (4.10). Λ_j is the length of the j-th coastal segment, and q_j is the population density per length.

Figure 4.6 presents D functions calculated from DIVA for 3 countries, using (4.10). Along with D, the figure shows $(1–L)^2$, the choice of F95a, and nonlinear fits of the equations in Table 4.2. The nonlinear fit was performed by using the nlinfit function of the software package MATLAB®. The distribution of population in the DIVA data is highly concentrated, and the exponent for $(1–L)^\beta$ should be much higher than $\beta = 2$, the value F95a used. In the bottom right panel, Figure 4.6 also presents different methods to create the D function: population and economic output from DIVA. The two methods produce similar results, which confirms that high concentration of population characterizes the basic feature.

As noted in the beginning of this chapter, F95a and Turner et al. (1995) found quite different optimal protection fraction. Presumably one reason is that F95a's choice of exponent was too small.

It is important to recognize that Figure 4.6 presents D's at the *country scale*. As Turner et al. (1995) found, capital is concentrated at the *local scale* as well. It is thus possible to create a D function at the *local* level. I discuss this in more detail when applying the cost function to DIVA.

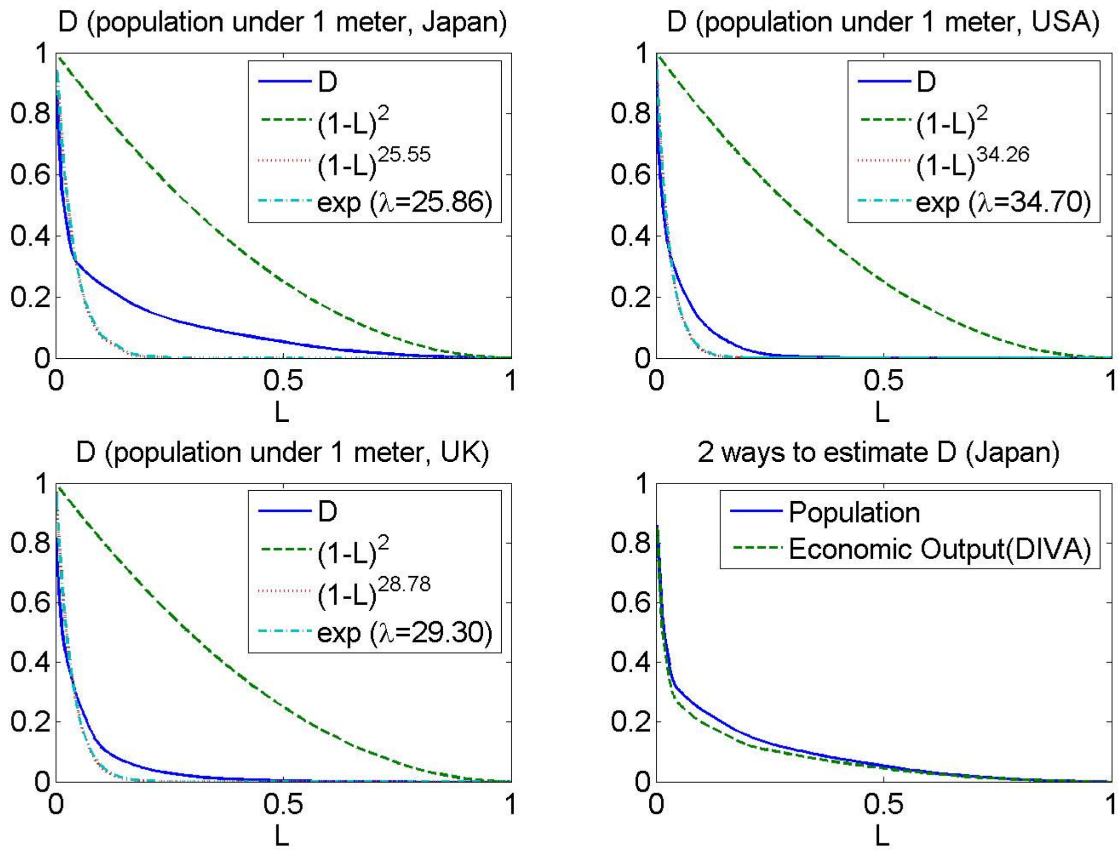

Figure 4.6. (Top right, top left, and bottom left panels) D from DIVA as estimated from (4.10), using the population under the 1-meter altitude divided by the coastline length as q_j. (Bottom right panel) D's estimated using two different measures: population under the 1-meter altitude and economic output under the 1-meter altitude as provided by DIVA.

4.4. Calculation of the present value of each cost item

This section derives analytic expressions for the present values of each cost item. A constant slope assumption simplifies the procedure greatly, and the following calculation makes use of it. The cost is obtained by simply multiplying a unit value (per area or per length per height) by an area or length times height. From the definitions in Table 4.1, it follows that

$$p_1^{(pv)} = \left[\pi \cdot \frac{dS}{dt}(t) \cdot \Lambda\right]^{(pv)}, \qquad d_0^{(pv)} = \left[\delta(t) \cdot \frac{S(t)}{\tan\psi} \cdot \Lambda\right]^{(pv)},$$

$$g_0^{(pv)} = \left(\gamma \cdot \alpha\, t \cdot \Omega\right)^{(pv)}, \qquad w^{(pv)} = \left[\gamma \cdot \frac{S(t)}{\tan\psi} \cdot \Omega\right]^{(pv)}, \tag{4.11}$$

where $p_1(t) = \pi \cdot dS/dt(t) \cdot \Lambda$ and so forth. F95a took the unit protection cost π as a function of the sea-level rise at the final time $S(\tau)$, but this thesis neglects it for simplicity.

It is possible to further simplify the equations by Taylor-expansion of sea-level rise. Writing

$$S(t) = \sum_{n=0}^{\infty} \frac{\sigma^{(n)}}{n!} t^n \tag{4.12}$$

allows us to write

$$\begin{aligned} p_1^{(pv)} &= \pi \cdot \Lambda \cdot \sum_{n=1}^{\infty} \frac{\sigma^{(n)}}{(n-1)!} \left(t^{n-1}\right)^{(pv)}, \\ d_0^{(pv)} &= \frac{\Lambda}{\tan\psi} \cdot \sum_{n=0}^{\infty} \frac{\sigma^{(n)}}{n!} \left[\delta(t) \cdot t^n\right]^{(pv)}, \\ w^{(pv)} &= \frac{\gamma\Omega}{\tan\psi} \sum_{n=0}^{\infty} \frac{\sigma^{(n)}}{n!} \left(t^n\right)^{(pv)}. \end{aligned} \tag{4.13}$$

Although F95a restricted himself to a linear sea-level rise, (4.13) demonstrates that it is possible to obtain analytic expressions of present values for any well-behaved sea-level rise scenario $S(t)$. Table 4.3 presents the detailed results for linear and quadratic case. For illustrative purposes, the present value operator here is taken to be

$$(\ )^{(pv)} = \sum_{t=0}^{\infty} (\ ) \cdot \left(\frac{1}{1+r}\right)^t \quad \text{and} \quad \delta(t) = \delta_0 (1+\varepsilon)^t.$$

Table 4.3. Analytic expressions of the cost component. The linear case corresponds to the equations of F95a. Tol (2002b) uses formulations almost identical to what is shown here. Subscripts in the sea-level rise function l and q denote linear and quadratic, respectively.

Linear $S = \sigma_l^{(1)} \cdot t$	$p_1^{(pv)} = \pi\sigma_l^{(1)}\Lambda \frac{1+r}{r}$, $g_0^{(pv)} = \gamma\alpha\Omega\frac{1+r}{r^2}$,	$d_0^{(pv)} = \frac{\delta_0}{\tan\psi}\sigma_l^{(1)}\Lambda\frac{(1+\varepsilon)(1+r)}{(r-\varepsilon)^2}$ $w^{(pv)} = \gamma\frac{1}{\tan\psi}\sigma_l^{(1)}\Omega\frac{1+r}{r^2}$
Quadratic $S = \sigma_q^{(1)} t + \frac{\sigma_q^{(2)} t^2}{2}$	$p_1^{(pv)} = \pi\Lambda\left(\sigma_q^{(1)}\frac{1+r}{r} + \sigma_q^{(2)}\frac{1+r}{r^2}\right)$, $d_0^{(pv)} = \frac{\delta_0\Lambda}{\tan\psi}\left\{\sigma_q^{(1)}\frac{(1+\varepsilon)(1+r)}{(r-\varepsilon)^2} + \frac{1}{2}\sigma_q^{(2)}\left(\frac{(1+\varepsilon)(1+r)}{(r-\varepsilon)^2} + \frac{2(1+\varepsilon)^2(1+r)}{(r-\varepsilon)^3}\right)\right\}$ $g_0^{(pv)} = \gamma\alpha\Omega\frac{1+r}{r^2}$ $w^{(pv)} = \frac{\gamma\Omega}{\tan\psi}\left\{\sigma_q^{(1)}\frac{1+r}{r^2} + \frac{1}{2}\sigma_q^{(2)}\left(\frac{1+r}{r^2} + \frac{2(1+r)}{r^3}\right)\right\}$	

4.5. Linear versus quadratic sea-level rise scenarios

Much of the past literature on impact assessment has been concerned with a linear sea-level rise. In actuality, we would expect that the rate of sea-level rise would accelerate in the future, and that a quadratic function or an exponential function might be a better choice to represent the future sea-level rise. Recent papers have used realistic sea-level rise scenarios such as those based on SRES. However, some of the recent literature still continues to rely on a linear sea-level rise, at least partially. For example, Nicholls and Tol (2006), while using SRES-based sea-level rise scenarios, assumed a linear sea-level rise for the purpose of calculating the optimal protection fraction, using the model of Tol (2004). It is thus important to analyze the effect of using a linear sea-level rise.

Figure 4.7 illustrates equivalent linear and quadratic sea-level rises. Such difference between them could actually change the cost estimate since, as is clear in Figure 4.7, a quadratic sea-level rise will postpone the bulk of cost, which would be substantially discounted in the present value. The key point here is that even though the sea levels in 2100 are the same for both scenarios, the costs could be substantially different between them.

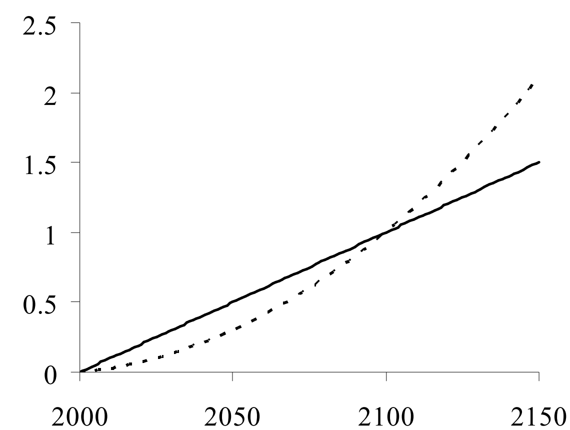

Figure 4.7. Illustration of equivalent linear and quadratic sea-level rises. The horizontal axis is the year whereas the vertical axis denotes the change of sea level in meters. The solid line represents a linear sea-level rise of 1 meter per century while the dotted line implies an equivalent quadratic sea-level rise. Both start from the same sea level in 2000 and reach 1 meter in 2100, but the quadratic one starts slowly and accelerates, exceeding the linear sea-level rise after 2100.

To address how different the cost would be between equivalent linear and quadratic sea-level rises, I compare the total costs for linear (Z_l) and quadratic (Z_q) sea-level rises. Recall that Z is defined as

$$Z = L^* {p_1}^{(pv)} + (1-L^*)^\beta {d_0}^{(pv)} - (1-L^*) {g_0}^{(pv)} + w^{(pv)} \quad .$$

The next equation defines equivalent linear and quadratic sea-level rises, assuming that the total sea-level rise is equal in 100 years from now:

$$S(t=100) = \sigma_l^{(1)} \cdot 100 = \sigma_q^{(1)} \cdot 100 + \frac{1}{2} \sigma_q^{(2)} \cdot 100^2 \quad . \tag{4.14}$$

This neglects subsidence and uplift for simplicity.

