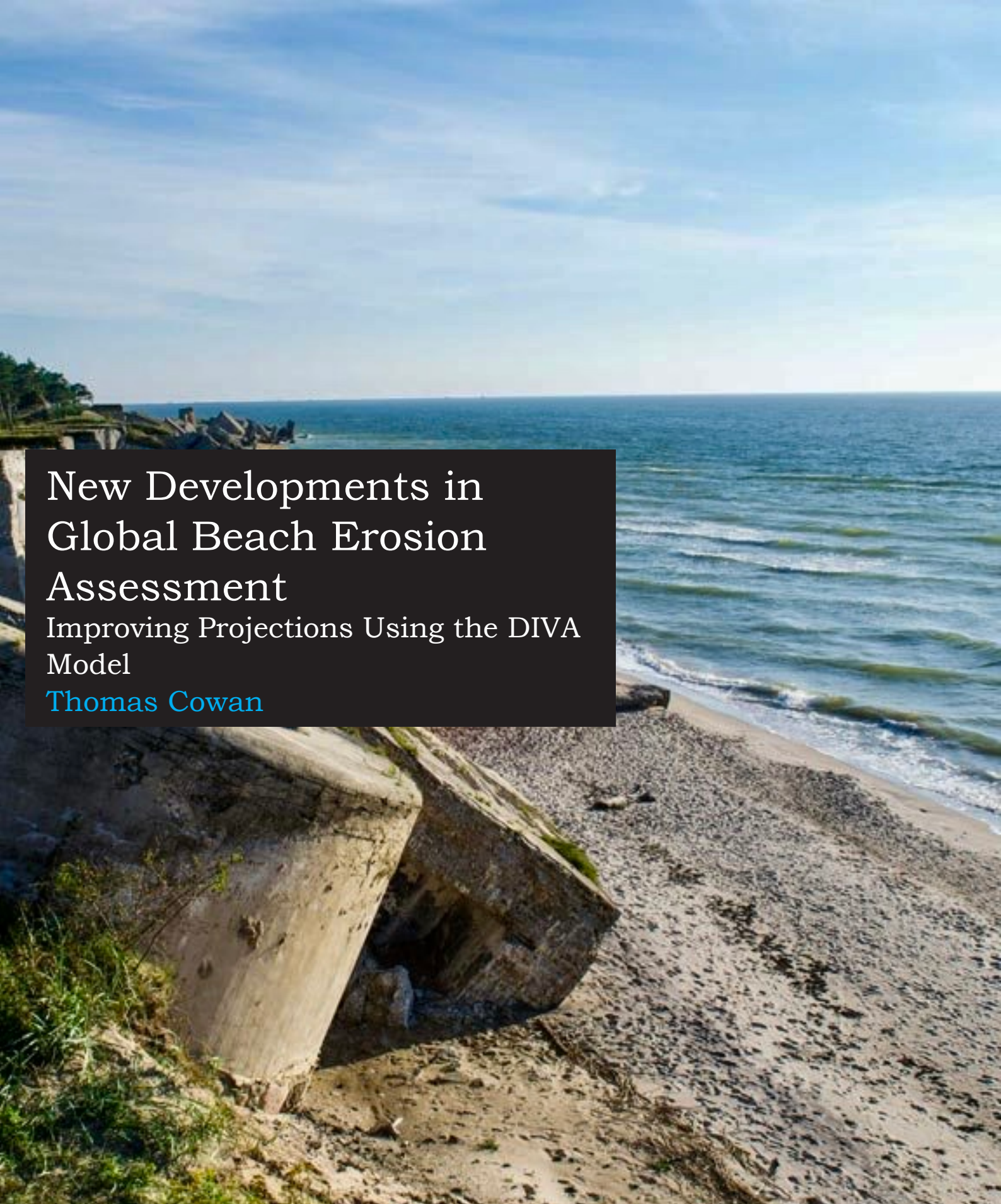
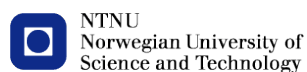




New Developments in Global Beach Erosion Assessment

Improving Projections Using the DIVA
Model

Thomas Cowan



New Developments in Global Beach Erosion Assessment

Improving Projections Using the DIVA Model

by

Thomas Cowan

in partial fulfillment of the requirements for the degree of

Master of Science

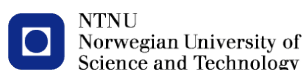
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Student number:	4653521	
Supervisor:	Mr. A. Luijendijk	
Thesis committee:	Prof. S. Aarninkhof,	TU Delft
	Mr. A Luijendijk,	TU Delft
	Mr. S. de Vries,	TU Delft
	Ir. R. J. Nicholls,	University of Southampton
	Mr. G. Hagenaars,	Deltares

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the CoMEM programme can be obtained from the programme coordinator: Øivind A. Arntsen,

Dr.ing.
Associate professor in Marine Civil Engineering
Department of Civil and Environmental Engineering
NTNU Norway

Mob.: +4792650455 Fax: + 4773597021

Email: oivind.arntsen@ntnu.no

CoMEM URL: <https://www.ntnu.edu/studies/mscomem>

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Summary

Sea Level Rise is anticipated to significantly affect human development in the coastal zone by the end of the Twenty-First Century. The rising waters bring greater risk of floods, submergence of low lying land, salinization of freshwater supplies, and the erosion of sandy beaches. Quantifying these impacts spurs action by those hoping to adapt to changing environmental conditions, but sea level rise acts at such large scales that this quantification proves difficult. Dynamic Interactive Vulnerability Analysis (DIVA) provides this capacity by modelling the growth of society parallel to environmental forcing from IPCC scenarios and human adaptation measures in the coastal zone. This thesis attempts to use new information and technology to expand existing tools which quantify the impacts of beach erosion due to sea level rise and human adaptation using beach nourishment on a global scale. This echoes earlier work by [Hinkel *et al.* \(2013\)](#). To accomplish this task, a methodology is developed to conduct and aggregate large amounts of information into the DIVA coastal database, and a secondary global risk model develops refined nourishment adaptation cost information.

Data collection over the large scales covered by the DIVA model is difficult, and existing approximations within the model are categorically applied to poorly resolved datasets and archived information. Recent developments in remote sensing created a new database which indicates the location of beaches at a global scale. The utility of this information is the primary motivation for this study. Similarly, adaptation costs in DIVA are not well resolved, and available expert judgment is leveraged to allow more insight into these practices.

These modifications have complex individual interactions with human coastal development, and simple superposition is not an effective tool to predict their combined impact. The locations most significantly impacted by the modifications are typically island states previously categorized without beaches. Adaptation favors wealthy locations with a large population density. The costs of lost land and forced migration in these areas outweigh adaptation costs by substantial margins in some cases, and nourishment .

Recreation of the [Hinkel *et al.* \(2013\)](#) study is not possible with the current DIVA architecture, and the lack of reasoned relation to this work limits interpretation. As a large scale model using aggregated parameters, DIVA is limited by its ignorance of local-level processes. Further limitations include a lack of resolved information for secondary erosive forcing from tidal basins, whose impacts are included, yet not specifically addressed.

DIVA does address the question of vulnerability at a national level, and can inform decision makers on the costs and protections provided through adaptation. It can highlight the growth and development of adaptation measures in response to sea level rise and weigh them against the cost of inaction. In doing so, DIVA highlights areas where protection is economically feasible and viable for the mitigation of sea-level-rise-induced beach erosion.

Structure

The research approach applied in this thesis differs from convention. Rather than standard chapters and sections, the main results of this thesis are condensed into Section 2: "New Developments in Global Coastal Erosion Assessment". The authors intend this paper to be suitable for publication in an academic journal with moderate adjustment. As such, it contains all sections expected in an academic journal, outside of a bibliography.

The remainder of this report is therefore set out as material supporting the academic paper. While the paper's results are not a complete picture of the entirety of the work that went into the preparation of this thesis, they formulate significant results to the scientific community and are combined with a suitably brief discussion of impacts, limitations, and next steps. More detailed methodologies, validations, and figures can be found in the appendices, which detail important and finished information with respect to aspects of this thesis which do not comprise the primary results or discussion of the paper.

Section 1 motivates the research carried out in this report and formulates a set of research questions which act as a guide for subsequent analysis.

Section 2 is "New Developments in Global Coastal Erosion Assessment", which provides justification, methodology, results, discussion, and conclusion for the key results of this thesis within the context of a scientific paper.

Section 3 subsequently identifies major impacts and limitations within the research at a more detailed level than in Section 2.

Section 4 identifies opportunities for future study, which are either directly descended from the results of this thesis, or which help to resolve the action pathway studied here.

Section 5 concludes the this thesis, echoing the conclusions presented in Section 2 and supporting information presented elsewhere.

Appendices A to D provide additional finished details on the status of existing research, Technical methodologies for the SDS-DIVA connection, a report on the validation of the SDS-DIVA connection, a more-detailed breakdown of the factors used to develop the new DIVA nourishment cost model, and a short memorandum outlining the differences between the baseline information from [Hinkel et al. \(2013\)](#) and the new baseline presented here.

Appendices E through G include extended outputs from the multiple configurations of the DIVA model used in this thesis.

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Contents

Summary	v
Structure	vii
List of Figures	xv
List of Tables	xvii
List of Abbreviations	xix
1 Introduction	1
1.1 Motivation	2
1.2 Significance	7
1.2.1 Existing Knowledge	7
1.2.2 Knowledge Gaps	8
1.3 Objectives	9
1.4 Approach	10
2 New Developments in Global Coastal Erosion Assessment	11
2.1 Introduction	13
2.2 Methodology	14
2.2.1 Beach Erosion in the DIVA model	14
2.2.2 Measured Impacts	15
2.2.3 Climate and Socioeconomic Scenarios	15
2.2.4 Baseline Information	16
2.2.5 New Beach Identification Information (GSCD)	17
2.2.6 New Nourishment Cost Model	17
2.3 Results	20
2.3.1 New Beach Identification Information Effects	20
2.3.2 Nourishment Cost Model Effects	23
2.3.3 Cumulative Effects	23
2.3.4 Unmitigated Effects	24
2.3.5 Mitigated Loss of Land	25
2.3.6 Mitigated Forced Migration	25
2.3.7 National Effects	26
2.4 Discussion	28
2.5 Conclusion	33
3 Discussion	37
3.1 Overview	38
3.2 DIVA	38
3.2.1 Scale	38
3.2.2 Signal Strength	38
3.2.3 Nourishment Driving Rationale	38
3.2.4 Aggregate Models	39
3.2.5 Baseline	40

3.3	GSCD Aggregation	42
3.3.1	Connection Validation	42
3.3.2	GSCD Validation	42
3.4	Nourishment Cost Model	42
3.4.1	Nourishment Sensitivity Analysis	44
3.4.2	Corruption	44
3.4.3	DIVA Segmentation	46
3.5	Impact	46
3.5.1	Model Integration	46
3.5.2	Long Term Cost Models	46
3.5.3	Nourishment Industry Forecasting	47
3.5.4	DIVA 2.0	47
4	Next Steps	49
4.1	introduction	50
4.1.1	Rocky Coastlines	50
4.1.2	Bruun Rule Slope Parameter	52
4.1.3	Indirect Erosion Information	53
4.1.4	Global Historic Assessment of Erosion	54
4.1.5	Nourishment Cost Model Optimization	55
5	Closure	57
5.1	Research Fulfillment	59
5.1.1	Research Questions	59
5.2	Key Impacts	60
5.3	Key Limitations	60
5.4	Recommendations	61
5.5	Closing Remarks	62
	Bibliography	63
A	Extended Context	73
A.1	Physical Aspects	73
A.1.1	Scale	73
A.1.2	Sea Level Rise	77
A.2	Technical Aspects	77
A.2.1	Satellite Imagery and Remote Sensing (RS)	77
A.2.2	Satellite Derived Shoreline (SDS)	79
A.2.3	Google Earth Engine (GEE)	81
A.2.4	SRES and RCP	81
A.2.5	Vulnerability Assessment	83
A.2.6	Dynamic Interactive Vulnerability Assessment (DIVA)	83
A.2.7	DIVA Model	84
A.2.8	Spatial Relation	92
A.3	Recent Analysis	93
A.3.1	Hinkel 2010	93
A.3.2	Nicholls, 2011	94
A.3.3	Hinkel, 2012	94
A.3.4	Hinkel, 2013	94
A.3.5	Spencer, 2016	96
A.3.6	Wolff, 2016	96

A.3.7	Wolff, 2018	96
B	Database Methods	99
B.1	Technical Methodology	99
B.1.1	Process	99
B.1.2	Reasoning	100
B.1.3	Database Connection	101
B.1.4	Modules	105
B.1.5	GSCD-Independent Updates	106
C	Nourishment Cost Model Methodology	111
C.1	results	114
C.2	Sensitivity Analysis.	114
D	DIVA Methodology	117
D.1	Recreate existing data	117
D.2	Alteration of individual Elements	118
D.2.1	Cumulative DIVA alterations	119
D.3	External Evaluation	119
E	Impact Timelines	121
F	Noursihment Sensitivity	129
F.1	Nourishment Cost Model Sensitivity Analysis	129
G	Additional Maps	141

List of Figures

1.1	Schematic - Processes Governing SLR -IPCC	2
1.2	Schematic - Beach-line and Shore Nourishment Practices	4
2.1	Plot - GSCD-DIVA Scatter Plot	18
2.2	Plot - Baseline Impact Timeline	21
2.3	Plot - GSCD Cumulative Impacts Across Key Metric Categories	24
2.4	Plot - NCM Cumulative Impacts Across Key Metric Categories	25
2.5	Plot - Fully Modified Cumulative Impacts Across Key Metric Categories	26
2.6	Map - Regional Distribution of Changes to Nourishment Impact Reduction	27
2.7	Plot - National-Level Rankings of Changes in Economic Adaptation Stress	28
2.8	Plot - National-Level Rankings of Changes in Economic Impact Intensity	30
2.9	Plot - National-Level Rankings of Changes in Scalar Economic Impact	31
2.10	Plot - National-Level Economic Adaptation Stress	32
2.11	Plot - National-Level Economic Impact Intensity	33
2.12	Map - Nourishment Viability Year	34
2.13	Map - Nourishment Viability Year with Sandy Coast Filter	34
3.1	Plot - Ratio of Sediment Demand from Direct and Indirect Sources	39
3.2	Plot - Comparison to Baseline Scenario	41
3.3	Plot - Bland-Altman Diagram for SDS/DIVA Connection	43
3.4	Image - Canada GSCD False Positive Conceptual Demonstration	43
3.5	Image - Saudi Arabia GSCD False Positive Conceptual Demonstration	44
3.6	Plot - Sensitivity Analysis - Total Protected Length	45
3.7	Schematic - Potential Future DIVA Sediment Budget Model	48
4.1	Map - Geological Provinces (USGS, 1997)	51
4.2	Schematic - Probabilistic Inference of Beach Nourishment Profile	52
A.1	Table - Coastal Tract (French <i>et al.</i> , 2016)	74
A.2	Schematic- Scales Affecting the Coastal Zone (French <i>et al.</i> , 2016)	74
A.3	Schematic- Factors Influencing SLR (Church <i>et al.</i> , 2013)	77
A.4	Schematic- IPCC SRES Storylines	82
A.5	Schematic- DIVA Erosion-Associated Modules	85
A.6	Schematic- IMAGE 2.2 Climate Model	86
A.7	Schematic- Hamburg Tourism Model	90
A.8	Schematic - DIVA Nourishment Decision Tree	92
B.1	Map - Illustration of Connection Difficulties	100
B.2	Schematic- GSCD-DIVA Connection Flowchart	102
B.3	Schematic- GSCD-DIVA Connection Part 1	103
B.4	Schematic- GSCD-DIVA Connection Part 2	104
B.5	Schematic- KD Tree Visualization	105
B.6	Map - Danish Straits Example of Coastal/Non-Coastal Islands	106
B.7	Plot - Scatter Plot Connection of GSCD and DIVA	108

B.8	Plot - Bland Altman Connection of GSCD and DIVA	109
C.1	Schematic- Factors Affecting Nourishment Cost	113
C.2	Map - Old Nourishment Costs Per Segment	115
C.3	Map - New Nourishment Costs Per Segment	115
C.4	Map - Effect of Nourishment Cost Model on projected price	116
E.1	Nourishment Impact Timeline - Baseline	122
E.2	GSCD Impact Timeline - No Adaptation	123
E.3	GSCD Impact Timeline - Adaptation	124
E.4	NCM Impact Timeline - No Adaptation	125
E.5	NCM Impact Timeline - Adaptation	126
E.6	Overall Impact Timeline - Adaptation	127
E.7	Overall Impact Timeline - No Adaptation	128
F.1	Sensitivity Analysis - SLR-induced Beach Erosion Monetary Impacts	130
F.2	Sensitivity Analysis - Cost per Area Protected	131
F.3	Sensitivity Analysis - Land-loss Avoided through Adaptation	132
F.4	Sensitivity Analysis - Migration Avoided through Adaptation	133
F.5	Sensitivity Analysis - Percentage Shoreline Protected	134
F.6	Sensitivity Analysis - Proportion Beach Nourishment	135
F.7	Sensitivity Analysis - Nourishment Length (Total)	136
F.8	Sensitivity Analysis - Nourishment Length (Beach)	137
F.9	Sensitivity Analysis - Nourishment Length (Shore)	138
F.10	Sensitivity Analysis - Total Nourishment Volume	139
F.11	Sensitivity Analysis - Nourishment Cost	140
G.1	This figure demonstrates coastal nourishment, forced migration, and loss of land as a portion of the available GDP mapped to physical locations. This map educates discussion on the regional variability of nourishment practices	142
G.2	This figure demonstrates the intensity of SLR adaptation stress by resolving coastal nourishment, forced migration, and loss of land per unit of coastline length. This map educates discussion on the regional variability of nourishment practices	142

List of Tables

2.1	Description of the parameters which develop the proposed coastal NCM, including relations which develop the cost based on existing DIVA database parameters	20
2.2	Impact on DIVA Outputs - Relative Effects	22
2.3	Impact on DIVA Outputs - Relative Effects	29
A.1	DIVA deprecated cost matrix	92
B.1	SDS/GSCD Electronic Storage Information	100
B.2	GSCD-DIVA Validation Locations	110
C.1	Nourishment Costs in Literature	112
C.2	Nourishment Cost Model Parameters	114

List of Abbreviations

AR	- Assessment Report
ASMITA	- Aggregated Scale Morphological Interaction between a Tidal inlet system and the Adjacent coast
CBC	-Coastal Beach Composition
CERC	- Coastal Engineering Research Center
DIVA	- Dynamic Interactive Vulnerability Analysis
DINAS-COAST	- Dynamic and Interactive Assessment of National, Regional and Global Vulnerability of Coastal Zones to Climate Change and Sea-Level Rise
E_f	- Erosion Factor
FAST	- Foreshore Assessment using Space Technology
GEE	- Google Earth Engine
GMSLR	- Global Mean Sea Level Rise
GSCD	- Global Sand Composition Database
GVA	- Global Vulnerability Analysis
HTM	- Hamburg Tourism Model
IPCC	- Intergovernmental Panel on Climate Change
LOICS	- Land and Ocean Interactions in the Coastal Zone
NCM	- Nourishment Cost Model
OAAT	- One At A Time
RCP	- Representative Concentration Pathway
RSLR	- Relative Sea Level Rise
SAUP	- Seas Around Us Project
SDS	- Satellite Derived Shoreline Detection
SLR	- Sea Level Rise
SRES	- Special Report on Emissions Scenarios
SSP	- SHared Socioeconomic Pathways
WG	- Working Group

1

Introduction

Chapter Summary

Sea Level Rise is a globally relevant issue given anticipated intensification of environmental forcing and accumulation of human development in the coastal zone. Large scale assessment of these impacts is infrequent within the scientific community, but essential to inform policy decisions and provide context for local studies. Dynamic Interactive Vulnerability Analysis (DIVA) is an established framework which is unique in it's scope and scale evaluating multiple impact-mitigation pathways. However, this framework endures some issues common to large-scale modelling initiatives. Namely, the scale of the phenomena exceeds that of all measured data sets or models. In order to better-define the SLR-induced beach erosion impact-mitigation pathway, we study the impacts of two new inclusions on DIVA-based projections. We include a new state-of-the-art satellite detection scheme to isolate coast vulnerable to beach erosion, and implement a new model for beach nourishment costs to predict consequences of and administrative responses to SLR.

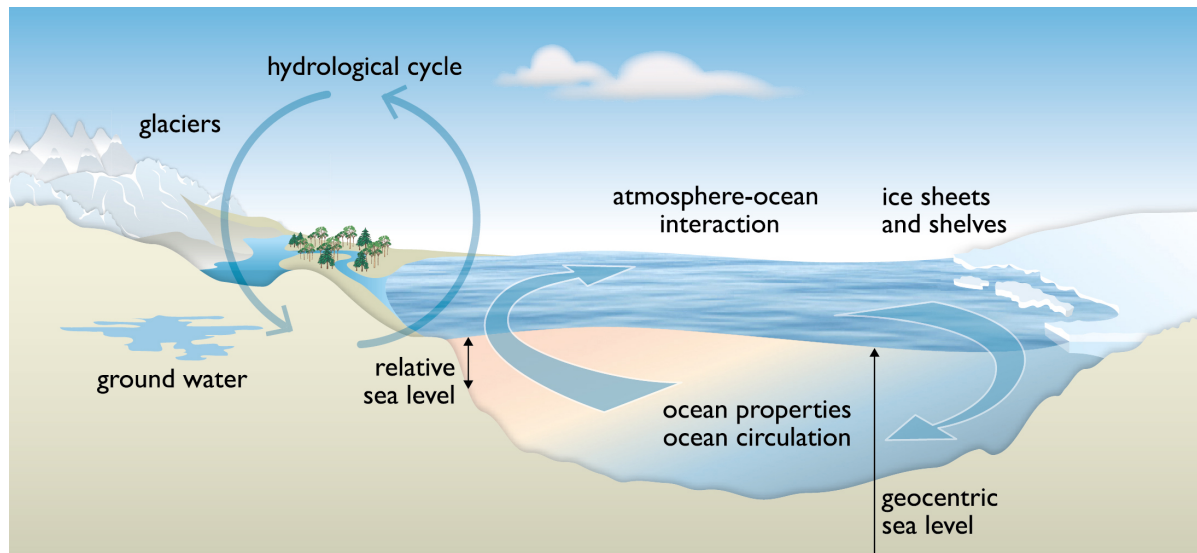


Figure 1.1: Processes identified by the IPCC to govern SLR and RSLR (Church *et al.*, 2013)

1.1. Motivation

The physical changes caused by Sea Level Rise (SLR) are likely to have a profound effect on global human development from social, economic, and environmental perspectives. The First Assessment Report of the International Panel on Climate Change (IPCC) formally recognizes the implications of SLR, a statement reaffirmed in each following IPCC report. Improvements in the methods and information used to predict these impacts therefore affect adaptation strategies and improve sustainable development practices at a large scale (IPCC, 1990, 2014a).

The Dynamic Interactive Vulnerability Analysis (DIVA) model supports this form of large-scale vulnerability analysis. By updating DIVA's global sand coverage information and parallel adaptation costs, this thesis addresses the large-scale implications of and adaptation to SLR on sandy coastline erosion first elaborated in Hinkel *et al.* (2013).

Sea Level Rise (SLR) In addition to SLR, waves, tides, weather systems, and cyclical climatic changes (e.g. El Nino) cause affect water levels on timescales varying from seconds to years and spatial scales from a few metres to the width of the Pacific Ocean (Pirazzoli, 1993). Compared to these relatively transient fluctuations, SLR itself is the result of processes which have a long-term impact on global water levels. The IPCC partitions SLR causes into oceanic, atmospheric, terrestrial, and hydrologic processes which are sensitive to climate change. In measurements, these manifest as changes to both local and globally averaged sea levels (IPCC, 2014a).

The fifth working group of the IPCC report includes an extensive evaluation of the current state of knowledge on SLR, and makes two important distinctions for its interpretation. First, changes to the Mean Global Sea Level (MGSL), generally referred to as SLR, are affected by large scale processes that impact the total volume of water in the oceans including the expansion of water due to changes in temperature and movement of water from ice sheets and glaciers into the ocean. Second, Relative Sea Level Rise (RSLR) refers to the rate of locally observed sea level rise. RSLR is unevenly distributed across the globe and differs from SLR due to processes affecting plate tectonics, land subsidence, large scale ocean currents, and the distribution of water within the world's oceans. If SLR is visualized as long term changes to the amount of water in a bathtub, RSLR might be visualized as changes to the shape of the

bathtub. The combination of these distinctions gives rise to a complex pattern of RSLR with significant local, regional, and global impacts. Figure 1.1 from Church *et al.* (2013) illustrates key processes which govern these changes and begins to formulate an understanding of the complexity of the phenomenon.

Vulnerability Retrospectively, humanity has always been vulnerable to SLR (Benjamin *et al.*, 2017) and ancient SLR events were likely catastrophic for some early agrarian societies (Weninger *et al.*, 2006). However, until recently the processes governing changing sea levels lay beyond established temporal and spatial scales in the planning and engineering disciplines (French *et al.*, 2016). Relatively recent globalization and an “un-paralleled magnitude of human-induced environmental changes” (Meyer and Turner II, 1992) has driven awareness of benefits from long term civil planning. The IPCC assessment reports are evidence themselves of a recent understanding among decision-makers of human vulnerability to issues associated with these large scales. In this thesis, we approach vulnerability through a lens informed by the IPCC Assessment Reports, which define this “vulnerability” as:

“The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt.” (Planton, 2013)

Human development is particularly vulnerable to long-term sea level trends. Indeed, while the coastal zone within 10 vertical metres of the ocean only represents 2% of the world’s land area, 10% of the global population resides there (McGranahan *et al.*, 2007). The disproportionality of these impacts and their forcing suggest human development meets these criteria for sensitivity to SLR within the IPCC definition.

In the coastal zone zone, SLR impacts society through a number of distinct yet interrelated pathways. Directly, SLR promotes shoreline regression and loss of land, increases the extents of coastal flooding, encourages saline intrusion into freshwater systems, and drowns valuable coastal ecosystems (Hinkel *et al.*, 2013; Jongman *et al.*, 2012; Masciopinto and Liso, 2016; Spencer *et al.*, 2016). As such, erosion, flooding, salinization, and loss of coastal ecosystems are focal points through which scientific literature assesses SLR.