The following calculation uses the parameters below:

$$\delta_0 = \$3\text{million/km}^2 , \quad \pi = \$1\text{million/km/m} , \quad \gamma = \$5\text{million/km}^2 , \quad \Omega / \Lambda = 0.2 ,$$

$$\psi = 1^\circ , \quad \alpha = 50\text{cm/year} , \quad \rho = 1\% , \quad \varepsilon = 2\% , \quad r = \varepsilon + \rho , \quad \beta = 2.$$

The values of δ_0, π, Ω/Λ, and ψ approximately correspond to averages for the United States, taken from DIVA. The values of γ and α are provided by F95a. The time rate of preference and the economic growth rate were arbitrarily set to the given numbers.

Using DIVA, I have already demonstrated that β should be much larger than 2. But I here choose $\beta = 2$ for the following reason. Because of the wetland gain term g, it is possible that the total cost Z can be zero or negative. This, however, leads to trouble since I am attempting to calculate the ratio Z_q / Z_l and must avoid division by zero. The choice of $\beta = 2$ does not cause this problem, and thus I use it for illustrative purposes. I discuss the issue of negative cost in detail when implementing F95a's approach in EPPA in the next section.

To gain more insight, one can obtain an approximate equation for the ratio of total costs Z_q / Z_l. As F95a and other analyses have shown, the cost of wetland loss tends to dominate the total cost of sea-level rise. We would therefore expect

$$\frac{Z_q}{Z_l} \approx \frac{w_q}{w_l} = \frac{\frac{\gamma \Omega}{\tan \psi} \left\{ \sigma_q^{(1)} (t)^{(pv)} + \frac{1}{2} \sigma_q^{(2)} \left(t^2\right)^{(pv)} \right\}}{\frac{\gamma \Omega}{\tan \psi} \sigma_l^{(1)} (t)^{(pv)}} = \frac{\sigma_q^{(1)}}{\sigma_l^{(1)}} + \frac{1}{100} \left(1 - \frac{\sigma_q^{(1)}}{\sigma_l^{(1)}} \right) \left(1 + \frac{2}{r} \right)$$

where (4.14) has been used. This indicates that Z_q / Z_l depends only on r and is insensitive to any other parameter listed above, as long as the wetland loss is the dominant component of the total cost.

Figure 4.8 shows the ratio of the total costs for equivalent linear and quadratic sea-level rises, Z_q / Z_l, for $\tau = 100$ and $\tau = \infty$. It also shows the ratio of wetland loss, w_q / w_l. Comparing top and bottom panels indicates that w_q / w_l generally explains Z_q / Z_l since wetland is a dominant component. However, a closer inspection of the top and bottom left panels reveals a difference between w_q / w_l and Z_q / Z_l, especially for small $\sigma_q^{(1)}$. For instance, comparison of the two right panels ($\tau = 100$) shows that for $\sigma_q^{(1)}$ = 1[mm/year], $S(t=100) \sim 0.2$, Z_q / Z_l is 0.6 whereas w_q / w_l

is about 0.7.

All the panels in Figure 4.8 show values less than 1, indicating that quadratic sea-level rise scenarios lead to reduction of the total cost, as expected. For $\tau = 100$, the lowest value of Z_q / Z_l is about 0.6 (top, left panel), implying that the total cost for a quadratic sea-level rise could be up to 40% lower than that of a linear sea-level rise. The right panels exhibit that even for an infinite time horizon ($\tau = \infty$), Z_q / Z_l can go down to 0.7, which means that there is a substantial cost difference. All this shows that the past literature that relied on a linear sea-level rise has probably overestimated the present value of the cost of sea-level rise in this regard.

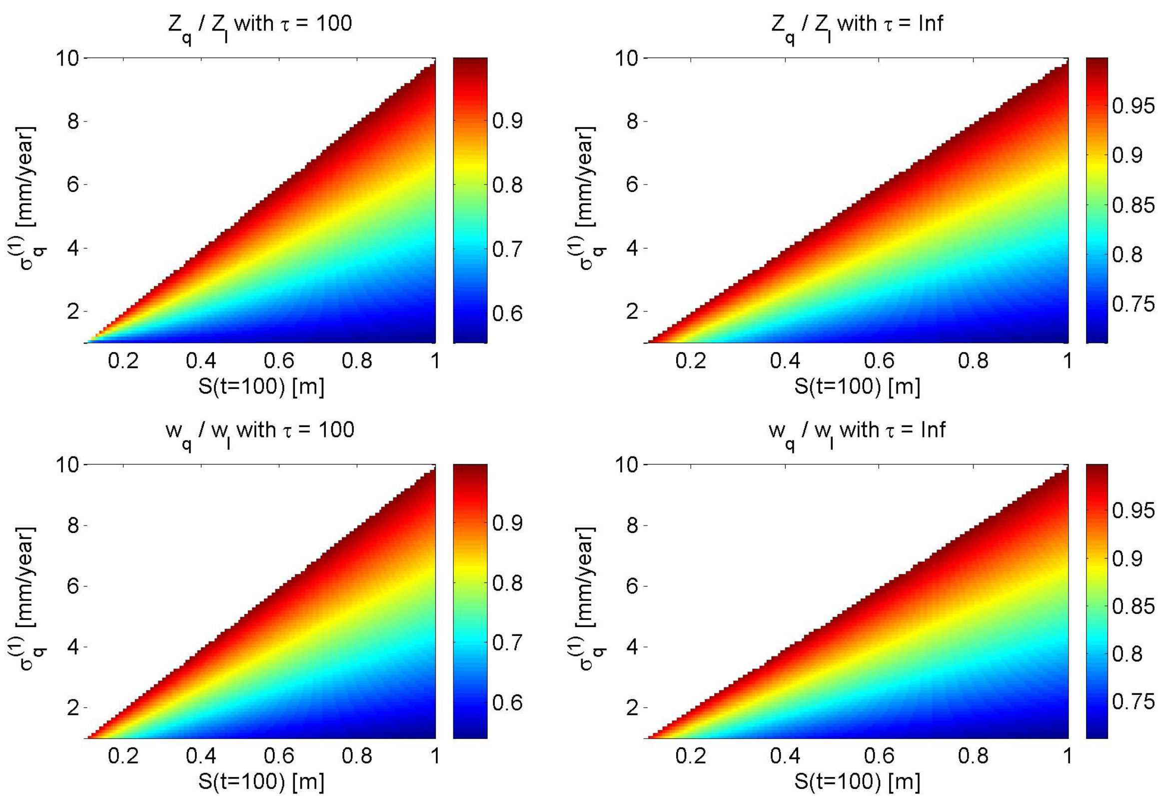

Figure 4.8. The total cost ratio between equivalent linear and quadratic sea-level rises (top left) for 100 years and (top right) an infinite time horizon. (Bottom) as in the top panels but for the wetland loss ratios. The horizontal axis is the sea-level rise in the final year, $S(t = 100)$ whereas the vertical axis represents the rate of a quadratic sea-level rise at the initial period, $\sigma_q^{(1)}$.

Having shown that a linear sea-level rise tends to overestimate the cost, the next question is, can we quantify whether the future sea-level rise is more likely to be quadratic or linear? Here the IGSM 1000 simulations can assist us in addressing the question. Figure 4.9 exhibits sea-level rise for randomly selected IGSM runs together with linear and quadratic fits. For all the cases presented here, the quadratic fit and model result are indistinguishable whereas the linear fit clearly deviates from the model result.

To quantify how much improvement quadratic fits can provide (a quadratic fit is always "better" since it has one more regression coefficient), Figure 4.10 displays (single and multiple) regression coefficients for linear and quadratic fits. It is clear that quadratic fitting equations are much better than linear fits, making a stronger case that a quadratic sea-level rise better represents realistic sea-level rise scenarios. It is actually possible to perform a statistical test to assess whether a quadratic equation is superior or not, but that is left to future research.

Presumably the reason why a quadratic fit performs very well is because the time scale of the ocean adjustment is long. Without stabilization of the concentration, the sea level continues to rise and can be approximated by an exponential function. Since its adjustment time scale is thousands of years, the first hundred years can be represented well by a quadratic equation.

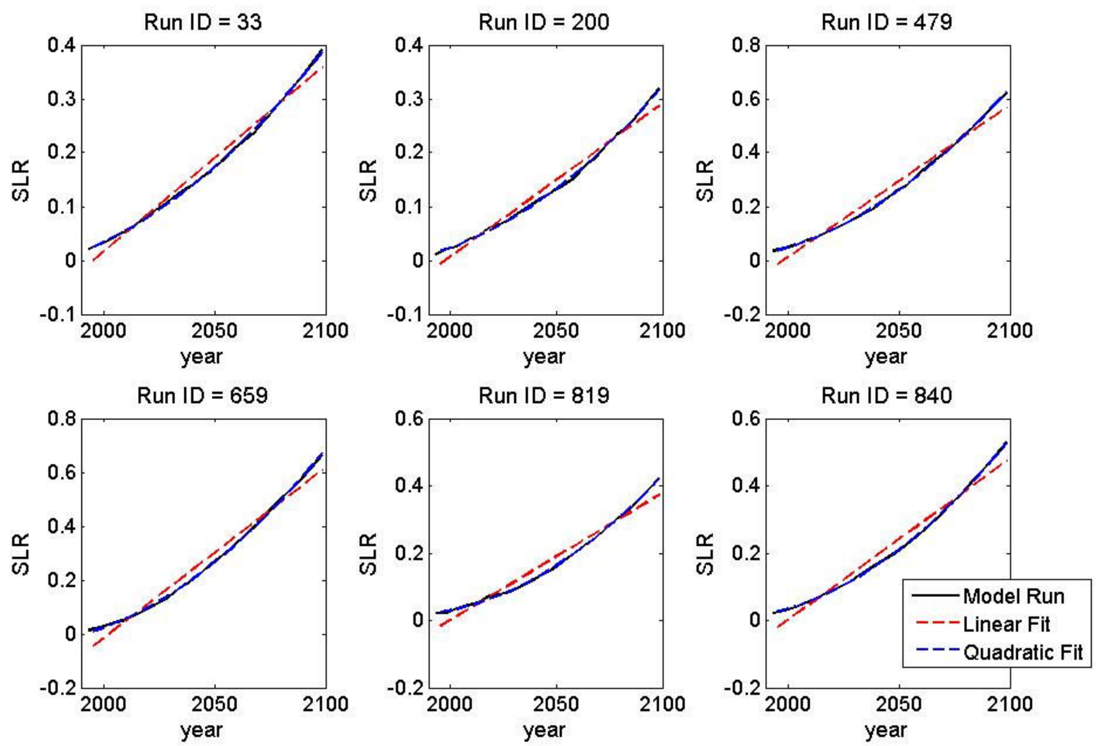

Figure 4.9. Sea-level rises from randomly selected IGSM simulations. Each panel corresponds to different runs, showing the model result (solid), a linear fit (red dashed), and a quadratic fit (blue dashed).

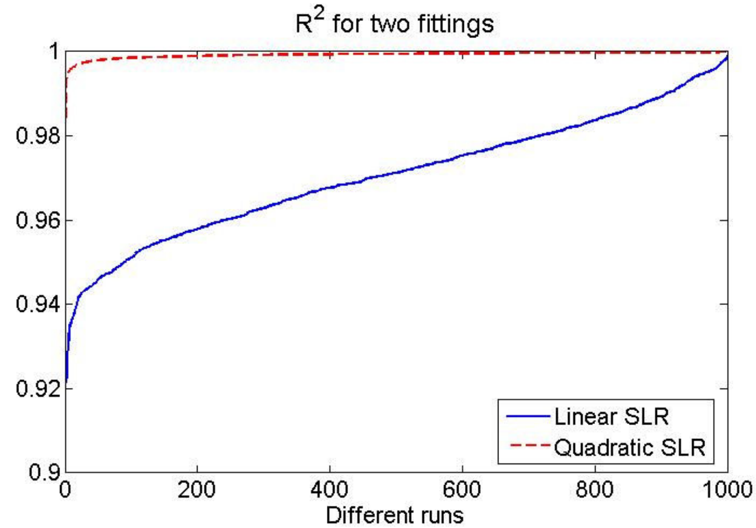

Figure 4.10. Regression coefficients R^2 for linear fits (solid) and quadratic fits (dashed). The result for each fit is sorted such that R^2 increases toward the right. Note that the order of runs is different between the linear and quadratic fits.