When considering Loss of land, however, secondary impacts are potentially much more damaging than the primary impact outlined above. In Hinkel *et al.* (2013), a preliminary analysis of SLR-induced erosion over the next 100 years showed equivalent economic costs of indirect impacts two orders of magnitude greater than direct impacts. Expenditure to provide coastal protection, forced migration of coastal populations, and conflicts arising due to environmental refugees are examples of major secondary impacts vital to the assessment of vulnerability to sea level rise (Hinkel *et al.*, 2013; Wetzel *et al.*, 2012; Reuveny, 2007).

Complicating these impact pathways, studies have found many factors which compound the influence of SLR on human development and restrict society’s ability to adapt. Historical trends and economic drivers indicate that human development concentrates towards coastal regions over time. Further, some members of the scientific community anticipate growing disparity as coastal migration and development outperform that for inland regions (McGranahan *et al.*, 2007; de Andres *et al.*, 2018; Mavromatidi *et al.*, 2018; Merkens *et al.*, 2016). McGranahan *et al.* (2007) posits that coastal vulnerability is particularly concentrated in developing countries in Asia and Africa, where coastal protection costs are more difficult to address. Further, Hardy and Hauer (2018) found in developed regions that impacts may be 5 times greater once local differences in demographic growth patterns and wealth are taken into account. The regional

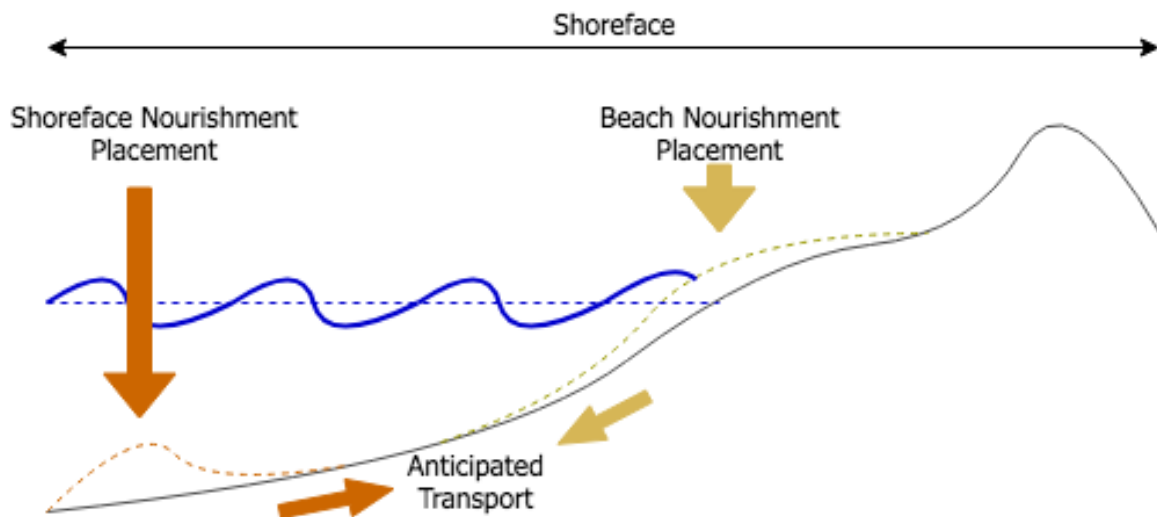


Figure 1.2: Illustration of different beach-line and shore placement of material for nourishment practices

accumulation of these socio-economic factors is vital to the interpretation of the challenges associated with climate change.

Response Addressing these pressures presents new political, engineering, and scientific challenges at all scales of development. Progressive world voices envisage solutions which predict and promote sustainable development with particular attention paid to the assessment of economic, sociological, and natural environments (ie [UNFCCC, 2015](#)).

One method developed to combat these issues is coastal nourishment. In this practice, artificially-sourced material is placed on a beach to combat coastal erosion. Beach nourishment mitigates the impact of negative sediment balances at beaches and protects tourism revenue by ensuring a wide beachfront ([Klein and Osleeb, 2010](#)). While traditionally applied at the beach-face in what we call here “beach-line” nourishment, modern “shore” nourishment techniques frequently place sand at the toe of the near-shore zone for a substantial cost savings at the expense of immediate benefits to tourism (Figure 1.2) ([Hinkel et al., 2013](#)).

As the most defined mitigation method with respect to coastal erosion, the use of beach nourishment over the 21st century is of scientific and commercial interest on a global scale. However, in the face of SLR these practices require a long-term commitment, and policy measures to combat SLR-induced coastal erosion can have longer lead times for these strategic responses than traditional engineering solutions ([McGranahan et al., 2007](#); [Vergouwe and Sarink, 2016](#); [TE 2100, 2012](#)). Therefore, maximizing the mitigation potential of this technique requires additional research to assess relationships between SLR, quantifiable changes in the economic and social environments, and mitigation practices over a long period. The [IPCC \(2014b\)](#) identifies this top-down, large-scale impact assessment as a part of a wider planned response to climate change and sea level rise.

“The difference in time scales between medium and long-term adaptation plans and pressing short-term issues poses a significant problem for prioritizing adaptation.” [IPCC \(2014b\)](#)

This statement clarifies the need for large scale and long term planning in the coastal zone to address regional and global issues encompassing the 21st Century and beyond. However, since the 1960s, scientific research in the coastal zone has focused primarily on process-driven

approaches to engineering. These smaller timescales are essential to better implementation of engineering controls and mitigation at a local level, but current industry standards are less suited to strategic assessment and policy development within the coastal zone as a whole. This focus lead to a dearth of knowledge with regards to the behaviour of coastlines at large scales (McFadden *et al.*, 2007).

Assessment Initiatives Instead of localized process-based models, the IPCC objectives require an interface between large scale socio-economic trends and the natural coastal environment. Initiatives which begin to meet these needs include the first Global Vulnerability Assessment (GVA), Land-Ocean Interactions in the Coastal Zone (LOICZ), EUROSION, and the Seas Around Us Project (SAUP) (Vafeidis *et al.*, 2008). While these databases provide significant and detailed information, they are limited in application to vulnerability assessment by one of four key factors:

- First, some databases are regional and are difficult to replicate on a global scale.
- Second, some databases do not represent information in a format suitable for analysis of the coastal zone.
- Third, some databases were not developed to treat socio-economic impacts of vulnerability assessment and cannot practically be adapted to do so.
- Fourth, some databases do not allow the assessment of mitigation strategies with respect to climate-impacts (Vafeidis *et al.*, 2008).

In response to these deficiencies, the European Commission funded the operation of the Dynamic and Interactive Assessment of National, Regional and Global Vulnerability of Coastal Zones to Climate Change and Sea-Level Rise (DINAS-COAST) project between 2001 and 2004. The program addresses the implications of SLR at a large scale:

"A consistent evaluation of coastal impacts and adaptation at national, regional and global scales is required to satisfy current information needs for climate policy. DINAS-COAST brings together the best available science and data to help policy to interpret and evaluate coastal vulnerability to climate change." (European Commission, 2005)

DINAS-COAST delivered as one of its key components the Dynamic Interactive Vulnerability Assessment (DIVA) Package, which includes the DIVA Database and Model. This deliverable begins to fill the knowledge gap at large temporal and spatial scales and improves the availability of data presented in earlier tools such as LOICZ and GVA (McFadden *et al.*, 2007). From its inception, the DIVA model was an ambitious venture to combine state-of-the art prediction techniques with the best available global data-sets. DIVA is uniquely capable of predicting global impacts resulting from a range of climate change scenarios up to 2100. Further, the model integrates the assessment of a number of adaptation strategies including beach nourishment (Hinkel and Klein, 2009).

DIVA has been used to evaluate long-term impacts of sandy beach erosion (Hinkel *et al.*, 2013), differentiate the regional impacts of climate change policy (Arnell *et al.*, 2013; Nicholls *et al.*, 2018), and resolve the vulnerability of coastal wetlands (Spencer *et al.*, 2016) among others (e.g. Nicholls *et al.*, 2011; Hinkel *et al.*, 2014; Pardaens *et al.*, 2011; Deltares, 2013). These studies highlight the versatility of the DIVA package and the breadth of it's modelling

capacity. DIVA provides an important capacity to quantify disparate sea level rise impacts across a range of climate and policy scenarios.

Any work intending to add to this substantial body of knowledge must adopt a focal point to assess changes made to the program. Because the DIVA Package models a large range of social, economic, and environmental processes, neglecting a singular focus imperils scientific discussion and validation. The assessment by [Hinkel *et al.* \(2013\)](#) predicts the global implications of SLR-induced beach erosion, and provides a suitably narrow lens to evaluate the DIVA Package. Following suite, this thesis evaluates coastal erosion, including the implication of beach nourishment as an adaptation strategy and its relation to coastal economic development.

In their study on global coastal erosion, [Hinkel *et al.* \(2013\)](#) recognizes the need for the DIVA model to evolve and match the knowledge and capacity of the current scientific community. Contextual and technological limitations originally necessitated heavy reliance on aggregation and inference for parameters within the original DIVA package. Specifically, the portion of coastline vulnerable to erosion is determined through coastal plane characteristic, wetland migratory potential, and expert judgment of sediment characteristics ([McGill, 1958](#); [Hoozemans *et al.*, 1993](#); [Vafeidis *et al.*, 2006](#)). This estimated erosion factor then drives a simplified nourishment cost decision matrix for which it is the singular input ([Hinkel *et al.*, 2013](#)). Localization of the information used to derive these model inputs provide better resolution for the results of the DIVA model.

Concluding their work, [Hinkel *et al.* \(2013\)](#) identifies the development of (1) sandy-coast distributions and (2) the costs of beach nourishment as areas for future research with significant implications for SLR adaptation planning.

Recent improvements in computational operations and image processing techniques have culminated in the development of a number of global sets of high-quality indirect measurements. Databases such as Aqua Monitor, the Satellite Derived Shoreline (SDS), Global Sand Composition Database (GSCD), and Foreshore Assessment using Space Technology (FAST) demonstrate a new capacity to resolve information in the coastal zone ([Luijendijk *et al.*, 2018](#); [Morris *et al.*, 2015](#); [Donchyts *et al.*, 2016](#)). Leveraging these techniques to improve the capacity of existing tools such as DIVA represents a substantial opportunity to expand the scientific body of knowledge without the need for costly field studies.

[Hinkel *et al.* \(2013\)](#) uses a coarse matrix to indicate beach nourishment costs. This factor currently allows relatively inexpensive nourishment practices even on coasts devoid of appropriate sediment sources. In this thesis, dredging and nourishment expertise at the Delft University of Technology is sufficiently developed to leverage a better-resolved Nourishment Cost Model (NCM) based on global risk factors that may be improved in subsequent iterations.

Therefore, this thesis will investigate improvements to the DIVA database made possible by recent developments in global information systems and a new NCM in relation to results of the [Hinkel *et al.* \(2013\)](#) publication. These changes will eventually broaden the scope and application of the DIVA package and help to better guide policy development with respect to SLR vulnerability.

key Points

1. Relative changes in sea level may have a significant impact on future human development and safety.
2. The IPCC recognizes the need for better prediction of the economic, social, and environmental impacts of sea level rise and policy development at large scales.
3. DIVA provides a unique capacity to evaluate SLR impact-adaptation pathways at a global scale.
4. [Hinkel *et al.* \(2013\)](#) studied the erosion of sandy coasts driven by SLR at a large scale.
5. [Hinkel *et al.* \(2013\)](#) identifies the resolution of sandy coast distribution and nourishment costs as future research items.
6. The nascent Global Sand Composition Database (GSCD) provides a wealth of previously-unavailable information.
7. TU Delft expertise in the field of beach nourishment may improve the existing nourishment cost information and elucidate the nourishment impact-adaptation pathway.

1.2. Significance

This thesis improves the available DIVA model and develops a methodology to connect new coastal information stored as satellite-derived transects. In doing so, we create a novel connection to extract fine-resolution spatial information in the coastal zone. This improves global vulnerability assessment of human populations. Our work further examines the affect of this connection on established vulnerability projections. Specifically, the application of DIVA by [Hinkel *et al.* \(2013\)](#) will be redeveloped with new information and contrasted to the existing work.

1.2.1. Existing Knowledge

DIVA Existing studies between 2004 and 2013 developed the methodology for the DIVA database and modelling tool ([McFadden *et al.*, 2007](#); [Vafeidis *et al.*, 2008, 2004](#)). Important to the understanding of DIVA is the conceptualization of its segmented coastline. The information presented in DIVA is developed on 12,148 linear coastline segments. Each segment, which effectively serves as a single grid-cell or measurement point, is selected such that its response to SLR is anticipated to be approximately homogenous ([Vafeidis *et al.*, 2004](#)).

A number of studies apply this tool at regional and global scales ([Hinkel *et al.*, 2013](#); [Spencer *et al.*, 2016](#); [Hinkel and Klein, 2009](#); [Nicholls *et al.*, 2011](#); [Pardaens *et al.*, 2011](#); [Hinkel *et al.*, 2010, 2012](#)). In [Hinkel *et al.* \(2014\)](#), new IPCC Representative Concentration Pathway (RCP) and Shared Socioeconomic Pathway (SSP) scenarios are incorporated into the DIVA framework to replace the existing Special Report on Emissions Scenarios (SRES) information.