4.6. Applying the cost function to DIVA, G-Econ, and EPPA

This section describes how the sea-level rise cost function derived above is applied to DIVA and EPPA. The basic idea is to apply the sea-level rise cost function to each of DIVA's 12,198 segments. Tol (2002a, 2002b) used GVA, which provides 192 polygons, to estimate the cost of sea-level rise. The increase in spatial resolution from GVA to DIVA is substantial. However, I still use $D(L) = (1-L)^{\beta}$ to incorporate the capital concentration effect since even within a coastal segment, capital is concentrated. In other words, D in this section is defined at the regional or coastline scale and different from those presented in Figure 4.6, which presents D's at a country scale. Indeed, Turner et al. (1995) found that some portion of East Anglia was not worth protecting, supporting capital concentration even at the regional scale. On the other hand, the degree of concentration would not be as high at the regional scale as at the national scale. The standard value is thus taken to be $\beta = 2$, and sensitivity tests are performed.

The calculation proceeds in the following way. First, the sea-level rise function developed in Chapter 3 is used to calculate global sea-level rise, which is converted into relative sea-level rise by adding geologic subsidence. Second, the cost function produces the cost items p_1, d_0, g_0, and w at each time step. Third, present values are obtained, using discount rates consistent with the economic model EPPA. Fourth, the cost function determines the optimal protection fraction and optimal cost. In the below each step is described.

Relative sea-level rise

In each time step of EPPA, the sea-level rise function depicted in the previous chapter estimates the sea-level rise. DIVA gives the rate of geological uplift and subsidence (parameter UPLIFT), and the relative sea-level rise is calculated as a sum of the global sea-level rise and the local geologic component.

There is an issue of the base year difference between IGSM 1000 simulations that were produced from the previous version of EPPA, and the current version of EPPA. EPPA 3, the previous version, took 1995 as the reference year whereas it is 1997 for EPPA 4. Ideally emissions of 1997 should be re-scaled to get values of 1995, but here I neglect this procedure since the resulting error should be relatively small.

Cost at each time step

For given relative sea-level rise, the costs are calculated as

$$p_1(t) = \pi \cdot \frac{dS}{dt}(t) \cdot \Lambda \cdot \Theta(S(t)), \qquad d_0(t) = \delta(t) \cdot \frac{S(t)}{\tan\psi} \cdot \Lambda \cdot \Theta(S(t)),$$

$$g_0(t) = \gamma \cdot \min\left(\alpha t, \frac{S(t)}{\tan\psi}\right) \cdot \Omega \cdot \Theta(S(t)), \qquad w(t) = \gamma \cdot \frac{S(t)}{\tan\psi} \cdot \Omega \cdot \Theta(S(t)), \tag{4.15}$$

where Θ is the Heviside step function. The step function is introduced to prevent negative costs. Now that S represents the relative sea-level rise, S can be negative since geologic uplift may exceed global sea-level rise. I assume that the cost is incurred only after S becomes positive (due to the acceleration of sea-level rise). Also note that the wetland gain g_0 now contains a minimum operator so that wetland gain does not exceed the wetland loss w; contrast (4.15) with (4.11). Although under some circumstances there can be *net* wetland gain (as a sum of *gross* wetland gain and wetland loss), it is difficult to figure out whether net wetland gain occurs or not for each coastal segment. The present thesis simply ignores such a possibility.

DIVA provides data on each parameter utilized in (4.15), which is summarized in Table 4.4. Some coastal segments have $\psi = 0$, and no cost is calculated for such segment. Other required parameters are given in Table 4.5. Note that S here represents *relative* sea-level rise for each coastal segment, rather than global sea-level rise. Note also that the value of wetland is not adjusted for inflation. In fact, the uncertainty in the value of wetland dwarfs adjustment due to inflation, and I perform a sensitivity test on the wetland value in Chapter 5.

For wetlands, DIVA provides the areas, not the lengths, Ω. To convert the areas into lengths, I assume that wetlands extend inland on average about 1 km, following F95a.

Table 4.4. Correspondence between DIVA variables and symbols. See Table 3.1. for definitions of DIVA variables.

Symbol	DIVA variable	Units in DIVA
π	SDIKECOST	U.S. \$m per m per km
Λ	LENGTHY	km
ψ	SLOPECST	Degrees
Ω	min((TOTALWETAR/100+MANGS_KM2)/1, LENGTHY)	TOTALWETAR in ha, LENGTHY in km, so that Ω in km

Table 4.5. Other parameters and sources.

Symbol	Descriptions	Source
α	50 cm per year	F95a
γ	$5\,\text{million USD} \times \left[\dfrac{\text{(GDP per capita)/\$20000}}{1+\text{(GDP per capita)/\$20000}}\right] \Bigg/ \left[\dfrac{\text{(GDP per capita)}_{\text{US}}\text{/\$20000}}{1+\text{(GDP per capita)}_{\text{US}}\text{/\$20000}}\right]$	F95a, Tol 2002a

I have yet to specify the time evolution of capital loss. A simple choice is

$$\delta(t)=\delta(t=0)\cdot\frac{Y(t)}{Y(t=0)}$$

where Y is economic output. There are two possible ways to specify $\delta(t=0)$:

$$\delta(t=0)=\text{(capital-output ratio)}\cdot\text{(economic output of segment per area)},$$

$$\delta(t=0)=\text{(economic output of segment per area)}.$$

What is at stake is not the capital but return on the capital, and thus the second specification appears more appropriate. Nevertheless, the next chapter conducts sensitivity tests. Also note that the formulation adopted here assumes that the population distribution in a country does not change.

To use the economic growth rate from EPPA, I associate each segment in DIVA with one of the 16 regions in EPPA. Since each of the coastline segments in DIVA belongs to a country, this task is to define a correspondence table between countries in DIVA and regions in EPPA. Appendix B gives such correspondence table.

There is a technical issue with the difference in the reference years between EPPA and DIVA. While EPPA uses 1997 as the reference year, DIVA utilizes 1995. A crude but simple approach to combine DIVA and EPPA is to multiply the economic output of DIVA by the growth rate of each region for 1995 – 1997. I attempted to obtain growth rates for each region by comparing the regional outputs from DIVA and EPPA, but they turned out to be very different, calling into question the validity of this method of estimating growth rates. Here I simply ignore the difference in the reference year, allowing for errors of up to 20% (for economically dynamic areas) in the unit capital loss. This should not, however, lead to substantial errors in the cost estimate since, in most cases, the cost is dominated by wetland loss and precious land is already protected. In any event, this problem must be remedied in the future.

DIVA provides economic output of each segment but G-Econ contains more detailed data. I therefore test the data from the two datasets. However, there are some issues with combining DIVA and G-Econ data. First, as in the case with DIVA and EPPA, the reference year is different (1995 for DIVA and 1990 for G-Econ), although both datasets adopt 1995 U.S. dollars as currency units. Second, DIVA and G-Econ are not provided on the same spatial grid.

The difference in the reference years can easily be accommodated by using the data from G-Econ for spatial scaling only. For the purpose of spatial scaling, I define the local economic multiplier as

$$(\text{local economic output multiplier}) = \frac{(\text{local economic output per capita})}{(\text{GDP per capita})}. \qquad (4.16)$$

DIVA provides this parameter as "GDP per capita multiplier." This parameter can also be readily calculated from G-Econ (since local economic output is gross cell product in G-Econ). Therefore, the economic output of each segment is calculated by multiplying GDP per capita from DIVA with the multiplier either from DIVA or G-Econ.

Next, it is necessary to assign each of the DIVA coastal segments to one of G-Econ grid cells. G-Econ grid cells and DIVA segments are matched by calculating the "distance":

$$(\text{distance}) = \sqrt{(\text{lat}_{\text{DIVA}} - \text{lat}_{\text{GEcon}})^2 + (\text{lon}_{\text{DIVA}} - \text{lon}_{\text{GEcon}})^2}. \qquad (4.17)$$

For a particular DIVA segment, the G-Econ grid cell that has minimum distance and that belongs to the same country as the DIVA segment is chosen. This chosen G-Econ grid cell gives per-capita economic output for the DIVA segment in question. I obtain economic output for this segment by multiplying population density of this DIVA segment. If (4.17) gives a "distance" larger than 2, G-Econ data is not utilized for that particular DIVA segment.

Admittedly this is a crude way to match DIVA and G-Econ. An ideal way is to utilize a GIS system to combine both datasets, which is left for future research.

Figure 4.11 shows the local economic output multipliers from DIVA and G-Econ for three countries. Comparison of blue lines (DIVA) and red lines (G-Econ) reveals that using G-Econ increases the maximum value of multiplier and decreases its minimum value. For the U.S., G-Econ implies that some grid cells have per-capita income more than 20 times larger than the

U.S. average. Overall, G-Econ shows more spatial concentration of per-capita economic output than DIVA.

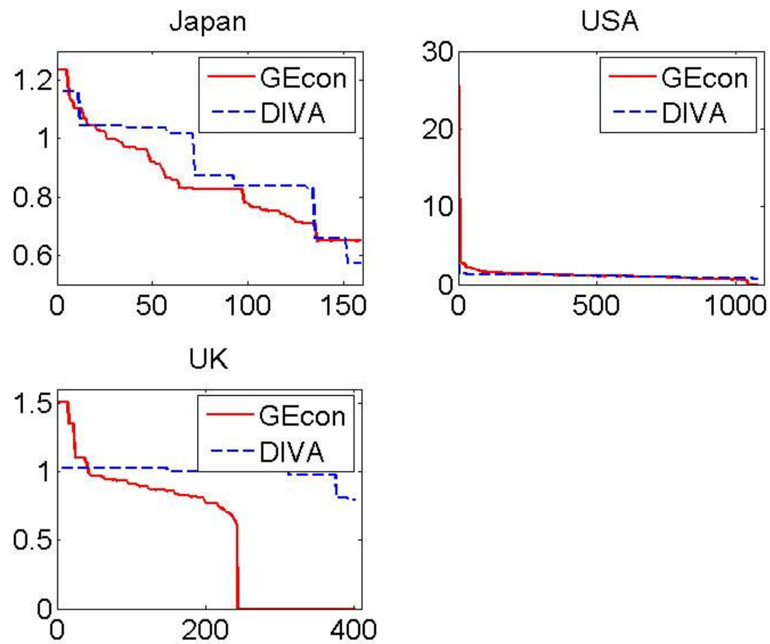

Figure 4.11. Local economic output multipliers for 3 countries. Red lines correspond to estimates from G-Econ whereas blue lines are from DIVA. The horizontal axes indicate different segments. Segments are sorted in the order of decreasing multiplier.

Present value calculation

The discount rate is assumed to be the economic growth rate plus the pure rate of time preference. The actual calculation is prompted by the relations

$$\frac{1}{1+\varepsilon(t)+\rho} \approx \frac{1}{1+\varepsilon(t)}\frac{1}{1+\rho}, \qquad \prod_{t=0}^{\tau} \frac{1}{1+\varepsilon(t)} = \frac{Y(t=0)}{Y(t=\tau)}, \text{ and}$$

$$\prod_{t=0}^{\tau} \frac{1}{1+\varepsilon(t)+\rho} \approx \frac{Y(t=0)}{Y(t=\tau)}\frac{1}{(1+\rho)^{\tau}},$$

where Y is the gross domestic product and ρ is the pure rate of time preference, which is taken to be 1%. In sum,

$$(\ )^{(pv)} = \sum_{t=0}^{\tau} (\ )\frac{Y(0)}{Y(t)}\frac{1}{(1+\rho)^{t}}. \tag{4.18}$$

The base year is taken to be 2000 (that is, $t = 0$ refers to 2000).

What do the discount rates based on Equation (4.18) look like? It is useful to define an equivalent discount rate as

$$\tilde{r}(t) \equiv \left(\frac{Y(t)}{Y(0)} \right)^{\frac{1}{t}} (1+\rho) - 1 \quad \text{so that} \quad \frac{1}{\{1+\tilde{r}(t)\}^t} = \frac{Y(0)}{Y(t)} \frac{1}{(1+\rho)^t} . \tag{4.19}$$

Table 4.6 displays the equivalent discount rate calculated for the United States, based on the EPPA reference economic scenario. It is about 4% initially and gradually decreases to about 3%, as the economic growth slows down. Table 4.7 shows the same parameter for all the EPPA regions for selected years. The equivalent discount rate is 3 – 4% on average.