Similarly, more recent work by [Wolff et al. 2016](#) performs a flood-risk sensitivity analysis by modifying the DIVA database for the Emilia-Romagna region of Italy, identifying particular sensitivities of the DIVA framework to changes in segment resolution, population, elevation, and vertical land movement. This study found significant changes to DIVA-projected impacts for an adapted DIVA model in the Emilia-Romagna region of Italy using a One-At-A-Time (OAAT) analysis methodology. Subsequent work in [2018](#) expanded this study to resolve DIVA at a much finer resolution for the entire Mediterranean basin ([Wolff et al., 2018](#)), a process with potential for application on a global scale in the future.

[Hinkel et al. \(2014\)](#) presents valuable information with respect to SLR-induced coastal flooding, and introduces RCP information into the DIVA model. [Wolff et al. \(2016\)](#) demonstrates substantial improvements by incorporating the most recent data into the DIVA framework. This process that has been repeated for SLR-induced erosion.

GSCD With respect to SLR-induced erosion, a significant improvement in detail is readily available through recent advances using the recent Google Earth Engine (GEE) platform ([Luijendijk et al., 2018](#)). GEE combines an extensive record of publicly available satellite imagery with cloud-based supercomputing capabilities which together overcome traditional obstacles preventing large scale image analysis the coastal zone. TU Delft and Deltares have together developed a number of techniques which allow detailed analysis of the global coastline at an unprecedented level of detail. These comprise a Global Sand Composition Database (GSCD) and a Satellite Derived Shoreline (SDS). Where the SDS represents a nascent source of global information on the geospatial position of the shoreline, the GSCD includes information on the location of sandy beaches ([Luijendijk et al., 2018](#); [Hagenaars et al., 2018, 2017](#)). The existing DIVA database identifies just 11% of the world's coast as sandy beach whereas the GSCD machine-learning algorithm identifies 31% of the world's coastline as sandy beach ([Luijendijk et al., 2018](#)). The methodology for each number differs significantly. Determining the source of this discrepancy and rectifying the underlying data has potentially large impacts to results from [Hinkel et al. \(2013\)](#).

Beach Nourishment Costs There has been relatively little recent work to quantify global trends in beach nourishment costs. Most studies focus at a regional level, and the rate of academic publication is relatively low ([NSCMG, 2000](#); [Trembanis et al., 1999](#); [Hillen et al., 2010](#)). However, global risk factors and generalized knowledge are better-developed for the construction industry at project and national levels ([Locatelli et al., 2017](#)), particularly with respect to risk modelling. These studies acknowledge that estimation is an inherently humanistic process which can be modelled at a generalized level ([Baloi and Price, 2003](#)).

1.2.2. Knowledge Gaps

DIVA is built to accommodate large scale analyses despite known knowledge gaps. The developers of the DIVA Database and Model were limited by the resolution of historical information available at the time of initial development, and therefore made many simplifying assumptions. These have been applied in numerous studies to predict the impacts of SLR (e.g. [Hinkel et al., 2013](#)). However, validation of the tool using historical data is problematic due to the erratic nature of global historical data collection. [Hinkel et al. \(2013\)](#) identify a number of knowledge gaps within the DIVA Model and Database in addition to the distribution of sandy beaches and nourishment costs:

Tidal Inlets The DIVA model currently includes 200 "major" tidal basins ranging from 55 to 59,100 km² (Saint Tropez and the Sea of Azov respectively) modelled in ASMITA. These basins

were identified and included on the basins of expert opinion at Deltares; however, the actual number of basins is almost certainly much higher (Hinkel *et al.*, 2013). The observed impact of tidal basins where they do exist in the model implies that missing basins could significantly alter the predicted shoreline regression (Hinkel *et al.*, 2013).

Sediment Pathways Aside from sediment transfer to tidal basins, DIVA does not take into account the transition of sediment between adjacent segments or from rivers. Tidal basins are also related to a single segment. The effects of tidal basins are therefore restricted to a singular, immediate segment, and their impacts on nourishment practices are likely unresolved if this segment is not sufficiently developed to merit adaptation.

Bruun Rule DIVA employs the Bruun Rule to determine SLR-induced beach erosion. Zhang *et al.* (2004) demonstrated a successful application of the Bruun rule by aggregating information across large spatial scales, and DIVA uses these findings to justify its application. However, Zhang *et al.* (2004) evaluated information between New York and South Carolina, a much larger portion of the coastline than typical DIVA segments. Further, DIVA assumes consistent slope of 1:100 on erodible coastlines, which is highlighted as a metric which could likewise change the composition of the DIVA results (Hinkel *et al.*, 2013).

Tourism Socioeconomic impacts in the DIVA model are applied through a number of modules. One such module is the tourism module which currently includes a country-level resolution of tourism revenues. Hinkel *et al.* (2013) postulate that improvements to the resolution of the tourism module, and specification to the coastal zone will improve the prediction capability of the DIVA modelling tool.

1.3. Objectives

The maintenance and improvement of existing tools to predict and quantify vulnerability to SLR at global scales is essential to identify particularly vulnerable regions and plan appropriate mitigation measures. The continued inclusion of SLR in policy decisions at all levels hinges on this ability to link the phenomenon with economic and social costs as identified in DIVA.

An initial review of the items outlined in 1.2.2 identifies the new GSCD shoreline and associated sandy beach information as the “lowest-hanging fruit” in an improvement plan for the DIVA model across multiple theses and papers. The subsequent interaction with nourishment expertise at the TU Delft also provides an opportunity to redevelop the DIVA cost model. The objectives of this thesis are therefore refined to the following key points:

Research Questions

1. Can we improve the performance of DIVA, which models large scale socio-economic impacts of SLR?
 - Specifically, can we improve DIVA by incorporating additional sandy beach information from the GSCD and nourishment cost information from expertise at TU Delft?
2. How do improvements to the DIVA model change global erosive patterns and the economic implications of adaptation? How do improvements to the DIVA model change the distribution of projected regional erosion?
3. How do improvements to the DIVA package change the social and economic impacts of SLR-induced erosion predicted by [Hinkel *et al.* \(2013\)](#)?
4. What do the results of the DIVA analysis reveal about the implementation of beach nourishment in the 21st Century?

1.4. Approach

Since multiple changes are proposed for the DIVA model, we apply a measured approach in a OAAT analysis. In this analysis, a reconstructed baseline is developed from updated physical information applied in studies more recent than 2013. Subsequently the effects of the GSCD and NCM are highlighted individually before a final combined run identifies multiplicative effects on nourishment adaptation information. Validation and sensitivity analyses, where possible, are tools to build confidence for the future application of the techniques developed here or avenues of future research.

2

New Developments in Global Coastal Erosion Assessment

New Developments in Global Coastal Erosion is intended to stand alone as a first step towards peer review and academic publication academic publication, including the following items:

Abstract

Dynamic Interactive Vulnerability Analysis projects the impacts of sea level rise on coastal development across the 21st century. In particular, this model provides perspective on the potential for key adaptation measures to reduce the impacts of sea level rise, notably the loss of land and forced migration from beach erosion. In an update to the analysis of global sea level rise-induced beach erosion by [Hinkel *et al.* \(2013\)](#), this paper derives a new coastal beach composition and parametric nourishment cost information. We evaluate these changes using a reconstructed baseline and three primary marker scenarios comprised of RCP2.6/SSP3, RCP4.5/SSP2, and RCP8.5/SSP5. First, the global sand coverage database presented by [Luijendijk *et al.* \(2018\)](#) is aggregated into the DIVA database using a spatial sorting algorithm. This shows an increase in the beach composition of the coastline from 16% to 27% with an associated increase in projected combined economic impacts of 50% with adaptation. The adoption of a new parametric equation which relies on sediment availability, corruption, and nourishment methodology to develop its cost adds regional variation to the model. From this model global adapted economic impacts of beach erosion increase by 14%. However, each of these models has regional distributions that result in a combined impact of only 41%. The countries most impacted by these changes are often small island nations including the Marshall Islands, Kiribati, and Guernsey. In these locations beach-erosion related impacts are projected as high as 0.25% of GDP. Information from the DIVA socioeconomic model provides an indication of the value of land and projections of the growth of nourishment practices are made. Substantial uncertainty remains within the model due to the prevalence of tidal basin impacts within the DIVA model and the lack of verification of their distribution and comportment.

2.1. Introduction

Sea Level Rise (SLR) globally threatens coastal communities through a network of biophysical and socioeconomic interactions (Wong *et al.*, 2014). The extent and consequences of the threat drives policy decisions at all levels of government where the coast is concerned (IPCC, 2014a). This forcing stems from encroaching human populations and simultaneous environmental drivers pushing ocean waters and human infrastructure together from opposing directions (McGranahan *et al.*, 2007).

Through SLR, this interaction causes temporary flooding; land submergence; erosion; loss of ecosystem services through destruction of wetlands; and saline intrusion into aquifers and surface water (Hinkel *et al.*, 2013; Jongman *et al.*, 2012; Masciopinto and Liso, 2016). To this end, the Dynamic Interactive Vulnerability Assessment (DIVA) assesses these processes and their human consequences through a convergence of global-scale biophysical, and socioeconomic models (Vafeidis *et al.*, 2008; Hinkel and Klein, 2009). DIVA measures its impacts through a globally consistent coastline segmented into discrete spatial entities. This segmentation approximates areas of homogeneous response with respect to SLR (Vafeidis *et al.*, 2008; Bartlett *et al.*, 1997).

DIVA has been used to investigate regional vulnerability and to develop global models isolating and improving scientific knowledge on individual SLR impact-adaptation pathways associated with erosion, flooding, and wetland change (Hinkel *et al.*, 2013; Spencer *et al.*, 2016; Hinkel *et al.*, 2014) as well as policy assessments (Nicholls *et al.*, 2018, 2011), and more detailed regional analyses (Wolff *et al.*, 2016). This paper focuses on developments and improvements in the erosion component of the DIVA model. Using DIVA, Hinkel *et al.* (2013) assessed the implications of SLR-induced erosion of sandy beaches at a global scale. While DIVA creates quantified projections for SLR impacts across all of the above risk categories, Hinkel *et al.*'s focus on SLR-induced erosion encourages discussion on the adaptation potential of beach nourishment and facilitates interpretation. We improve this knowledge by redeveloping Hinkel *et al.*'s work using current DIVA information, and subsequently applying two new techniques which refine available knowledge on the beach erosion impact-adaptation pathway.

Beach erosion is a long-term morphodynamic process by which sediment in the coastal zone is shifted seawards or into back-barrier and terrestrial stores by hydrodynamic processes such as waves and currents, causing a physical retreat of the coastline. This is distinct from both land submergence and back-barrier erosion in tidal basins. During land submergence, rising sea levels cover existing land irrespective of changes to topology (Hinkel *et al.*, 2013). Back-barrier erosion, conversely, is the result of a complex interaction between a basin's outer delta, channels, and tidal flats (van Goor *et al.*, 2003). This loss occurs at the edges of the basin which is analogous to projected changes for tidal flat surface areas (Hinkel *et al.*, 2013). Basins are considered within the DIVA erosion module as a component of a coastal sediment balance. DIVA models adaptation of sandy coasts through beach nourishment, which balances coastal sediment demand where prevention is economically sound.

Within this framework, Hinkel *et al.* (2013) identified coastal beach content and nourishment cost information among topics suitable for elaboration at a global scale.

Recent advances in remote sensing have spurred the development of a large scale database identifying beaches on the coastline (Luijendijk *et al.*, 2018). This Global Sand Coverage Database (GSCD), whose scientific application is only nascent, is more-closely related to the physical coastline than pre-existing information and its extent is unparalleled (Hagenaars *et al.*, 2017). Importantly, GSCD information indicates that the actual CBC could be approximately three times that of the original DIVA projections (Luijendijk *et al.*, 2018).

Given dependencies within the DIVA model, the development of the new CBC forces the redevelopment of nourishment cost information as the physical interpretation of information changes. Development of a new Nourishment Cost Model (NCM) is therefore an opportunistic addition to the work presented here. The involvement of the GSCD team places dredging industry expertise in close-contact with the DIVA model, which is leveraged to develop the new information. The replacement model presented here is capable of more nuance than the pre-existing matrix.

We therefore perform three primary actions which improve scientific knowledge with respect to the impacts of sea level rise: (1) we integrate the results of this novel Satellite Derived Shoreline (GSCD) into the DIVA Database ([Luijendijk et al., 2018](#)). The new information provides a much finer detail for CBC measurements and directly changes the length of erodable coast within the DIVA Database. (2) We initialize an NCM using country- and local- level risk-factors and expert judgment. By tying costs to localized factors, we model differences in physical, social, and administrative factors which improve the expression of beach nourishment as an adaptation method. The improvement to the variability of beach nourishment costs also opens new research pathways to investigate administrative responses to climate change. (3) To resolve these primary actions, we re-evaluate SLR-induced beach erosion at a global scale, echoing the formative analysis by [Hinkel et al. \(2013\)](#). The baseline information representing this formative study is redeveloped using current standards. In doing so, we identify discrepancies to [Hinkel et al. \(2013\)](#) work before quantifying new changes to the baseline.

Within this paper, Section 2.2 outlines the DIVA model, re-establishes a baseline, and develops methodologies for each of the proposed changes. Section 2.3 subsequently identifies the impact of the proposed changes on the baseline run both individually and together with specific reference to [Hinkel et al. \(2013\)](#). Section 2.4 discusses the implications of these results and proposes avenues for further work. Finally, Section 2.5 closes the paper with concluding remarks.