Table 4.6. Equivalent discount rate as defined in Equation (4.19) for the United States, estimated from the EPPA reference case economic scenario and a pure rate of time preference of 1%. Units are in percent.

2005	3.50	2055	3.79
2010	4.02	2060	3.71
2015	4.17	2065	3.63
2020	4.18	2070	3.55
2025	4.14	2075	3.48
2030	4.10	2080	3.41
2035	4.06	2085	3.34
2040	4.01	2090	3.28
2045	3.94	2095	3.23
2050	3.87	2100	3.18

Optimal protection fraction

Given the present values of each cost item, it is now possible to determine the optimal protection fraction. Recalling Equation (4.1), it is imperative to notice that the nature of the problem is forward-looking. What is being calculated is the trade-off between future economic growth and current cost of building a sea dike. Such trade-off cannot be appropriately dealt within a dynamic-recursive model like the standard version of EPPA. Nevertheless, I apply F95a's method to the DIVA and EPPA, with a caution that this method should be improved in the future.

With F95a's approach, I can take the sea-level rise scenario from the "reference" case and calculate the present value. I further assume $D(L) = (1 - L)^{\beta}$ and choose $\beta = 2$. There is no information about capital distribution within each of the coastal segments in DIVA and it is impossible to justify $\beta = 2$, which motivates sensitivity tests on β. By combining the present values of each cost item and the cumulative distribution function D, Equation (4.7) gives the optimal protection fraction L^*.

Table 4.7. As in Table 4.6 but for all the EPPA regions and selected periods.

	2005	2010	2020	2040	2060	2080	2100
United States	3.50	4.02	4.18	4.01	3.71	3.41	3.18
Canada	3.85	4.26	4.34	4.09	3.76	3.46	3.21
Mexico	3.07	3.69	3.89	3.77	3.51	3.35	3.23
Japan	2.07	3.16	3.72	3.92	3.72	3.45	3.21
Australia & New Zealand	4.42	4.64	4.60	4.33	4.00	3.67	3.40
European Union	2.79	3.50	3.80	3.76	3.57	3.34	3.13
Eastern Europe	4.30	4.37	4.36	4.27	4.13	3.93	3.75
Former Soviet Union	5.55	5.23	5.14	4.89	4.45	4.09	3.83
Higher Income East Asia	4.47	4.49	4.51	4.35	4.16	3.91	3.71
China	7.14	6.52	6.02	5.46	5.02	4.58	4.24
India	6.15	5.76	5.34	4.66	4.28	4.05	3.86
Indonesia	3.41	3.93	4.25	4.36	4.14	3.92	3.73
Africa	4.61	4.87	4.80	4.10	3.87	3.70	3.55
Middle East	4.05	4.46	4.45	3.96	3.72	3.49	3.32
Central & South America	2.74	3.57	4.11	4.44	4.33	4.07	3.82
Rest of World	4.46	4.39	4.18	3.63	3.53	3.48	3.44

Optimal cost

Given the optimal protection fraction L^*, it simply follows that the optimal costs are

$$p^*(t) = L^* p_1(t), \quad d^*(t) = (1-L^*)^\beta d_0(t), \quad g^*(t) = (1-L^*) g_0(t). \tag{4.20}$$

The total cost in each time period is thus

$$L^* p_1(t) + (1-L^*)^\beta d_0(t) + w(t) - (1-L^*) g_0(t),$$

where all terms are defined in (4.15). Note that there is no optimal wetland loss since wetland loss does not involve the choice variable L.

The next chapter presents the results.

Chapter 5. Results

5.1. Socio-economic and sea-level rise scenarios

This chapter presents the results of numerical cost calculations. Socio-economic scenarios are taken from the reference run of the EPPA. The following results ignore the effect of capital loss on economic welfare. As noted in Chapter 4, ideally, I should utilize a forward-looking model to capture the trade-off between protection cost and loss of future economic welfare due to reduced capital. And yet I do not take this approach, using the cost function derived in the previous chapter instead. Also, the present results are based on partial equilibrium calculations, rather than general equilibrium calculations, which is another limitation of the present thesis.

Several scenarios of sea-level rise are examined to illustrate the sensitivity:

(1) A one-meter-per-century linear sea-level rise for comparison with F95a;

(2) An average of IGSM 1000 simulations;

(3) A statistical fit to IGSM results (two specifications).

All the results presented below are in 1995 U.S. dollars, although EPPA's reference year is 1997. This is because the costs presented below are based on DIVA, which takes 1995 as the reference year.

5.2. One-meter-per-century linear sea-level rise

This section discusses a linear sea-level rise of 1 meter over a century, which facilitates comparison with F95a. Tables 5.1 and 5.2 display the results in market exchange rate (MER) and purchasing power parity (PPP) terms, respectively. The conversion between MER and PPP is performed using the conversion rates described by Paltsev et al. (2005), who in turn relied on the Penn World Tables (Heston et al. 2002). The results are later compared with those of F95a.

The review of cost items is in order. In each period, there are four kinds of cost incurred: protection cost $p(t)$, dryland/capital loss $d(t)$, wetland loss $w(t)$, and wetland gain $g(t)$. Protection cost $p(t)$ represents the cost of building an *additional* dike at each period. Maintenance cost is neglected here. Capital loss $d(t)$ in each period is the loss of capital because of inundation in that period. Net wetland loss $w(t) - g(t)$ is wetland loss w minus wetland gain g. Section 4.1 describes the detailed definitions of each cost item. Note that all the tables in this section show present values: $[\ p(t)\ ]^{(pv)}$, $[\ d(t)\ ]^{(pv)}$, $[\ w(t) - g(t)\ ]^{(pv)}$, where $(\ \ )^{(pv)}$ is the present value operator defined in (4.18).

The global estimate shows the relative importance of cost items. Table 5.1 shows that wetland loss is on the order of \$1000 billion, while protection cost \$100 billion and capital loss \$40 billion in MER. For PPP, Table 5.2 indicates larger cost estimates, but the relative magnitude of each cost remains the same. Wetland loss constitutes a dominant component, as in previous studies (F95a, etc.), and each cost item differs by an order of magnitude.

Several countries make up the majority of wetland loss: the United States, Canada, Australia & New Zealand, the European Union, and Central & South America (and Indonesia, if PPP is used). Nicholls et al. (1999) list regions with vulnerable wetlands: the Atlantic coast of North and Central America, the Mediterranean, and the Baltic. The present results show that more regions are vulnerable than Nicholls et al. (1999) suggested.

For MER, regions with highest protection cost are European Union, Central & South America,

Table 5.1. Results from the reference case socio-economic scenario and linear one-meter-per-century sea-level rise in 1995 U.S. billion dollars in MER. A simple sum based on MER is given as the global cost, without taking PPP conversion into account.

	Present values of cost and loss					Protection
EPPA regions	Total	Protection	Capital	Net wetland	% of wetland	fraction[%]
Global	1182.21	126.35	37.94	1017.93	86.10	29.86
United States	317.72	10.31	3.32	304.09	95.71	40.14
Canada	123.04	5.78	3.29	113.98	92.63	6.66
Mexico	29.01	3.46	1.64	23.91	82.42	47.83
Japan	14.56	9.52	0.15	4.88	33.54	97.88
Australia & New Zealand	145.64	4.77	5.11	135.76	93.21	40.57
European Union	147.20	28.23	4.48	114.48	77.78	34.64
Eastern Europe	1.01	0.56	0.03	0.42	41.44	92.10
Former Soviet Union	7.96	3.73	2.79	1.44	18.05	6.35
Higher Income East Asia	33.11	9.81	0.68	22.62	68.31	79.83
China	6.45	5.55	0.21	0.69	10.74	93.19
India	5.92	3.64	0.12	2.16	36.48	80.92
Indonesia	36.87	3.89	1.64	31.34	85.02	51.37
Africa	21.45	5.57	3.20	12.68	59.10	30.49
Middle East	20.39	1.96	0.58	17.85	87.53	51.36
Central & South America	249.74	19.89	7.44	222.41	89.06	40.52
Rest of World	22.15	9.67	3.25	9.22	41.65	45.66

and the United States, whereas the highest capital loss is incurred by Central & South America, Australia & New Zealand, and European Union. This order changes for PPP. Regions with highest protection cost are Central & South America, the Rest of World, and the European Union; those with highest capital loss are Central & South America, Rest of World, and Africa. In light of their low GDP, it is noteworthy that Africa and Rest of World incur high protection cost and capital loss in PPP, implying that poorer countries tend to suffer more.

The optimal protection fraction shows interesting behavior. It is highest for Japan, followed by China and Eastern Europe, all of which have protection levels exceeding 90%. Japan's high protection level is consistent with the finding of F95a. F95a also found high protection levels for the United States and Europe, but the results here show moderate protection fractions (about 40% and 30%, respectively) for these regions. Why do Japan, the United States, and Europe show different behaviors in terms of protection fraction?

Figure 4.6 gives some hints for this difference. Comparing the upper two panels reveals that Japan has a long tail of modest *D* while *D* falls sharply for the United States. In other words,

Table 5.2. As in Table 5.1. but for PPP based on conversion described by Paltsev et al. (2005).

	Present values of cost and loss					Protection
EPPA regions	Total	Protection	Capital	Net wetland	% of wetland	fraction[%]
Global	1991.24	285.75	87.66	1617.78	86.10	29.86
United States	317.72	10.31	3.32	304.09	95.71	40.14
Canada	148.88	6.99	3.98	137.92	92.63	6.66
Mexico	43.81	5.22	2.48	36.10	82.42	47.83
Japan	10.05	6.57	0.10	3.37	33.54	97.88
Australia & New Zealand	184.96	6.06	6.49	172.42	93.21	40.57
European Union	176.64	33.88	5.38	137.38	77.78	34.64
Eastern Europe	2.85	1.58	0.08	1.18	41.44	92.10
Former Soviet Union	34.31	16.08	12.02	6.21	18.05	6.35
Higher Income East Asia	97.01	28.74	1.99	66.28	68.31	79.83
China	28.77	24.75	0.94	3.08	10.74	93.19
India	31.79	19.55	0.64	11.60	36.48	80.92
Indonesia	147.11	15.52	6.54	125.05	85.02	51.37
Africa	82.58	21.44	12.32	48.82	59.10	30.49
Middle East	50.98	4.90	1.45	44.63	87.53	51.36
Central & South America	539.44	42.96	16.07	480.41	89.06	40.52
Rest of World	94.36	41.19	13.85	39.28	41.65	45.66

Japan's D doesn't reach 0 until L = ~0.8 whereas that of the United States becomes indistinguishable from 0 at L = ~0.4. Presumably such a difference in the D would explain differing protection levels.

After the results are examined, Table 5.3 compares the results here with those of F95a for selected countries. Note that the present values are now in 1990 U.S. dollars rather than 1995 dollars, unlike other tables in this chapter. One prediction of the cost function derived in Chapter 4 is that using DIVA should result in smaller protection fractions. In fact, Table 5.3 shows exactly this, except that Japan's protection fraction decreases only little, which I just discussed. It is noteworthy that the protection cost of $9.13 billion for the United States is even lower than $36.1 billion estimated by Yohe et al. (1996); see Tables 2.1 and 5.3.

However, it is likely that the difference in protection fraction is not entirely due to the effect of capital concentration. The average value of the dryland could be different between the two calculations. Unfortunately, such comparison is not easy since F95a calculated the cost for different types of coastal areas (e.g., cities, harbors, open coasts), while the present thesis does not distinguish them. Most likely we are seeing the combined effect of capital concentration and differing values of dryland.

In spite of lower protection fractions, the new cost estimates are not necessarily lower than

Table 5.3. Comparison of the results of this thesis and F95a and Fankhauser (1995b). The protection fraction for F95a is taken to be an average of protection levels for open coasts, beaches (see his Figure 2), cities, and harbors (100%) weighted by coastline lengths as presented in Fankhauser (1995b). Because of open coasts accounts for the majority of a country's coastline, protection fractions from F95a closely follow that of open coasts. Units are in 1990 U.S. dollars. For conversion between 1990 and 1995 dollars, a GDP deflator of 1.129 is used, which was taken from the GDP price implicit deflator in the National Income and Product Accounts Tables (Table 1.1.9 of http://bea.gov/bea/dn/nipaweb/SelectTable.asp?Selected=Y).