2.2. Methodology

2.2.1. Beach Erosion in the DIVA model

The global spatial and temporal scales analyzed by DIVA overextend existing scientific capabilities for process-based modelling ([Cowell et al., 2003a](#)). DIVA instead relies on the ASMITA model and a simplified Bruun Rule calculation to quantify a basic sediment balance for beach erosion on an aggregated scale ([Zhang et al., 2004](#); [van Goor et al., 2003](#)).

The use of the Bruun Rule here is contentious within scientific literature (eg. [Ranasinghe et al., 2012](#)), however many critics still recognize the term's formulation as a component of the sediment balance responsible for erosion ([Ranasinghe et al., 2013](#)). Building towards this balance, ASMITA builds projected equilibrium states for each of 200 identified tidal basins which interact with beach grade sediment on adjacent coastal segments. Empirical coefficients driving these models are taken from well-studied tidal basins in the Netherlands ([Wang et al., 2007](#)). The corresponding mass balance accelerates coastal beach erosion imposed by the Bruun Rule ([Hinkel et al., 2013](#)). DIVA simplifies this Bruun-rule with a globally uniform slope of 1%. An associated depth of closure related to LOICZ wave classifications and local tidal ranges completes the information necessary to obtain a rudimentary sediment balance ([Hinkel et al., 2013](#); [Stive, 2004](#); [Hallermeier, 1978](#); [Pickering et al., 2017](#)). By including the adaptation methodology native to the DIVA model, a set of impacts with and without adaptation is developed for SLR-induced beach erosion.

Erosion from the above balance is applied only at beaches, currently identified in the DIVA database from a decision matrix using large-scale coastal plain characteristics (McGill, 1958), wetland migratory potential (Hoozemans *et al.*, 1993), and expert judgment on sediment types. This matrix anticipates whether the coastline is comprised of beach, pocket beaches, or non-beach morphology (Vafeidis *et al.*, 2006). This is referred to an "Erosion Factor" (E_f) in Hinkel *et al.* (2013) which indicates the proportion of the coastline that is "beach" and therefore vulnerable to beach erosion induced by SLR.

DIVA estimates land-loss, land-loss cost, forced migration, forced migration cost, and lost tourism income from beach erosion. These are driven by the physical model of the coastal zone (Hinkel and Klein, 2009; Collins *et al.*, 2011), population and economic scenarios (Strengers *et al.*, 2004; van Vuuren *et al.*, 2012), and combined models which refine tourism revenues for beaches based on national environmental parameters (Hamilton *et al.*, 2005a). From these models DIVA records loss of land and forced population migration as primary indicators of coastal zone impacts resulting from SLR. Secondary impacts include subsequent economic costs and loss of tourism revenue due to the loss of beaches (Hinkel *et al.*, 2013).

The valuation of impacts and mitigating response is a core part of the DIVA package. Administrative elements within the program model known adaptation techniques for a number of SLR impacts. Of these, beach nourishment most directly reduces beach erosion and associated loss of land. DIVA may also model adaptation by nourishment of tidal basins to treat the indirect causes of erosion, but this impact-adaptation pathway needs additional elaboration at small scales before it can be successfully modelled globally (e.g. Ysebaert *et al.*, 2016). The DIVA costing and adaptation module therefore drives a Cost-Benefit Analysis (CBA) which decides the application of shore and beach nourishment. The module compares projected costs of nourishment against projected changes in tourism revenue, value loss of land, and secondary impacts of forced migration, resulting in a binary decision with respect to beach nourishment (Hinkel *et al.*, 2013).

2.2.2. Measured Impacts

Hinkel *et al.* (2013) presents loss of land as the primary impact of SLR through the beach erosion impact-adaptation pathway. Changes to the physical coastline model such as CBC or RSLR will have the strongest effect on physical land-loss. Conversely, forced migration and economic costs are second-order effects which are influenced by the loss of land, but whose impacts depend heavily on the population and economic activity of the associated coastline. Changes to economic models, including per-capita GDP and agricultural land values have a strong impact within this category. Finally, adaptation of land-loss by nourishment acts as adaptation feedback, stopping erosion of the coastline in highly-valued regions. In this way socioeconomic changes represented by different scenarios have the potential to feedback into the loss of land calculation for coastal segments with a high intrinsic value. Tourism is not considered directly as a projected impact, even though it is considered in the CBA for beach nourishment in an embedded tourism module. Hinkel *et al.* (2013) argue that further resolution of tourism income within each country is needed before these damages can be fully assessed.

2.2.3. Climate and Socioeconomic Scenarios

The scenarios developed in Hinkel *et al.* (2013) use the now-outdated SRES information to present their results. The report best resolves environmental variability in the SRES A1B scenario, in which society's adaptation capacity is relatively large (van Vuuren *et al.*, 2012; IPCC, 2000). This cross-section, however, ignores worst case scenarios with high environmental stressors and low adaptation capacity. van Vuuren *et al.* (2012) recommends a minimum set

of RCP/SSP combinations which contains the best- and worst-case scenarios for use in climate assessments. Following this, more recent work using DIVA approximates this space by highlighting RCP scenarios 2.6, 4.5 and 8.6 in conjunction with SSP2, SSP3, and SSP5 respectively (Hinkel *et al.*, 2014; Wolff *et al.*, 2016).

These three marker scenarios frame the effects of the GSCD and cost model changes on DIVA projections and encompass the impact and adaptation dimensions recommended for use in climate-change impact analysis (van Vuuren *et al.*, 2012). In-text discussion here highlights the RCP 4.5/SSP2 scenario, since it represents a median of in both socioeconomic growth and global SLR dimensions. However, RCP2.6/SSP3, RCP2.6/SSP2, RCP8.5/SSP2 and RCP8.5/SSP5 are retained to highlight the impact of climate sensitivity and socioeconomic models as needed. Subsequently, we redevelop the Hinkel *et al.* (2013) nourishment adaptation projections in a One-At-A-Time (OAAT) analysis which isolates the individual effects of the modifications (Wolff *et al.*, 2016). Finally, we re-develop DIVA projections using both DIVA modifications simultaneously. By approaching these changes in an incremental manner, the specific impacts from each source highlight effect interactions and compound forcing which cause deviations that pure superposition cannot predict.

2.2.4. Baseline Information

DIVA relies on multiple underlying physical, social, and economic input information which has major impacts on the results of any study. This information has improved since the 2013 paper. For this baseline, we generally opt to retain the models used by Hinkel *et al.* (2013):

- Hadley Global Environment Model2 - Earth System (HADGEM2-ES) physical circulation model (Collins *et al.*, 2011)
- High, medium and low ice components developed by Hinkel *et al.* (2014), for RCPs 8.5, 4.5, and 2.6 respectively (Hinkel *et al.*, 2014; van Vuuren *et al.*, 2012)
- Global Land One-Kilometer Base Elevation (GLOBE) Digital Elevation (DEM) model
- LandScan (LS) global population dataset

However, some models demonstrate a significant theoretical improvement and corresponding substantial impact on the original work. Similarly some of the old datasets are now deprecated within the DIVA model Hinkel *et al.* (2014); Wolff *et al.* (2016). Therefore we propose a number of changes to the input information for baseline calculations:

- A new geo-spatial re-projection of the coastline has reduced it's total recorded length by 40%, however the impact of this change is limited by the location of sandy beaches away from poles where this change was most significant (Luijendijk *et al.*, 2018)
- New tidal data for each segment improve depth of closure prediction and impact local sediment balances (Pickering *et al.*, 2017)
- Improved uplift information develops a more accurate picture of relative sea level rise
- Redeveloped per capita GDP and population drives a larger economy, which affects both societal vulnerability and adaptation capacity
- RCP and SSP scenarios where Hinkel *et al.* (2013) used SRES scenarios.

2.2.5. New Beach Identification Information (GSCD)

Recent publication by [Luijendijk et al.](#) establishes a global database on the occurrence and movement of sandy shorelines. This machine-learning driven algorithm successfully develops transects and associated beach indicators at 500 metre intervals for 81% of the world's coastlines ([Luijendijk et al., 2018](#)). The information resolves the coastline at a significantly finer scale than the DIVA segmentation, and the two cannot be directly related. Instead, we spatially relate this information to the DIVA segmentation at a global scale by translating each GSCD datapoint into an X-Y-Z component which is then related to the DIVA database through a fast spatial kd-tree search algorithm ([Maneewongvatana and Mount, 2001](#)). This nearest-point approach has the benefits of including important coastal morphology not captured in the original DIVA segmentation as part of the database for which impacts would otherwise be neglected. Morphology not captured by the original DIVA coastline includes important delta and barrier island morphology specifically vulnerable to SLR ([Wong et al., 2014](#)). These features also form a part of the traditional coastal zone tract posited by [Cowell et al. \(2003b\)](#), which DIVA aims to emulate ([McFadden et al., 2007](#)). However, in order to prevent over-extension of the link between the two databases, we apply two filters to the incoming dataset and link to remove the following information:

- GSCD points with an associated SDS 33-year variance in shoreline position change exceeding 50 m^2 , which indicates some as-of-yet undefined issue in the GSCD algorithm
- GSCD points with a geodetic distance to the nearest DIVA segment exceeding 12.7 km, which captures 99.7 percent of the available GSCD information. This boundary is qualitatively set to ensure that the Wadden Sea Islands which have no associated DIVA segment are attributed to adjacent coastlines.

Applying these filters places DIVA reference information for the vast majority of the GSCD transects. These two datasets have a mean distance of 2 km separating them. Once reference information is obtained, the sandy GSCD transects are aggregated over each segment to indicate the prevalence of beaches for that segment between 1 and 0. This "Coastal Beach-Component" (CBC) better indicates the information anticipated by DIVA's E_f , this the percentage of each segment which is vulnerable to beach erosion as a result of SLR.

The GSCD-DIVA reference information is, however, subject to natural error at narrow channels, inland waterbodies, and barrier islands not covered within the DIVA coastal entity. To assay the effectiveness of the automated connection, 6 coastal engineering students were asked to manually develop reference information for 1019 DIVA segments based on the concept of a singular coastline (Figure 2.1). The CBC results of the algorithmic methodology show good correlation to the same metrics for the nearest-point algorithm. Within the validation areas, average CBC in each segment is 0.1% larger when solved by the algorithm than by manual determination. the 95% confidence bound of this error measurement at a segment level extends to a CBC of 0.13 in either direction. Finally, the algorithm demonstrates a Brier Skill Score score of 0.97 when compared to the global mean CBC indicated by the GSCD information (0.31) ([Luijendijk et al., 2018](#); [Fawcett, 2008](#)). These statistics demonstrate the stability of the proposed connection methodology for CBC information.

2.2.6. New Nourishment Cost Model

Beach nourishment is the primary adaptation pathway considered by the DIVA model with respect to SLR-induced beach erosion. DIVA uses local CBC characteristics to drive a decision tree which determines local nourishment costs. The cost-benefit-analysis (CBA) system checks beach nourishment against economic impacts of land loss, forced migration, and loss

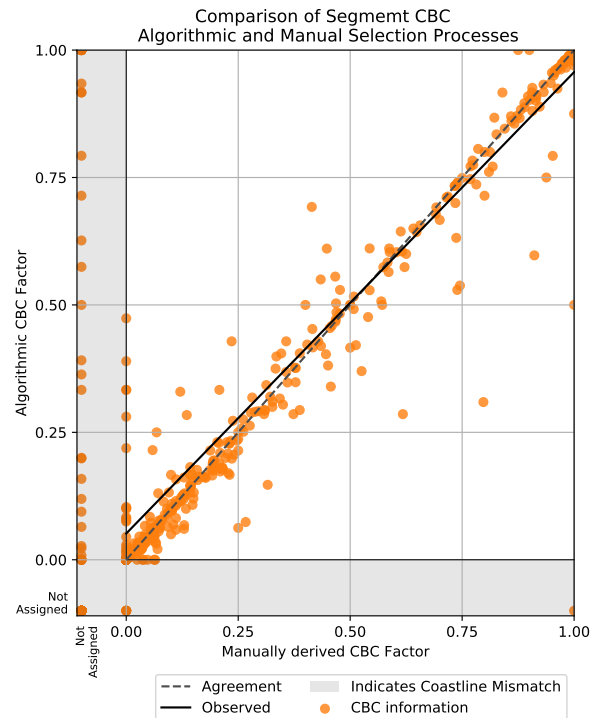


Figure 2.1: CBC factor for the nearest-point algorithm compared to CBC factors manually referenced to the DIVA segmentation. Note the "Not Assigned" values.

of tourism revenues ([Hamilton et al., 2005a,b](#)). We improve this methodology through the development of a volumetric NCM using location-specific parameters including cultural, administrative, economic, and environmental considerations. To this end, we posit six key drivers for the cost of beach nourishment projects:

1. availability of sediment
2. extraction depth
3. project size
4. short and long term market fluctuations
5. nourishment placement method
6. corruption and graft
7. administrative barriers and protectionism
8. calibration

Of these, short term market fluctuations, extraction depth, and project size are expected to have a negligible impact on the long-term viability of nourishment programs and are ignored. However, we retain a long-term temporal market factor to promote future elaboration of impacts from market escalation and scarcity models.

In the absence of globally-scaled studies on the costs of nourishment, the new cost model builds upon industry expertise and analogue indicators from other industries, where available.

Such analogues compare infrastructure construction prices across varying per-capita GDP and corruption parameters ([Locatelli et al., 2017](#); [Okoye et al., 2018](#); [Kaufmann et al., 1999](#)).