		Total	Protection	Capital loss	Net wetland loss	% of net wetland loss	Protection fraction [%]
United States	This thesis	281.42	9.13	2.94	269.34	95.71	40.14
	Fankhauser	425.16	62.59	15.96	346.61	81.52	81
Japan	This thesis	12.90	8.43	0.13	4.32	33.54	97.88
	Fankhauser	141.47	6.83	0.03	134.55	95.11	99
Canada	This thesis	108.98	5.12	2.91	100.96	92.63	6.66
	Fankhauser	6.92	3.73	3.12	N/A	N/A	28
Australia & New Zealand	This thesis	129.00	4.22	4.53	120.25	93.21	40.57
	Fankhauser	50.76	44.58	5.94	N/A	N/A	76
Europe Union	This thesis	130.38	25.00	3.97	101.40	77.78	34.64
	Fankhauser	300.66	55.24	1.90	243.52	81.00	95

F95a's. Wetland loss, which tends to be dominant, can account for most of the differences. The wetland loss for the United States is 24 % lower than that of F95a, and the total cost is 35% lower but still comparable. F95a did not provide wetland loss for Canada and Australia & New Zealand; adding this substantially increases the total cost for these countries. Why the results here based on DIVA show lower wetland loss for Japan and European Union is not clear.

It is instructive to see the sensitivity of the present results to parameters of interest. The following lists parameters and motivation for sensitivity calculations:

(1) *Wetland price*. Titus et al. (1991) show a wide range of wetland price, from ~\$1.5 million to ~\$7.4 million per km^2. Moreover, wetland loss tends to dominate the total cost;
(2) *Protection cost*. Although the present study considers only sea dike construction as protection measure, different coastal types require different options. For example, beaches require beach nourishment which, according to F95a, is more costly than protection;
(3) *The exponent of cumulative capital distribution function*, β. Chapter 4 estimated β at the *country scale*, but the value at the *coastline scale* is unknown;
(4) *Discount rate*. Impact assessment is generally susceptible to the choice of discount rate, as was confirmed for sea-level rise by F95a. How sensitive is my result to the discount rate?;
(5) *Capital-output ratio*. Ideally, one should evaluate the return on capital rather than capital itself in calculating the cost. Although DIVA and G-Econ provide local economic output, this may not be directly related to return on capital. Therefore a sensitivity test is performed on the capital-output ratio to explore how to treat this; and
(6) *Use of DIVA-based economic output*. As Chapter 4 showed, using G-Econ renders the geographic distribution of economic output even more skewed. How does it affect the cost of sea-level rise damage?

Table 5.4 lists the sensitivity calculations, focusing on the United States. Halving the wetland price reduces wetland loss and the total cost approximately by half. Doubling the unit protection cost increases protection cost to about twice the reference-case cost, but the total cost does not change appreciably since it is dominated by wetland loss. Using the DIVA-based economic output rather than the G-Econ dataset does not alter the cost estimates significantly. Reducing β from 2 to 1 increases both protection cost and capital loss. This is because the capital is assumed to be uniform at the coastline scale. Increasing β to 5 leads to less protection cost but slightly more capital loss. For both values of β, the total cost does not change because of the predominance of wetland loss. Setting the capital-output ratio to 1 reduces both protection cost and capital loss as expected, but the total cost does not differ much.

Table 5.4 also shows the sensitivity of the cost to the discount rate. For the last 3 rows of Table 5.4, a fixed discount rate is used for the entire periods. As expected, a lower discount rate gives a higher present value of the costs. The reference case falls between discount rates of 3 –

Table 5.4. Sensitivity tests of the costs for the United States for a one-meter-per-century linear sea-level rise.

	Total	Protection	Capital loss	Net wetland loss	% of net wetland loss	Protection fraction [%]
Reference	317.72	10.31	3.32	304.09	95.71	40.14
Half wetland price	165.58	10.43	2.93	152.23	91.93	40.59
Double protection cost	327.51	18.83	4.79	303.89	92.79	36.99
DIVA-based economic output	317.47	10.18	3.32	303.97	95.75	39.72
$\beta = 1$	318.50	10.68	3.43	304.39	95.57	41.50
$\beta = 5$	312.14	8.14	3.38	300.62	96.31	31.67
Capital-output ratio = 1	314.71	8.84	2.82	303.04	96.29	34.89
Discount rate = 1%	1180.82	27.01	10.81	1143.00	96.80	44.58
Discount rate = 3%	423.10	12.71	4.27	406.12	95.99	40.69
Discount rate = 5%	201.35	7.71	2.25	191.39	95.06	37.68

5%, which is confirmed by Table 4.6 that shows equivalent discount rates for all the periods.

The results here are only for the United States, and the total costs of other countries behave differently since, for example, Japan has small wetland loss and changing the protection cost does affect the total cost. Nevertheless, all the results are intuitive.

5.3. Average of IGSM 1000 simulations

Although a linear sea-level rise of 1 meter is important for comparison purposes, it is higher than IPCC projections of 9 – 88 cm in 2100. This section therefore discusses the effect of a more realistic sea-level rise scenario, using an average of 1000 sea-level rise scenarios produced by IGSM. It also compares linear and quadratic sea-level rises.

The calculation utilizes the quadratic fit to the average of IGSM simulations across different runs. Since the multiple regression coefficient is extremely high ($R^2 > 0.9999$), the error should be negligible from the use of a quadratic fit. The sea-level rise in 2100 is about 0.44 m. In conjunction with the quadratic effect, the cost here is anticipated to be reduced substantially.

Table 5.5 lists the cost estimates for the United States in the same format as Table 5.4. The reference case exhibits much lower costs than presented in Tables 5.1 and 5.2. The last row describes the cost associated with the equivalent linear sea-level rise. As expected, the equivalent linear sea-level rise leads to about 60% higher cost. The results of other sensitivity tests are easy to understand as in the previous section.

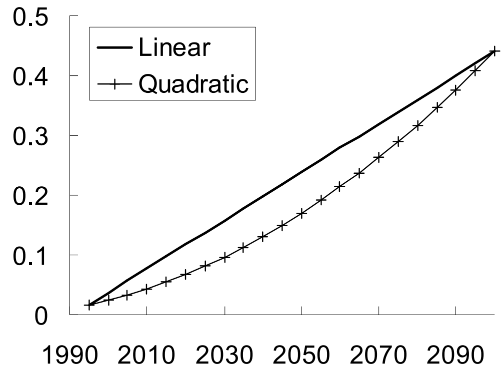

Figure 5.1. A quadratic fit to the average of the IGSM 1000 sea-level rise scenarios. Also shown is an equivalent linear sea-level rise scenario.

Table 5.5. Sensitivity tests of the costs for the United States for the mean of 1000 sea-level rise scenarios.

	Total	Protection	Capital loss	Net wetland loss	% of net wetland loss	Protection fraction [%]
Reference	75.72	2.42	1.71	71.58	94.54	40.22
Half wetland price	39.76	2.47	1.17	36.13	90.86	41.06
Double protection cost	77.98	4.28	2.20	71.50	91.69	36.97
DIVA-based economic output	75.59	2.40	1.70	71.49	94.57	40.05
$\beta = 1$	76.56	2.52	1.24	72.80	95.09	41.99
$\beta = 5$	71.88	1.91	1.80	68.18	94.85	31.46
Capital-output ratio = 1	73.76	1.94	2.24	69.57	94.33	33.71
Linear equivalent sea-level rise	125.75	3.80	1.99	119.96	95.40	39.95

5.4. Statistical fits to IGSM simulation outputs

Next I turn to the statistical fit of sea-level rise to the IGSM 1000 runs that were developed in Chapter 3. The statistical fits take C_s, K_v, and F_{aer} as inputs. I use the mode of each variable reported by Forest et al. (2006): C_s = 2.9 K, K_v = 0.65 cm^2/s, F_{aer} = 0.5 W/m^2. The new results of Forest et al. (2006) indicate that the effective ocean diffusivity K_v is smaller than previously assumed, implying a lower sea-level rise.

Using the probability distribution functions of these climate parameters, as estimated by Forest et al. (2006), it is possible to conduct an uncertainty calculation, but that is left to future research.

There is an issue with the different reference years. I have performed the regressions for the initial periods with the emissions for 1995. However, the reference year for the current version of EPPA is 1997, which leads to inconsistency with the dependent variables used and statistical fits. Although errors from such difference would be small, the future work should resolve this issue.

Figure 5.2 depicts sea-level rise scenarios calculated by the two statistical fitting equations, (3.6) (Specification 2) and (3.9) (Specification 3). The two statistical equations lead to different sea-level rises, creating an error of ~0.07 m in 2100. One reason is that the value of K_v used here is in the lower range of the IGSM simulation runs, and the statistical fit does not perform well.

How does this difference translate into cost? Table 5.6 compares the costs for the United States under all the sea-level-rise scenarios discussed here. The differences between Specifications 2 and 3 are fairly large for two reasons. Specification 2 leads to not only a smaller sea-level rise, but it also postpones the cost in the future, which is discounted. The discounting effect is the same as I discussed in relation with the linear versus quadratic sea-level rise scenarios.

Unfortunately, great sensitivity to statistical fits casts a question on the usefulness of a simple statistical fit to sea-level rise.

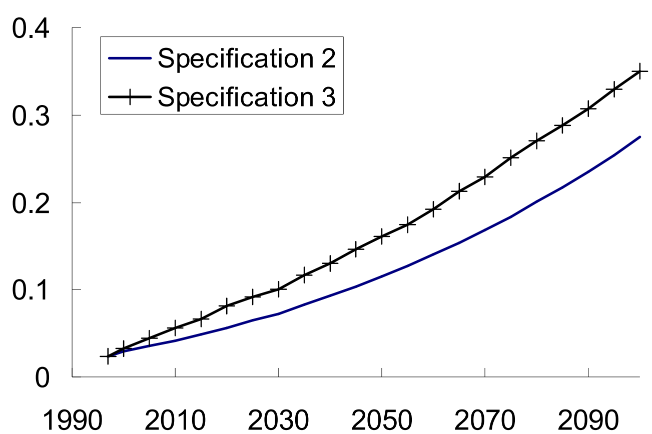

Figure 5.2. Comparison of the two statistical fits under the EPPA reference case socio-economic scenario.

Table 5.6. The costs for five sea-level-rise (SLR) scenarios for the United States.

	Total	Protection	Capital loss	Net wetland loss	% of net wetland loss	Protection fraction [%]
1-meter-over-century linear	317.72	10.31	3.32	304.09	95.71	40.14
IGSM average	75.72	2.42	1.71	71.58	94.54	40.22
IGSM equivalent linear	125.75	3.80	1.99	119.96	95.40	39.95
SLR function Specification 2	55.40	1.32	7.07	47.01	84.86	38.97
SLR function Specification 3	78.15	2.17	1.84	74.14	94.87	40.01

5.5. Summary

This chapter has produced new estimates of the cost of sea-level rise. Results presented here affirm some classical results and provide new insight:

(1) Replacing GVA with the new vulnerability database DIVA leads to lower optimal protection fractions, generally reducing the protection cost;

(2) Wetland loss continues to be the dominant cost item. Nevertheless, capital loss and protection cost may not be negligible for developing countries, in light of their small GDP;

(3) Different sea-level rises yield different cost estimates. What matters is not the final sea-level rise but the *path* of sea-level rise, which reaffirms the finding of Chapter 4 about the difference between linear and quadratic sea-level rises; and

(4) The role of D (cumulative capital distribution function) at the *country level* is subtle for some countries because a simple equation may not approximate the capital distribution derived from DIVA because of a long tail.

The next chapter addresses what can be done to further improve the cost estimates.

Chapter 6. Conclusions and discussions

6.1. Conclusions

As part of an effort to incorporate the sea-level rise damage effect in EPPA, this thesis generalized the sea-level rise cost function originally developed by F95a, and made an initial attempt to calculate the cost of global sea-level rise, using EPPA.

F95a's cost function has been generalized in two ways. First, I have shown that the cumulative capital distribution function is not restricted to a quadratic function but can take any form; as long as its derivative is invertible, it is possible to obtain a closed form solution for the optimal protection fraction. Using DIVA, I demonstrated that capital is quite concentrated, much more than F95a's choice of a quadratic function. Second, I have clarified that F95a's methodology can take nonlinear sea-level rise, and calculated some closed-form solutions. I also showed that because a nonlinear sea-level rise causes more damage in later periods, the cost and protection fraction for nonlinear sea-level rise are usually lower than those of an equivalent linear one. These two effects combine to indicate that the cost estimate from F95a's method and GVA could be an overestimate.

Having extended F95a's methodology, I used an economic scenario from EPPA and utilized DIVA and G-Econ, producing novel estimates of the cost of global sea-level rise. Wetland loss continues to be the dominant cost item for most countries, and there is no drastic change in the total cost for a linear one-meter-per-century sea-level rise for regions where the wetland loss remains about the same. Realistic nonlinear sea-level rises yield appreciably lower costs. The role of D (capital distribution function) at the country level is subtle because a simple equation may not appropriately represent the capital distribution based on DIVA because of a long tail.

6.2. Discussions

Further extension of the generalized F95a's approach

Despite progress made in this work, a number of issues need to be addressed. Indeed, there are potential improvements to be made within F95a's framework. Examples include:

(1) *Protection cost other than sea dikes, such as beach nourishment*. In this thesis, I assumed that the cost arises in the form of dike protection, and yet a better model should include other

protection measures such as beach nourishment;

(2) *Representation of wetland loss that takes accretion into account*. Wetlands are treated as passive in the present model, but they are active agents. They accumulate sediment (accrete) and may be able to keep up with relative sea-level rise, at least to some extent. Moreover, the current formulation assumes instantaneous gain and loss of wetlands although there is a finite response time for such changes. Ecology of wetland is extremely complex, but some simple models do exist (e.g., Nicholls 2004), and can be included in F95a's framework;

(3) *Emigration cost*. Sea-level rise will not only lose useful land but also displace people living there. Some argue that the cost associated with emigration could be substantial. Tol (2002a, 2002b) provides such estimates as an additional cost component, determined outside of the cost minimization problem, but it should be possible to include this as another item in the generalized F95a's approach; and

(4) *Dynamic optimal protection fraction*. One of the key assumptions of F95a is that the optimal protection fraction does not change with time, which greatly simplifies the model solution strategy. For example, the model does not allow a situation where a coastline may be protected until 2050 and then abandoned. A simple dynamic optimization problem will certainly give a solution, but the question is how tractable that model would be. Creating a detailed but still tractable model is an interesting research topic.

Other improvements

In addition to the improvement of the cost functions, there are possible options for better cost estimates. One issue is the changing distribution of population. Currently the coastal areas are experiencing faster rates of population growth than national averages. Some studies took this trend into account by assuming that the present trends will continue (e.g., Nicholls et al. 1999). The future study may take advantage of the work of Asadoorian (2005), who derived empirical relations that can be used to forecast future population distributions.

Another issue concerns with the use of economic output from DIVA. It would be ideal to use the DIVA for spatial scaling only (to calculate the economic output of a coastal segment for a given GDP), since DIVA's economic data may not be compatible with the GTAP database that underlies EPPA. One can follow the way G-Econ is utilized in this thesis as described in Chapter 4.

The difference in reference years is another concern. DIVA's GDP data are for 1995, whereas the reference year for EPPA is 1997. Statistical fits for the initial period are produced using the 1995 emissions, and yet EPPA starts its integration from 1997. Although we would not expect a substantial error from such inconsistency, it is desirable to resolve such problem.

It is also possible to relax the constant slope assumption since DIVA contains the areas at different elevations. In the current calculation, no cost is estimated for coastal segments with a zero slope, which might have led to an underestimate of the costs. Making use of the area data can overcome this problem.

Beyond Fankhauser

Those presented above are presumably straightforward problems. But we are confronted with more challenging questions.

F95a's optimization problem is a dynamic one, exposing the forward-looking nature of adaptation to sea-level rise. This means that in including sea-level rise damage in an economic model, ideally one should be using a forward-looking model. Currently the standard version of EPPA is recursive-dynamic, and it is inconsistent to use F95a's approach in an ad hoc manner. One could, however, develop a rule of thumb to mimic the forward-looking calculation by exploiting a fact that the cost of the damage is quite small relative to economic output. A starting point is a neoclassical growth model with a decision variable on coastal protection. There is no guarantee that this approach leads to a reasonable methodology, but if successful, the result would be helpful since a forward-looking model is usually expensive to run.

The most difficult issue is about imperfect information and extreme events associated with sea-level rise. Both are strongly related with how humans would adapt to an uncertain, gradual sea-level rise that is punctuated with extreme events. F95a's model requires perfect information about the future sea-level rise up to 2100. And yet, such information simply does not exist in the literature of future sea-level rise projections. Another relevant point is that what matters is not about gradual sea-level rise itself, but extreme events that would be exacerbated by it. Admittedly the future projection is full of uncertainty, but it is steadily taking place. Nevertheless, we do not see coastal planners deciding on which coastal segments to protect. It might be that people would feel the effect of sea-level rise only when there occurred an extreme event. Modeling such human behavior in a simple manner, and teasing out the *portion* of the extreme event damage due to sea-level rise is, indeed, challenging.

Appendix A. Regression results

Table A.1. Regression results for Equation (3.4).

R_squared_SLR 0.835

	B_i	**t_i**		**B_i**	**t_i**
const	-4.89E-03	-6431	sqrt(Kv)	4.39E-04	4172
SLR	4.82E-02	29425	Faer	6.04E-04	739
S	2.62E-03	14188	CO2	1.64E-04	15331
			N2O	4.81E-05	2275

cross correlations	SLR	S	sqrt(Kv)	Faer	CO2	N2O
SLR	1	0.231	0.043	-0.066	0.707	0.442
S	0.231	1	-0.024	0.228	-0.023	-0.034
sqrt(Kv)	0.043	-0.024	1	0.074	0.049	-0.011
Faer	-0.066	0.228	0.074	1	-0.04	-0.03
CO2	0.707	-0.023	0.049	-0.04	1	0.577
N2O	0.442	-0.034	-0.011	-0.03	0.577	1

confidence level	0.95	0.99	0.999	0.9999
R^2_critical	0.00053	0.00072	0.00098	0.0012
t_critical_2_sided	1.96	2.58	3.29	3.89

Table A.2. Regression results for Equation (3.5).

R_squared_SLR 0.843

	B_i	**t_i**		**B_i**	**t_i**
const	-5.37E-03	-7220	CO2	1.67E-04	14682
SLR	4.52E-02	27801	SO2	7.32E-08	35
S	2.73E-03	15412	CH4	-2.62E-04	-7004
sqrt(Kv)	4.40E-04	4372	N2O	1.47E-04	5989
Faer	-2.17E-04	-276			

cross correlations	SLR	S	sqrt(Kv)	Faer	CO2	SO2	CH4	N2O
SLR	1	0.231	0.043	-0.066	0.707	0.384	0.02	0.442
S	0.231	1	-0.024	0.228	-0.023	0.006	-0.054	-0.034
sqrt(Kv)	0.043	-0.024	1	0.074	0.049	0.062	-0.03	-0.011
Faer	-0.066	0.228	0.074	1	-0.04	0.008	-0.105	-0.03
CO2	0.707	-0.023	0.049	-0.04	1	0.569	0.198	0.577
SO2	0.384	0.006	0.062	0.008	0.569	1	0.013	0.305
CH4	0.02	-0.054	-0.03	-0.105	0.198	0.013	1	0.551
N2O	0.442	-0.034	-0.011	-0.03	0.577	0.305	0.551	1

confidence level	0.95	0.99	0.999	0.9999
R^2_critical	0.00067	0.00088	0.0012	0.0014
t_critical_2_sided	1.96	2.58	3.29	3.89

Table A.3. Regression results for Equation (3.6).

R_squared_SLR	0.839

	B_i	**t_i**
const	-1.03E-02	-6871
SLR	4.72E-02	29194
S	4.66E-03	7153
S^2	-2.37E-04	-2902
sqrt(Kv)	2.13E-03	4359
Kv	-1.87E-04	-3412
S*sq(Kv)	-1.31E-04	-1173
Faer	3.43E-04	427
CO2	1.68E-04	15967
N2O	5.41E-05	2606

cross correlations

	SLR	S	S^2	sqrt(Kv)	Kv	S*sq(Kv)	Faer	CO2	N2O
SLR	1	0.231	0.209	0.043	0.033	0.164	-0.066	0.707	0.442
S	0.231	1	0.954	-0.024	-0.013	0.593	0.228	-0.023	-0.034
S^2	0.209	0.954	1	-0.009	0	0.584	0.197	-0.014	-0.01
sqrt(Kv)	0.043	-0.024	-0.009	1	0.967	0.744	0.074	0.049	-0.011
Kv	0.033	-0.013	0	0.967	1	0.728	0.075	0.051	-0.009
S*sq(Kv)	0.164	0.593	0.584	0.744	0.728	1	0.188	0.019	-0.025
Faer	-0.066	0.228	0.197	0.074	0.075	0.188	1	-0.04	-0.03
CO2	0.707	-0.023	-0.014	0.049	0.051	0.019	-0.04	1	0.577
N2O	0.442	-0.034	-0.01	-0.011	-0.009	-0.025	-0.03	0.577	1

confidence level	0.95	0.99	0.999	0.9999
R^2_critical	0.00074	0.00096	0.0012	0.0015
t_critical_2_sided	1.96	2.58	3.29	3.89

Table A.4. Regression results for Equation (3.7).

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
R^2	7.52E-01	7.77E-01	7.87E-01	7.93E-01	7.82E-01	7.61E-01	7.37E-01	7.32E-01	7.25E-01	7.25E-01	7.33E-01

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
R^2	7.38E-01	7.41E-01	7.44E-01	7.49E-01	7.52E-01	7.55E-01	7.57E-01	7.59E-01	7.60E-01	7.61E-01	7.62E-01

B_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
const	2.83E-02	3.56E-02	4.49E-02	5.41E-02	5.90E-02	6.64E-02	6.53E-02	6.26E-02	6.39E-02	6.00E-02	5.69E-02
S	5.46E-03	7.21E-03	8.98E-03	1.10E-02	1.32E-02	1.60E-02	1.91E-02	2.28E-02	2.68E-02	3.15E-02	3.63E-02
sqrt(Kv)	7.33E-04	7.47E-04	9.62E-04	1.04E-03	1.34E-03	1.59E-03	2.20E-03	2.51E-03	2.60E-03	2.89E-03	3.38E-03
Faer	-4.11E-02	-4.65E-02	-5.32E-02	-6.03E-02	-6.74E-02	-7.37E-02	-7.76E-02	-8.21E-02	-8.66E-02	-9.02E-02	-9.31E-02
CO2	-1.61E-04	-2.70E-04	-3.54E-04	-3.50E-04	-2.62E-04	-1.47E-04	7.90E-06	1.78E-04	3.27E-04	4.83E-04	6.26E-04
N2O	5.57E-05	1.28E-04	2.22E-04	3.32E-04	4.22E-04	5.38E-04	6.58E-04	7.48E-04	8.84E-04	1.03E-03	1.19E-03