Basic cost information is developed for the Netherlands with information taken from the Rijkswaterstaat and the North Sea Coastal Management Group in support of theses at the Delft University of Technology. We set a base cost average of 7.16 2014 USD per cubic metre with an approximate confidence interval between 3.47 and 10.84 USD per cubic metre in 2014 USD. Similarly, aggregated studies show a ratio of 0.47 between the costs of shoreface nourishment when compared to beach nourishment ([NSCMG, 2000](#); [Trembanis et al., 1999](#); [Hillen et al., 2010](#); [Langedijk, 2008](#); [Flick and Ewing, 2007](#); [Kok et al., 2008](#)). DIVA corrects all prices to 2014 in order to facilitate comparison, and inflation of nourishment costs is implicitly treated within the program.

In comparison to this baseline, we employ DIVA corruption, per-capita GDP, and physical parameters to identify the impact of local conditions and workers for a long-term nourishment program. Studies have shown that GDP can have a significant impact on the cost of infrastructure projects ([Okoye et al., 2018](#)), however others note that nourishment typically relies on an international market requiring relatively little local labor ([Langedijk, 2008](#)). There are nourishment markets, however, which see substantial price differences on the basis of administrative barriers and local dredging economies, particularly the United States and China.

In these countries we fit a local economy factor through a linear fit between 1.0 at Netherlands, and 0.70 in the lowest income market (Liberia) on the basis of per-capita GDP in 1995. this 70/30 split approximates a relation in which local labor costs account for 30 percent of the total cost of infrastructure projects based on a topical review of construction industry opinions.

Corruption parameters represent 1997 conditions estimated from [Kaufmann et al. \(1999\)](#) with interpolation using GDP for missing data-points. [Locatelli et al. \(2017\)](#) compared differences in infrastructure costs between Italy and the Netherlands in an attempt to isolate the consequences of corruption in that field. We emulate the 20% difference found there to fit a linear model between the two countries to resolve the [Kaufmann et al.](#) corruption parameter ([Locatelli et al., 2017](#)).

Sediment availability, conversely, is fit to an exponential model using the Netherlands as a base-point with a factor of 1.0, and a theoretical country with a CBC of 0.0 resulting in a sediment cost factor 3 times that of the Netherlands. Further, we assume that the majority of the associated cost increase occurs only when less than half of the coastal segment is no longer beach. This assertion mirrors the inherent DIVA assumption that coastal segments are relatively homogeneous in their response to SLR; beaches are assumed to be randomly distributed along them. Therefore, we fit the relationship to a third point at a CBC of 0.5, which exhibits only 20% of the difference in cost between the lower and upper bounds. The functions used to fit the NCM are found in Table 2.1

Finally, this model reserves an “administrative calibration” factor for locations where significant and demonstrable factors impact the cost of nourishment projects over the long term at a country level. At the time of writing, Singapore is the only country with an applied factor of 5. It appears here that the GSCD detection algorithm has detected the man-made features constructed using imported sand which is artificially lowering calculated nourishment costs.

The existing DIVA database, when combined with GSCD information, contains sufficient information to approximate the remaining driving factors as presented in Table 2.1. With incremental adjustment and validation of underlying information, the model presents a valuable tool in assessing long-term trends in adaptation strategies.

Factor	Range	Description	Country	Analogue
$F_{s,i}$	1.0 - 5.0	$0.558 + 4.442 * e^{-2.609 * CBC_{mean}}$	NL	
F_{nm}	0.47, 1.0	$F_{n,beach} = 1.0$ $F_{n,shore} = 0.47$	NL	
$F_{le,i}$	0.7 - 1.0	$0.00000723 * pcGDP + 0.749$	NL	(Okoye <i>et al.</i> , 2018)
$F_{cr,i}$	0.94 - 1.71	$-0.154 * CORR + 1.323$ varies per country	NL, IT	(Locatelli <i>et al.</i> , 2017; Kaufmann <i>et al.</i> , 1999)
$F_{c,i}$	1.0	further study or Professional Judgement)		
$F_{ma,t}$	1.0	varies slowly over time (further study)		

Table 2.1: Description of the parameters which develop the proposed coastal NCM, including relations which develop the cost based on existing DIVA database parameters

This model improves the existing DIVA nourishment cost methodology, but represents broad patterns rather than costs at a local level. We rely here on expert judgment to loosely fit the five parameters to a limited number of data points and anticipated global patterns.

$$C_{i,m} = C_{base,t} * F_{s,i} * F_{nm} * F_{le,i} * F_{cr,i} * F_{c,i} * F_{ma,t} \quad (2.1)$$

Applying this new cost model to the DIVA segmentation in its base year has a complex interaction with the DIVA model. The average theoretical cost of nourishment per segment rises, however costs are more favorable in a number of highly populated areas.

2.3. Results

We develop a reconstructed baseline from Hinkel *et al.* (2013) using climate information, and socioeconomic scenarios developed in Section 1. Subsequent changes to this baseline are measured with respect to the 2100 cumulative impacts shown here, but the shape of these progressions is driven by regional variations in input scenario information and is relatively consistent (Table 2.3 and Figure 2.2).

From this baseline, changes to each parameter are measured Overall results are presented in Figure 2.3, which identifies the isolated effects of each change on DIVA outputs relative to the reconstructed baseline and provides new information for the final DIVA Package presented here.

2.3.1. New Beach Identification Information Effects

Information from the GSCD database directly impacts land loss projections by adapting the CBC parameter to match satellite observations of beach content. This action changes both the global mean CBC and the regional distribution of “erodible land”, with secondary impacts on the economic costs of impacts and the feasibility of adaptation measures.

Unmitigated land-loss Unmitigated loss of land rises 38% from 170 to 234 km² annually in 2100 or 25.8% from 13,222 to 16,634km² cumulatively from 2015 to 2100 in RCP 4.5 (Figure 2.3). This erosion is directly related to the rate of SLR such that GSCD information has the largest scalar impact for the RCP 8.5 scenario, an effect which increases through the duration of the simulation. The loss of land relative to it’s associated cost is almost a one-to-one relationship, with costs rising uniformly relative to land loss across all scenarios. The costs show an increase of 25.6% cumulatively between baseline and GSCD information (RCP 4.5). While the scale of the difference varies between each timestep, relative cumulative

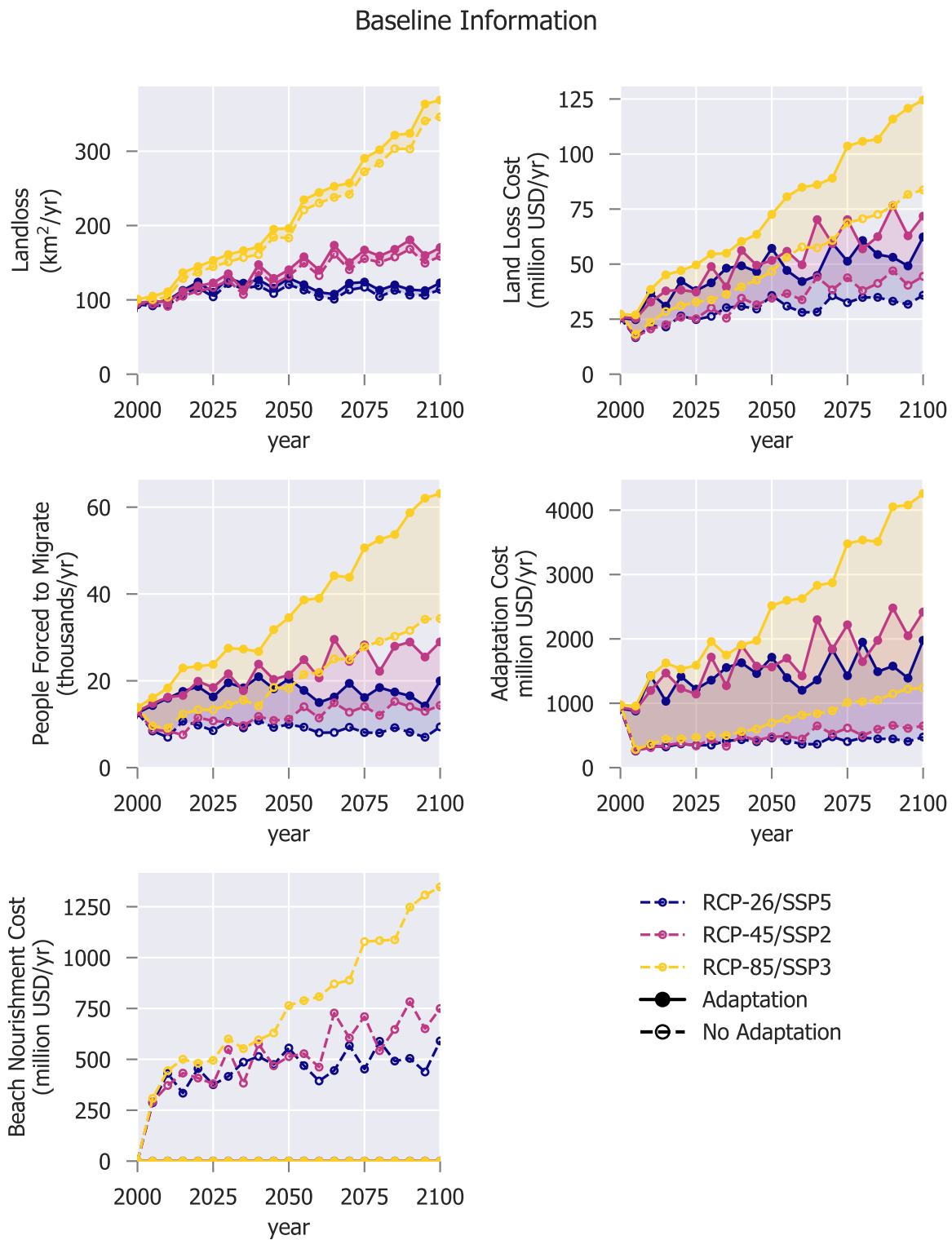


Figure 2.2: This figure demonstrates the baseline projections using new underlying data across the three marker scenarios selected for our analysis. The solid lines represent unmitigated SLR impacts while dashed lines show impacts after adaptation. (a) Land-loss, (b) cost of lost land, (c) Forced Migration, and (d) cost of forced migration. (d) includes information on the comparable expenditure to protect assets through beach nourishment

Parameter	Nourishment	Low (RCP 2.6)				Middle (RCP 4.5)				High (RCP 8.5)			
		Baseline		New Model		Baseline		New Model		Baseline		New Model	
		No SDS	SDS	No SDS	SDS	No SDS	SDS	No SDS	SDS	No SDS	SDS	No SDS	SDS
Forced Migration	No Adaptation	1606	2202	1606	2202	2106	3124	2106	3124	3622	5947	3622	5947
	Reduction	789	1049	734	1124	1007	1421	900	1525	1620	2511	1367	2699
Land Loss	No Adaptation	10684	12767	10684	12767	13222	16634	13222	16634	21418	29494	21418	29494
	Reduction	655	709	550	745	814	905	662	970	1283	1493	979	1625
Land Loss Costs	No Adaptation	4392	5187	4392	5187	4976	6249	4976	6249	7328	10135	7328	10135
	Reduction	1636	1859	1450	1887	1789	2129	1565	2211	2457	3164	2075	3364
Migration Costs	No Adaptation	134987	171117	134987	171117	159621	216859	159621	216859	243481	366433	243481	366433
	Reduction	98148	119929	93893	123048	114812	148637	108282	153117	172485	243610	158954	252006
Nourished Length	No Adaptation	336622	518751	186688	449676	309332	478768	169908	400259	299472	459943	160727	371278
	Nourishment Cost	42753	51531	42207	54713	50569	64516	49088	68539	75631	105233	73659	114675

Table 2.2: Detail of the impacts of GSCD and cost model changes with respect to 5 DIVA output categories. Adaptation follows the DIVA CBA methodology.

costs are well correlated to relative cumulative loss of land across all three scenarios which demonstrates an approximately linear relation.

Unmitigated Forced Migration Forced migration, when using the new GSCD information and unmitigated by beach nourishment, increases 51% from 29,000 to 43,800 persons annually in year 2100 or 48% from 2.1 to 3.1 million between 2015 and 2100 (RCP 4.5). Similarly to loss of land, the change in number of migrants is approximately proportionate to the rate of SLR such that the greatest scalar effect is observed in RCP 8.5, which increases through the duration of the simulation.

Adaptation by Nourishment GSCD information interacts with the beach nourishment adaptation pathway at it's second order (Figure 2.3). Compared to the 20% rise in unmitigated erosion, DIVA indicates GSCD only increases protected land in mitigated scenarios by 9% in 2100. This indicates that valuable land is substantially less-impacted by the GSCD information than remote locations. Regional variability makes a large difference in global averages of second-order results in the mitigated scenario. The cumulative number of displaced persons increases by 41% as compared to 37% when unmitigated (RCP 4.5). This equates to a 33% increase in the number of people protected via the nourishment adaptation pathway. Finally, GSCD information increases the total volume of material for beach and shore nourishment practices by only 8% over a nourished coastline that is 30% longer than in baseline runs for RCP 4.5.

2.3.2. Nourishment Cost Model Effects

The information from the NCM restricts its effect on DIVA results to adaptation scenarios only. It does not change the overall vulnerability of the coastal zone, instead altering society's modelled capacity to mitigate beach erosion.