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
const	5.17E-02	4.63E-02	4.07E-02	3.77E-02	2.97E-02	2.53E-02	1.67E-02	7.05E-03	-1.33E-03	-1.18E-02	-2.14E-02
S	4.13E-02	4.62E-02	5.16E-02	5.75E-02	6.31E-02	6.93E-02	7.57E-02	8.20E-02	8.86E-02	9.58E-02	1.03E-01
sqrt(Kv)	3.92E-03	4.59E-03	5.26E-03	6.02E-03	7.09E-03	7.90E-03	8.89E-03	1.02E-02	1.16E-02	1.30E-02	1.47E-02
Faer	-9.57E-02	-9.93E-02	-1.02E-01	-1.05E-01	-1.08E-01	-1.11E-01	-1.13E-01	-1.15E-01	-1.18E-01	-1.20E-01	-1.22E-01
CO2	7.88E-04	9.32E-04	1.08E-03	1.24E-03	1.38E-03	1.54E-03	1.69E-03	1.84E-03	2.01E-03	2.17E-03	2.32E-03
N2O	1.34E-03	1.50E-03	1.70E-03	1.89E-03	2.09E-03	2.32E-03	2.54E-03	2.77E-03	3.02E-03	3.28E-03	3.54E-03

t_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
S	6.87E+03	7.50E+03	7.12E+03	6.60E+03	5.53E+03	4.44E+03	3.56E+03	3.08E+03	2.59E+03	2.23E+03	1.98E+03
sqrt(Kv)	1.50E+03	1.27E+03	1.24E+03	1.01E+03	9.14E+02	7.16E+02	6.64E+02	5.52E+02	4.07E+02	3.32E+02	2.98E+02
Faer	-1.09E+04	-1.02E+04	-8.88E+03	-7.62E+03	-5.96E+03	-4.31E+03	-3.05E+03	-2.35E+03	-1.77E+03	-1.35E+03	-1.07E+03
CO2	-6.60E+02	-9.21E+02	-1.02E+03	-9.07E+02	-5.70E+02	-2.56E+02	1.13E+01	2.27E+02	3.60E+02	4.54E+02	5.18E+02
N2O	3.63E+02	6.77E+02	9.39E+02	1.14E+03	1.07E+03	9.49E+02	8.17E+02	7.09E+02	6.24E+02	5.55E+02	5.05E+02

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
S	1.72E+03	1.49E+03	1.29E+03	1.14E+03	1.00E+03	8.93E+02	7.94E+02	7.17E+02	6.48E+02	5.89E+02	5.43E+02
sqrt(Kv)	2.65E+02	2.40E+02	2.14E+02	1.93E+02	1.83E+02	1.65E+02	1.51E+02	1.45E+02	1.38E+02	1.30E+02	1.26E+02
Faer	-8.41E+02	-6.77E+02	-5.41E+02	-4.40E+02	-3.64E+02	-3.04E+02	-2.51E+02	-2.13E+02	-1.83E+02	-1.57E+02	-1.37E+02
CO2	5.58E+02	5.64E+02	5.53E+02	5.34E+02	5.11E+02	4.83E+02	4.50E+02	4.23E+02	3.97E+02	3.69E+02	3.46E+02
N2O	4.49E+02	4.00E+02	3.60E+02	3.24E+02	2.96E+02	2.73E+02	2.51E+02	2.36E+02	2.20E+02	2.07E+02	1.96E+02

confidence level	0.95	0.99	0.999	0.9999
R^2_critical	0.011	0.015	0.020	0.026
t_critical_2_sided	1.96	2.58	3.30	3.91

Table A.5. Regression results for Equation (3.8)

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
R^2	7.57E-01	7.83E-01	7.95E-01	8.11E-01	8.15E-01	8.12E-01	8.06E-01	8.09E-01	8.06E-01	8.07E-01	8.10E-01

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
R^2	8.10E-01	8.09E-01	8.08E-01	8.07E-01	8.06E-01	8.05E-01	8.02E-01	8.01E-01	8.00E-01	7.99E-01	7.98E-01

B_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
const	3.69E-02	3.65E-02	3.50E-02	4.45E-02	5.03E-02	5.88E-02	5.97E-02	5.95E-02	6.32E-02	6.09E-02	5.90E-02
S	5.47E-03	7.23E-03	8.99E-03	1.10E-02	1.32E-02	1.60E-02	1.91E-02	2.27E-02	2.68E-02	3.14E-02	3.62E-02
sqrt(Kv)	7.54E-04	7.67E-04	9.38E-04	1.00E-03	1.30E-03	1.54E-03	2.16E-03	2.49E-03	2.60E-03	2.92E-03	3.42E-03
Faer	-4.10E-02	-4.65E-02	-5.33E-02	-6.07E-02	-6.82E-02	-7.52E-02	-7.99E-02	-8.52E-02	-9.04E-02	-9.48E-02	-9.85E-02
CO2	-3.50E-04	-1.35E-04	5.36E-05	4.55E-05	1.22E-04	2.07E-04	3.09E-04	4.09E-04	5.23E-04	6.50E-04	7.67E-04
SO2	-2.57E-05	-3.20E-05	-1.77E-05	-2.53E-05	-3.59E-05	-4.50E-05	-5.46E-05	-6.13E-05	-7.22E-05	-7.96E-05	-8.37E-05
CH4	1.62E-04	-1.23E-04	-4.72E-04	-6.50E-04	-9.17E-04	-1.26E-03	-1.64E-03	-1.96E-03	-2.27E-03	-2.60E-03	-2.90E-03
N2O	5.19E-05	1.33E-04	2.91E-04	4.89E-04	7.03E-04	9.73E-04	1.27E-03	1.49E-03	1.73E-03	1.99E-03	2.23E-03

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
const	5.45E-02	4.98E-02	4.48E-02	4.23E-02	3.47E-02	3.05E-02	2.21E-02	1.25E-02	4.34E-03	-6.22E-03	-1.61E-02
S	4.11E-02	4.60E-02	5.14E-02	5.73E-02	6.28E-02	6.90E-02	7.54E-02	8.17E-02	8.82E-02	9.54E-02	1.02E-01
sqrt(Kv)	3.97E-03	4.65E-03	5.32E-03	6.08E-03	7.15E-03	7.94E-03	8.92E-03	1.02E-02	1.16E-02	1.30E-02	1.46E-02
Faer	-1.02E-01	-1.06E-01	-1.10E-01	-1.14E-01	-1.17E-01	-1.21E-01	-1.24E-01	-1.27E-01	-1.30E-01	-1.33E-01	-1.36E-01
CO2	9.04E-04	1.03E-03	1.16E-03	1.31E-03	1.44E-03	1.59E-03	1.74E-03	1.88E-03	2.04E-03	2.19E-03	2.33E-03
SO2	-8.56E-05	-8.77E-05	-9.06E-05	-9.18E-05	-9.35E-05	-9.42E-05	-9.30E-05	-9.03E-05	-9.02E-05	-8.73E-05	-8.34E-05
CH4	-3.24E-03	-3.59E-03	-3.93E-03	-4.26E-03	-4.57E-03	-4.89E-03	-5.20E-03	-5.49E-03	-5.84E-03	-6.20E-03	-6.49E-03
N2O	2.48E-03	2.74E-03	3.01E-03	3.27E-03	3.52E-03	3.78E-03	4.03E-03	4.27E-03	4.55E-03	4.84E-03	5.10E-03

t_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
S	6.99E+03	7.69E+03	7.37E+03	7.20E+03	6.50E+03	5.61E+03	4.80E+03	4.30E+03	3.67E+03	3.14E+03	2.77E+03
sqrt(Kv)	1.57E+03	1.33E+03	1.25E+03	1.06E+03	1.04E+03	8.77E+02	8.80E+02	7.64E+02	5.78E+02	4.74E+02	4.24E+02
Faer	-1.10E+04	-1.04E+04	-9.20E+03	-8.35E+03	-7.07E+03	-5.54E+03	-4.22E+03	-3.40E+03	-2.61E+03	-2.00E+03	-1.58E+03
CO2	-2.47E+02	-1.66E+02	9.69E+01	1.00E+02	2.72E+02	4.17E+02	5.56E+02	6.82E+02	7.49E+02	7.86E+02	7.98E+02
SO2	-8.88E+02	-9.67E+02	-6.19E+02	-8.46E+02	-9.99E+02	-9.58E+02	-8.87E+02	-7.94E+02	-7.12E+02	-6.02E+02	-5.04E+02
CH4	1.35E+02	-1.75E+02	-9.00E+02	-1.30E+03	-1.59E+03	-1.69E+03	-1.67E+03	-1.56E+03	-1.34E+03	-1.15E+03	-9.91E+02
N2O	3.36E+02	7.07E+02	1.20E+03	1.64E+03	1.82E+03	1.84E+03	1.78E+03	1.64E+03	1.44E+03	1.26E+03	1.11E+03

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
S	2.36E+03	2.01E+03	1.71E+03	1.47E+03	1.28E+03	1.11E+03	9.70E+02	8.64E+02	7.72E+02	6.96E+02	6.34E+02
sqrt(Kv)	3.69E+02	3.30E+02	2.88E+02	2.53E+02	2.35E+02	2.08E+02	1.86E+02	1.75E+02	1.65E+02	1.54E+02	1.47E+02
Faer	-1.23E+03	-9.78E+02	-7.70E+02	-6.15E+02	-5.02E+02	-4.12E+02	-3.36E+02	-2.83E+02	-2.41E+02	-2.05E+02	-1.78E+02
CO2	7.83E+02	7.44E+02	6.95E+02	6.43E+02	5.97E+02	5.50E+02	5.02E+02	4.64E+02	4.32E+02	3.98E+02	3.70E+02
SO2	-4.02E+02	-3.25E+02	-2.64E+02	-2.11E+02	-1.74E+02	-1.43E+02	-1.15E+02	-9.36E+01	-7.89E+01	-6.49E+01	-5.36E+01
CH4	-8.39E+02	-7.15E+02	-6.02E+02	-5.06E+02	-4.34E+02	-3.72E+02	-3.18E+02	-2.79E+02	-2.48E+02	-2.20E+02	-1.97E+02
N2O	9.60E+02	8.32E+02	7.19E+02	6.20E+02	5.45E+02	4.83E+02	4.26E+02	3.86E+02	3.50E+02	3.21E+02	2.96E+02

confidence level	0.95	0.99	0.999	0.9999
R^2_critical	0.014	0.018	0.024	0.030
t_critical_2_sided	1.96	2.58	3.30	3.91

Table A.6. Regression results for Equation (3.9)

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
R^2	7.87E-01	8.19E-01	8.34E-01	8.40E-01	8.29E-01	8.11E-01	7.91E-01	7.84E-01	7.77E-01	7.76E-01	7.81E-01

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
R^2	7.83E-01	7.83E-01	7.84E-01	7.87E-01	7.88E-01	7.91E-01	7.92E-01	7.93E-01	7.95E-01	7.96E-01	7.96E-01

B_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
const	1.72E-02	2.05E-02	2.47E-02	2.93E-02	2.94E-02	3.00E-02	2.04E-02	1.07E-02	3.08E-03	-1.07E-02	-2.31E-02
S	1.16E-02	1.53E-02	1.94E-02	2.31E-02	2.74E-02	3.27E-02	3.91E-02	4.57E-02	5.34E-02	6.20E-02	7.03E-02
S^2	-9.27E-04	-1.17E-03	-1.41E-03	-1.58E-03	-1.79E-03	-2.04E-03	-2.38E-03	-2.65E-03	-3.00E-03	-3.36E-03	-3.64E-03
sqrt(Kv)	2.19E-03	2.90E-03	4.31E-03	5.79E-03	7.44E-03	9.94E-03	1.32E-02	1.54E-02	1.83E-02	2.15E-02	2.50E-02
Kv	-1.83E-04	-2.37E-04	-3.25E-04	-4.60E-04	-5.61E-04	-7.84E-04	-1.04E-03	-1.17E-03	-1.41E-03	-1.65E-03	-1.89E-03
S*sq(Kv)	-3.30E-05	-1.46E-04	-3.62E-04	-5.28E-04	-7.66E-04	-1.01E-03	-1.32E-03	-1.70E-03	-2.09E-03	-2.57E-03	-3.04E-03
Faer	-4.17E-02	-4.74E-02	-5.43E-02	-6.15E-02	-6.88E-02	-7.53E-02	-7.95E-02	-8.43E-02	-8.91E-02	-9.30E-02	-9.63E-02
CO2	-1.49E-04	-2.51E-04	-3.30E-04	-3.28E-04	-2.45E-04	-1.34E-04	1.61E-05	1.80E-04	3.25E-04	4.77E-04	6.17E-04
N2O	6.85E-05	1.43E-04	2.41E-04	3.56E-04	4.54E-04	5.78E-04	7.08E-04	8.08E-04	9.54E-04	1.11E-03	1.28E-03