Adaptation by Nourishment While the effect of the new cost model on nourished impacts is complex, overall it exacerbates society's modelled cost of adaptation to sea level rise (Figure 2.4). On a global scale, loss of land during mitigated scenarios rises less than 2% from 158 to 160 km² annually in 2100 (RCP4.5). Cost projections for the loss of land shift 7% down from the baseline annual land loss cost projections valued at 44.4 million USD annually. With the new model, DIVA projects an average 6% more displaced persons in the 21st century owing, but also shows a major to an 42% drop in the length of nourished coastline (RCP4.5). The magnitude of this length effect is tied to both society and the economy and no change in protected length is observed across SSP2. Minor changes across RCP2.6/SSP5 and RCP8.5/SSP3 indicate that the primary factor here is likely the physical distribution of population centres. These changes reflect a new balance point between global nourishment costs and SLR forcing. The economic impact of forced migrants rises 15% from it's baseline of 1.7 to 2.4 billion USD/yr while the effect on land-lost costs similarly rises 7% up from a baseline of 0.4 to 0.6 Billion USD/yr (RCP4.5). Despite these changes, the overall cost of nourishment remains relatively constant, showing a reduction change of just 3% in RCP4.5.

2.3.3. Cumulative Effects

Cumulative effects on SLR impacts demonstrate a significant level of interaction between the two changes made here. We observe that where the new NCM tempers global adaptation capacity to climate change on it's own, the same model strengthens that capacity when the GSCD physical information is applied. Most notably, the cumulative effect of our changes on post-adaptation economic impacts associated with loss of land and forced migration drops

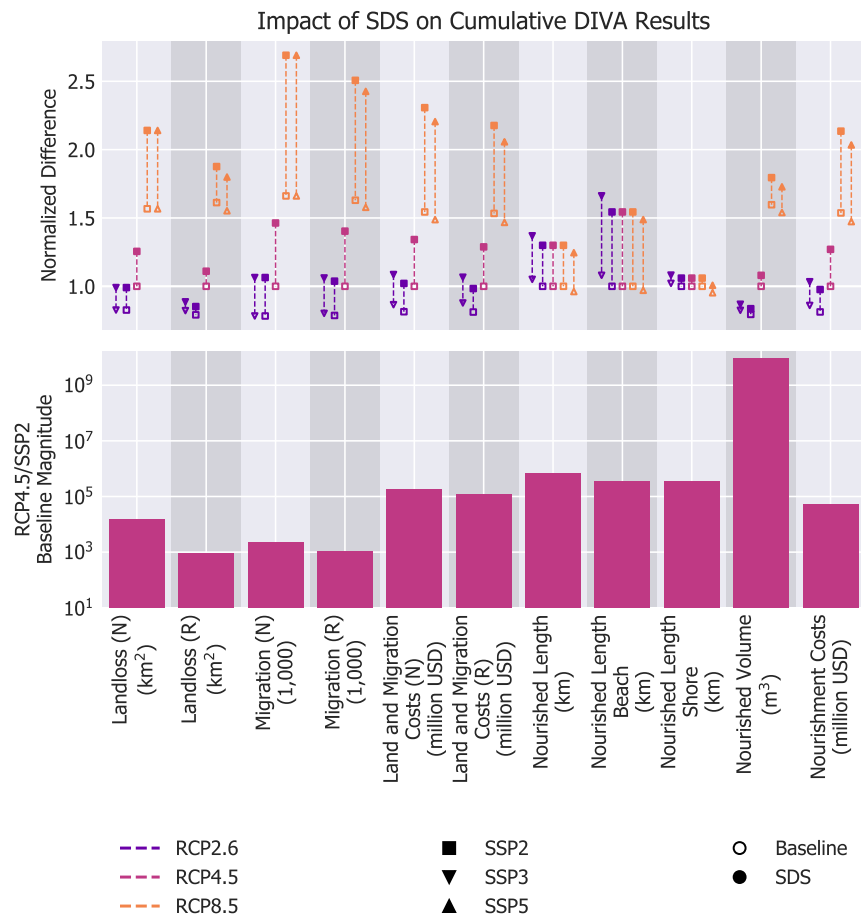


Figure 2.3: This figure demonstrates the cumulative impact of CBC information from the GSCD database on key DIVA projections for the 21st Century normalized to the baseline RCP4.5/SSP2 scenario. (N) - No adaptation by means of beach nourishment. (R) - Reduction of impacts through the application of beach nourishment.

8.0% when applied to the original data yet rises 3.4% when applied to the GSCD data. The NCM still reduces the total nourished length using the GSCD data as anticipated, albeit at a lower rate than with the original dataset. Similarly, investment in nourishment and the length of nourished beach are 67 and 31% higher than anticipated by superposition across all RCP scenarios. One explanation for this compounding effect is the inclusion of countries segments bereft of sandy beach within the original dataset. DIVA interprets these “non-erosive” segments with no associated impacts. The GSCD resolves many segments with beach where none existed before, and these newly resolved segments are more favorably impacted by the cost model. It follows, then, that both changes exhibit a strongly regional effect on the model 2.6. Lebanon is a prime example of this behaviour.

2.3.4. Unmitigated Effects

Since the cost model restricts its effects to mitigated scenarios, the unmitigated impacts of SLR remain identical to those discussed for the GSCD information. Loss of land from 147 to 539 km² and forced migration between 28 and 106 thousand displaced persons per annum (RCP 2.6-8.5). Cumulative totals for these items range between 12,767 and 29,494 km² and 2.2 and 5.9 million persons without intervention (RCP 2.6-8.5).

2.3.5. Mitigated Loss of Land

The new cost model on its own has a relatively small impact on the primary outputs of the DIVA model, but a much larger impact on economic projections. adaptation by means of beach nourishment is economically feasible to reduce the cumulative loss of land by approximately 6% or between 745 and 1,625 km². Prioritization of valuable land plays a major role in the decision to protect that land. As such, nourishment mitigates economic costs at a much higher rate than loss of land itself by between 36 and 33% across RCP scenarios 2.6 and 8.5. The scalar quantity of this reduction is highly dependant on the rate of sea level rise, and increases substantially with environmental sensitivity and time, however this variability does not extend to the length of coast nourished. in 2100, projections indicate that reduction decreases the scale of total annual economic impacts from a ranges between 2.6 and 6.4 to 0.6 and 2.1 million USD (RCP 2.6-8.5).

2.3.6. Mitigated Forced Migration

Of the impacts considered in the DIVA module, forced migration is associated with the highest economic densities per area of land loss, meaning that the cost-benefit analysis more often opts to protect areas vulnerable to forced migration than other impacts. Perfect adaptation

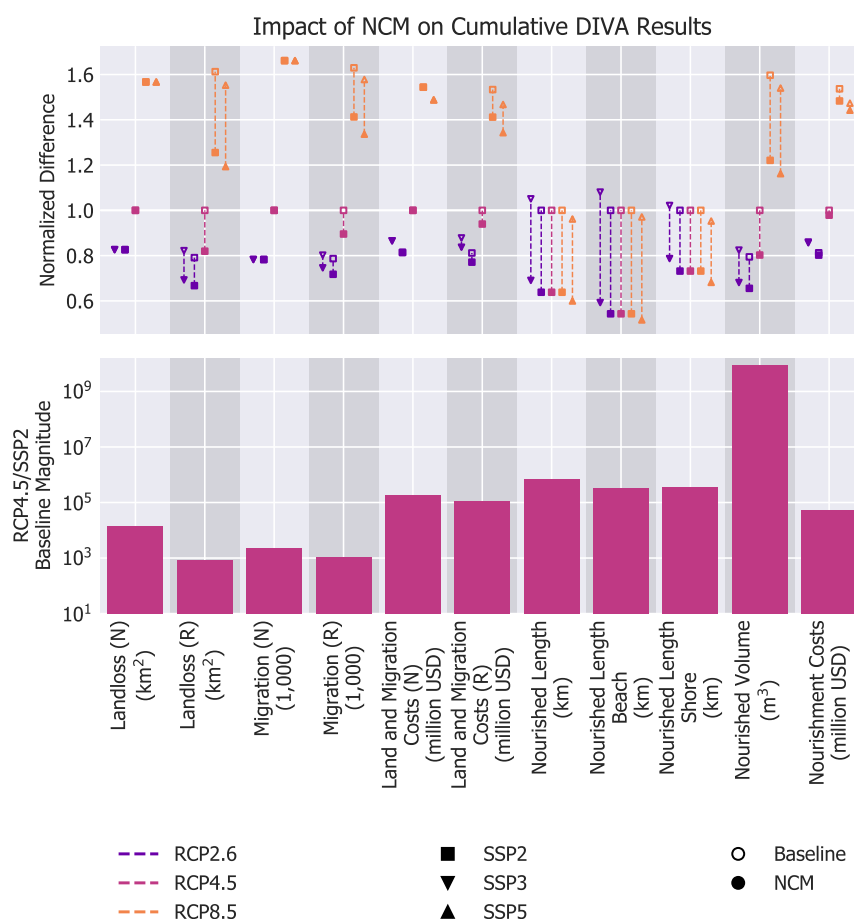


Figure 2.4: This figure demonstrates the impact of the NCM from the GSCD database on key cumulative DIVA projections over the course of the 21st century normalized to the baseline RCP4.5/SSP2 scenario. (N) - No adaptation by means of beach nourishment. (R) - Reduction of impacts through the application of beach nourishment.

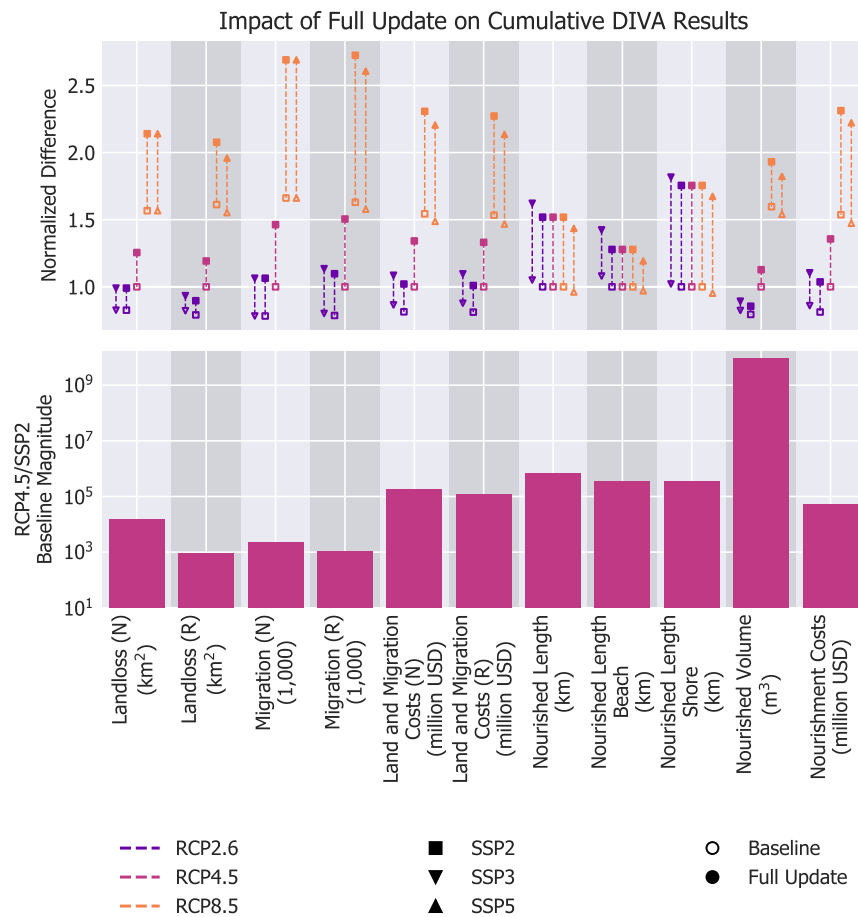


Figure 2.5: Demonstrates the impact of the combined GSCD and NCM information on key cumulative DIVA projections over the course of the 21st century normalized to the baseline RCP4.5/SSP2 scenario. (N) - No adaptation by means of beach nourishment. (R) - Reduction of impacts through the application of beach nourishment.

by nourishment reduces forced migration impacts by between 46 and 60% which corresponds to a scalar reduction of 16.5 to 49.2 thousand displaced persons per year or 2.0 to 4.6 billion from a baseline of 2.5 to 6.7 billion USD annually (RCP 2.6-8.5).

2.3.7. National Effects

National-scale variations in the GSCD CBC cause significant differences in the distribution of vulnerability when compared to the deprecated DIVA E_f . Here, we compare results on the basis of information normalized to coast length and GDP. Figure 2.7 and 2.8 identify the intensity and relative adaptation capacity and adaptation intensity for the ten countries with the most significant deviations in either direction from the new information. The majority of the administrations most affected by the changes are identified as beach-deprived using DIVA's E_f information, but contain moderate or high amounts of beach from GSCD information.