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
const	-3.81E-02	-5.31E-02	-6.84E-02	-8.34E-02	-1.02E-01	-1.20E-01	-1.42E-01	-1.65E-01	-1.87E-01	-2.13E-01	-2.35E-01
S	7.89E-02	8.76E-02	9.72E-02	1.08E-01	1.17E-01	1.29E-01	1.41E-01	1.53E-01	1.64E-01	1.78E-01	1.89E-01
S^2	-3.99E-03	-4.39E-03	-4.92E-03	-5.49E-03	-6.01E-03	-6.73E-03	-7.53E-03	-8.18E-03	-8.92E-03	-9.96E-03	-1.08E-02
sqrt(Kv)	2.87E-02	3.23E-02	3.54E-02	4.00E-02	4.42E-02	4.86E-02	5.32E-02	5.87E-02	6.46E-02	6.96E-02	7.50E-02
Kv	-2.18E-03	-2.46E-03	-2.72E-03	-3.17E-03	-3.52E-03	-3.91E-03	-4.37E-03	-4.87E-03	-5.46E-03	-5.98E-03	-6.57E-03
S*sq(Kv)	-3.46E-03	-3.81E-03	-4.04E-03	-4.25E-03	-4.47E-03	-4.76E-03	-4.90E-03	-5.10E-03	-5.17E-03	-5.10E-03	-4.92E-03
Faer	-9.92E-02	-1.03E-01	-1.06E-01	-1.10E-01	-1.13E-01	-1.17E-01	-1.20E-01	-1.22E-01	-1.25E-01	-1.28E-01	-1.31E-01
CO2	7.76E-04	9.19E-04	1.07E-03	1.22E-03	1.37E-03	1.52E-03	1.67E-03	1.82E-03	1.99E-03	2.15E-03	2.30E-03
N2O	1.44E-03	1.61E-03	1.82E-03	2.02E-03	2.22E-03	2.47E-03	2.70E-03	2.95E-03	3.20E-03	3.48E-03	3.74E-03

t_i

	1991	1996	2001	2006	2011	2016	2021	2026	2031	2036	2041
S	4.44E+03	5.13E+03	5.15E+03	4.70E+03	3.84E+03	3.00E+03	2.40E+03	2.01E+03	1.67E+03	1.41E+03	1.22E+03
S^2	-2.78E+03	-3.08E+03	-2.94E+03	-2.53E+03	-1.97E+03	-1.46E+03	-1.14E+03	-9.17E+02	-7.35E+02	-5.98E+02	-4.96E+02
sqrt(Kv)	1.10E+03	1.27E+03	1.50E+03	1.54E+03	1.37E+03	1.19E+03	1.06E+03	8.92E+02	7.47E+02	6.40E+02	5.68E+02
Kv	-8.17E+02	-9.27E+02	-1.01E+03	-1.09E+03	-9.20E+02	-8.39E+02	-7.49E+02	-6.06E+02	-5.15E+02	-4.37E+02	-3.84E+02
S*sq(Kv)	-7.20E+01	-2.79E+02	-5.48E+02	-6.13E+02	-6.11E+02	-5.29E+02	-4.63E+02	-4.26E+02	-3.73E+02	-3.33E+02	-3.01E+02
Faer	-1.28E+04	-1.27E+04	-1.15E+04	-1.00E+04	-7.71E+03	-5.52E+03	-3.91E+03	-2.98E+03	-2.23E+03	-1.69E+03	-1.34E+03
CO2	-7.06E+02	-1.05E+03	-1.21E+03	-1.09E+03	-6.77E+02	-2.93E+02	2.87E+01	2.84E+02	4.38E+02	5.47E+02	6.18E+02
N2O	5.15E+02	9.30E+02	1.30E+03	1.57E+03	1.46E+03	1.28E+03	1.10E+03	9.46E+02	8.26E+02	7.28E+02	6.57E+02

	2046	2051	2056	2061	2066	2071	2076	2081	2086	2091	2096
S	1.04E+03	8.83E+02	7.56E+02	6.57E+02	5.74E+02	5.11E+02	4.53E+02	4.08E+02	3.67E+02	3.35E+02	3.06E+02
S^2	-4.12E+02	-3.48E+02	-3.00E+02	-2.63E+02	-2.31E+02	-2.09E+02	-1.90E+02	-1.72E+02	-1.56E+02	-1.47E+02	-1.36E+02
sqrt(Kv)	4.94E+02	4.26E+02	3.61E+02	3.20E+02	2.83E+02	2.52E+02	2.24E+02	2.05E+02	1.89E+02	1.72E+02	1.59E+02
Kv	-3.35E+02	-2.90E+02	-2.48E+02	-2.27E+02	-2.02E+02	-1.81E+02	-1.64E+02	-1.52E+02	-1.43E+02	-1.32E+02	-1.24E+02
S*sq(Kv)	-2.59E+02	-2.19E+02	-1.79E+02	-1.48E+02	-1.25E+02	-1.07E+02	-8.95E+01	-7.76E+01	-6.58E+01	-5.47E+01	-4.53E+01
Faer	-1.05E+03	-8.35E+02	-6.63E+02	-5.39E+02	-4.45E+02	-3.71E+02	-3.08E+02	-2.62E+02	-2.25E+02	-1.94E+02	-1.70E+02
CO2	6.60E+02	6.61E+02	6.42E+02	6.20E+02	5.89E+02	5.56E+02	5.18E+02	4.87E+02	4.57E+02	4.25E+02	4.00E+02
N2O	5.78E+02	5.08E+02	4.53E+02	4.06E+02	3.67E+02	3.39E+02	3.10E+02	2.90E+02	2.70E+02	2.54E+02	2.41E+02

confidence_level	0.95	0.99	0.999	0.9999
R^2_critical	0.015	0.020	0.026	0.032
t_critical_2_sided	1.96	2.58	3.30	3.91

Appendix B.
Correspondence table of DIVA countries and EPPA regions

Table B.1. EPPA Regions and abbreviations.

Region	Abbreviation	Region	Abbreviation
United States	USA	Higher Income East Asia	ASI
Canada	CAN	China	CHN
Mexico	MEX	India	IND
Japan	JPN	Indonesia	IDZ
Australia & New Zealand	ANZ	Africa	AFR
European Union	EUR	Middle East	MES
Eastern Europe	EET	Central & South America	LAM
Former Soviet Union	FSU	Rest of World	ROW

Table B.2. Correspondence between DIVA countries and EPPA regions.

DIVA ID	DIVA country	EPPA region
0	Afghanistan	ROW
1	Albania	ROW
2	Algeria	AFR
3	Andorra	ROW
4	Angola	AFR
5	Antigua and Barbuda	LAM
6	Argentina	LAM
7	Armenia	FSU
8	Aruba	LAM
9	Australia	ANZ
10	Austria	EUR
11	Azerbaijan	FSU
12	Bahamas	LAM
13	Bahrain	MES
14	Bangladesh	ROW
15	Barbados	LAM
16	Belarus	FSU
17	Belgium	EUR
18	Belize	LAM
19	Benin	AFR
20	Bermuda	ROW
21	Bhutan	ROW

22	Bolivia	LAM
23	Bosnia and Herzegovina	ROW
24	Botswana	AFR
25	Brazil	LAM
26	Brunei Darussalam	ROW
27	Bulgaria	EET
28	Burkina Faso	AFR
29	Burundi	AFR
30	Cambodia	ROW
31	Cameroon	AFR
32	Canada	CAN
33	Cape Verde	AFR
34	Central African Rep	AFR
35	Chad	AFR
36	Chile	LAM
37	China	CHN
38	Colombia	LAM
39	Comoros	AFR
40	Congo	AFR
41	Congo, Dem Rep	AFR
42	Costa Rica	LAM
43	Cote d'Ivoire	AFR
44	Croatia	ROW
45	Cuba	LAM
46	Cyprus	ROW
47	Czech Rep	EET
48	Denmark	EUR
49	Djibouti	AFR
50	Dominica	LAM
51	Dominican Rep	LAM
52	East Timor	IDZ
53	Ecuador	LAM
54	Egypt	AFR
55	El Salvador	LAM
56	Equatorial Guinea	AFR
57	Eritrea	AFR
58	Estonia	FSU
59	Ethiopia	AFR
60	Fiji	ROW
61	Finland	EUR
62	France	EUR
63	French Guiana	EUR
64	French Polynesia	ROW
65	Gabon	AFR
66	Gambia	AFR
67	Georgia	FSU
68	Germany	EUR
69	Ghana	AFR
70	Greece	EUR
71	Grenada	LAM
72	Guadeloupe	ROW
73	Guatemala	LAM
74	Guinea	AFR
75	Guinea-Bissau	AFR
76	Guyana	LAM
77	Haiti	LAM
78	Honduras	LAM
79	Hong Kong, China SAR	CHN
80	Hungary	EET
81	Iceland	EUR
82	India	IND
83	Indonesia	IDZ
84	Iran, Islamic Rep	MES
85	Iraq	MES
86	Ireland	EUR
87	Israel	MES
88	Italy	EUR
89	Jamaica	LAM
90	Japan	JPN
91	Jordan	MES

92	Kazakhstan	FSU
93	Kenya	AFR
94	Kiribati	ROW
95	Korea, Dem People's Rep	ROW
96	Korea, Rep	ASI
97	Kuwait	MES
98	Kyrgyzstan	FSU
99	Lao People's Dem Rep	ROW
100	Latvia	FSU
101	Lebanon	MES
102	Lesotho	AFR
103	Liberia	AFR
104	Libyan Arab Jamahiriya	AFR
105	Liechtenstein	EUR
106	Lithuania	FSU
107	Luxembourg	EUR
108	Macau	ROW
109	Macedonia, FYR	ROW
110	Madagascar	AFR
111	Malawi	AFR
112	Malaysia	ASI
113	Maldives	ROW
114	Mali	AFR
115	Malta	ROW
116	Marshall Islands	ROW
117	Martinique	EUR
118	Mauritania	AFR
119	Mauritius	AFR
120	Mexico	MEX
121	Micronesia, Fed States	ROW
122	Moldova, Rep	FSU
123	Monaco	ROW
124	Mongolia	ROW
125	Morocco	AFR
126	Mozambique	AFR

127	Myanmar	ROW
128	Namibia	AFR
129	Nauru	ROW
130	Nepal	ROW
131	Netherlands	EUR
132	Netherlands Antilles	LAM
133	New Caledonia	ROW
134	New Zealand	ANZ
135	Nicaragua	LAM
136	Niger	AFR
137	Nigeria	AFR
138	Norway	EUR
139	Oman	MES
140	Pakistan	ROW
141	Palau	ROW
142	Panama	LAM
143	Papua New Guinea	ROW
144	Paraguay	LAM
145	Peru	LAM
146	Philippines	ASI
147	Poland	EET
148	Portugal	EUR
149	Puerto Rico	USA
150	Qatar	MES
151	Reunion	EUR
152	Romania	EET
153	Russian Federation	FSU
154	Rwanda	AFR
155	Samoa	ROW
156	San Marino	ROW
157	Sao Tome & Principe	AFR
158	Saudi Arabia	MES
159	Senegal	AFR
160	Seychelles	AFR
161	Sierra Leone	AFR

162	Singapore	ASI
163	Slovakia	EET
164	Slovenia	EET
165	Solomon Islands	ROW
166	Somalia	AFR
167	South Africa	AFR
168	Spain	EUR
169	Sri Lanka	ROW
170	St. Kitts and Nevis	LAM
171	St. Lucia	LAM
172	St. Vincent & Grenadines	LAM
173	Sudan	AFR
174	Suriname	LAM
175	Swaziland	AFR
176	Sweden	EUR
177	Switzerland	EUR
178	Syrian Arab Rep	MES
179	Taiwan, Province of China	ASI
180	Tajikistan	FSU
181	Tanzania, United Rep	AFR
182	Thailand	ASI
183	Togo	AFR
184	Tonga	ROW
185	Trinidad and Tobago	LAM
186	Tunisia	AFR
187	Turkey	ROW
188	Turkmenistan	FSU
189	Tuvalu	ROW
190	Uganda	AFR
191	Ukraine	FSU
192	United Arab Emirates	MES
193	United Kingdom	EUR
194	United States	USA
195	Uruguay	LAM
196	Uzbekistan	FSU
197	Vanuatu	ROW
198	Venezuela	LAM
199	Viet Nam	ROW
200	Virgin Islands, U.S.	USA
201	West Bank and Gaza	MES
202	Western Sahara	AFR
203	Yemen	MES
204	Yugoslavia	ROW
205	Zambia	AFR
206	Zimbabwe	AFR

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