A general overview of the results indicates that the United States sees the highest scalar impacts, owing to the size of its coastline and strength of its economy. However, the United States also sees the largest scalar reduction in the economic effectiveness of beach nourishment given changes to the DIVA model. Observations across several categories show that the updates cause the most significant impacts for island administrations. The most affected

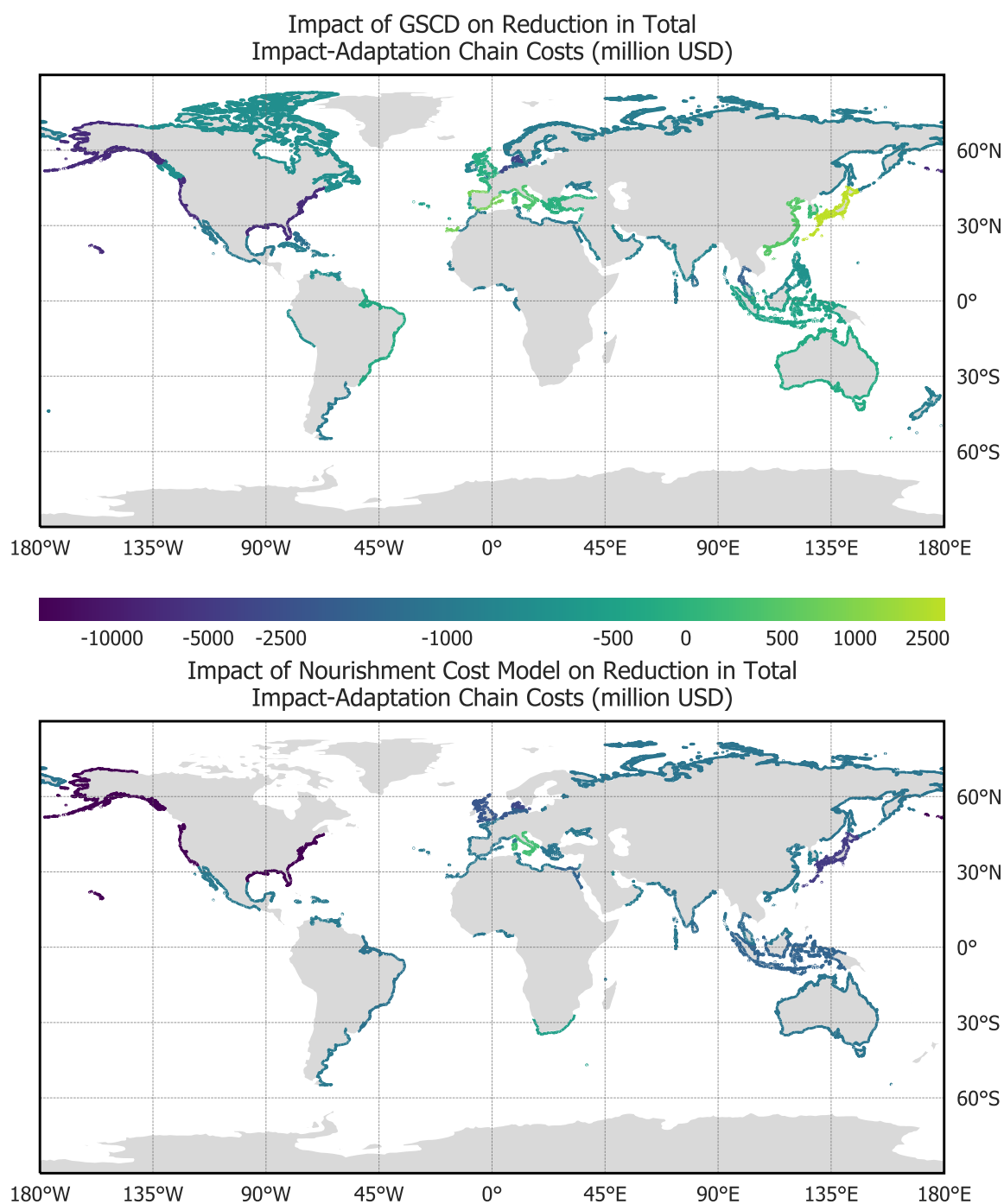


Figure 2.6: Demonstrates the impact of the combined GSCD and NCM information on aggregated land and forced migration costs over the course of the 21st century in the baseline RCP4.5/SSP2 scenario. countries with no color show no modelled changes to impact pathways with new information

by the new model are the Northern Mariana Islands, Barbados, and Malta, in terms of ability to cope with the costs of SLR (Figure 2.10) and Singapore, Macau, and Malta in terms of length-normalized impacts (Figure 2.11). We further identify the countries with the greatest accumulated impacts in the beach nourishment impact-adaptation chain in figure 2.9. Of these countries see substantial increases of cost owing newly identified beaches within the DIVA framework. Of particular note, Singapore appears in this list due to substantial beach detection by remote sensing, which we posit to be the result of the presence of sand at current large-scale nourishment sites. This identified “beach” is subsequently subject to large nourishment costs due to the high value of the associated land and calibration within the NCM.

Existing economically dense areas such as the US, northern Europe, China, and Japan are most impacted in terms of the economic implications from beach-erosion owing to a combination of high population densities and high economic productivity. Small island states likewise show the largest portion of their GDP impacted by beach-erosion. Typically, these percentages are many times larger than their mainland counterparts. All but one of the 20 most vulnerable countries to beach erosion are island states or overseas departments.

2.4. Discussion

Building upon the results of the global erosion assessment by Hinkel *et al.* (2013), new information developed with respect to coastal beach content and nourishment costs has a significant impact on global projections for SLR-induced beach erosion, and the effectiveness of nourishment adaptation.

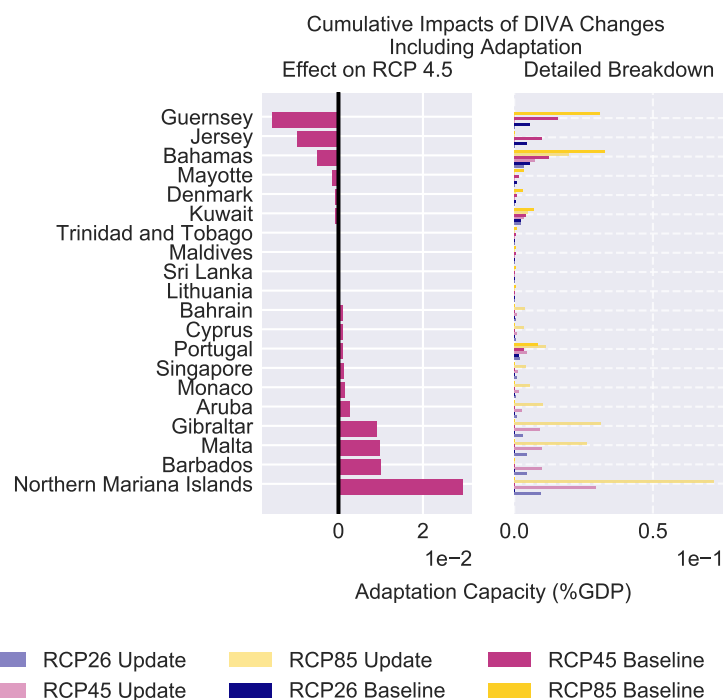


Figure 2.7: Isolates the impact of DIVA updates on the projected capacity of nations to adapt to SLR compares beach nourishment, forced migration, and land loss costs normalized to GDP. These figures include cost of lost land, cost of forced migration, and beach nourishment expenditure where applicable. (R) Displays the scale of impact of 10 countries showing the most change in either direction for the RCP 4.5 scenario. (L) Breakdown of impacts of SLR by country across each scenario.

RCP 2.6 / SSP5 Information	Land Loss (km ²)		Forced Migration (thousands)		Land Loss Cost (million USD)		Migration Cost (million USD)		Protected Length (km)	Nourishment Cost (million USD)
	N	R	N	R	N	R	N	R		
Baseline	10684	655	1606	789	4392	1636	134987	98148	3740	42753
SDS Impact	19%	8%	37%	33%	18%	14%	27%	22%	54%	21%
Cost Model Impact	0%	-16%	0%	-7%	0%	-11%	0%	-4%	-45%	-1%
Combined Impact	19%	14%	37%	42%	18%	15%	27%	25%	34%	28%
Final Run	12767	745	2202	1124	5187	1887	171117	123048	4996	54713

RCP 4.5 / SSP2 Information	Land Loss (km ²)		Forced Migration (thousands)		Land Loss Cost (million USD)		Migration Cost (million USD)		Protected Length (km)	Nourishment Cost (million USD)
	N	R	N	R	N	R	N	R		
Baseline	13222	814	2106	1007	4976	1789	159621	114812	3437	50569
SDS Impact	26%	11%	48%	41%	26%	19%	36%	29%	55%	28%
Cost Model Impact	0%	-19%	0%	-11%	0%	-12%	0%	-6%	-45%	-3%
Combined Impact	26%	19%	48%	51%	26%	24%	36%	33%	29%	36%
Final Run	16634	970	3124	1525	6249	2211	216859	153117	4447	68539

RCP 8.5 / SSP 3 Information	Land Loss (km ²)		Forced Migration (thousands)		Land Loss Cost (million USD)		Migration Cost (million USD)		Protected Length (km)	Nourishment Cost (million USD)
	N	R	N	R	N	R	N	R		
Baseline	21418	1283	3622	1620	7328	2457	243481	172485	3327	75631
SDS Impact	38%	16%	64%	55%	38%	29%	50%	41%	54%	39%
Cost Model Impact	0%	-24%	0%	-16%	0%	-16%	0%	-8%	-46%	-3%
Combined Impact	38%	27%	64%	67%	38%	37%	50%	46%	24%	52%
Final Run	29494	1625	5947	2699	10135	3364	366433	252006	4125	114675

Table 2.3: Summary of the impacts of GSCD and cost model changes with respect to 5 DIVA output categories. Adaptation follows the DIVA CBA methodology.

The new volumetric NCM is a formative step intended to provide a reasonable first estimate at multi-decadal nourishment costs with a global scope. The application of a data-driven fitting process to better-fit this model is a vital next-step to provide a more robust analysis of nourishment costs. Additional work could include analysis to determine the impacts of increasing nourishment costs on the decadal and regional patterns of nourishment practices (e.g. 2.12). Under this model, nourishment prices rise in this new model from 196 325\$ per metre of coastline nourished. The effect of this 66% price increase on the total length of nourishment-protected shore is on the order of 40%. Further, we note that the actual price paid for nourishment remains relatively constant, with the associated length of shore dropping to offset the difference.

Many of the largest observed changes are observed where DIVA previously assumed a coast deprived of beaches. This change allows more land to be eroded than identified in previous reports. By increasing the Coastal Beach Content by 72%, we model a greater contact-area between environmental forcing on littoral systems and society. The inclusion of this information has immediate implications for previously neglected countries, and increases the length of coastline suitable for nourishment as an adaptation strategy.

As noted in Section 2.3, the regional interactions of the NCM override pure superposition when applying these models together. Figure 2.6 qualitatively elaborates the reasons for this difference. As an example, the United States under the NCM sees an increase in nourishment prices, which decreases the observed benefits in that scenario. The GSCD information reduces the total length of sandy beach in the United States, and so reduces both the total projected impacts of SLR and the benefits of adaptation. When these two patterns combine the result is a higher nourishment cost for a smaller length of beach. While the benefits of nourishment

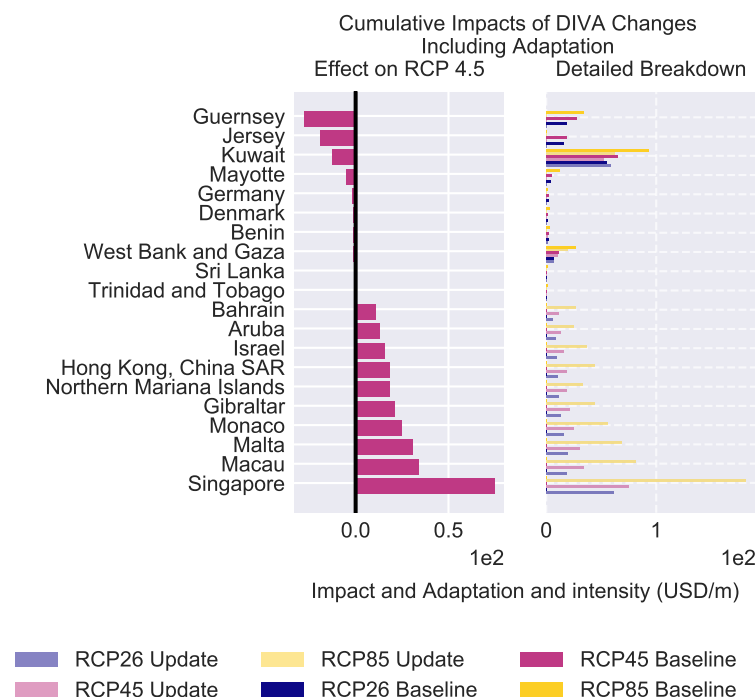


Figure 2.8: Isolates impact of new information on projected intensity of SLR adaptation stress resolves beach nourishment, forced migration, and land loss for national administrations normalized to coastline length. (R) Displays the scale of impact of 10 countries showing the most change in either direction for the RCP 4.5 scenario. (L) Breakdown of impacts of SLR by country across each scenario.

still drop in this area, the drop will not be as significant. In contrast, a location such as Italy where both changes projection more favorable nourishment conditions encounters a much greater theoretical application of nourishment. These regional variations in the effect of these two improvements highlights important effects at national levels for future elaboration.

This study reaffirms conclusions by [Hinkel *et al.* \(2013\)](#) that many small-island states are among the least capable to pay for the consequences and adaptation associated with SLR-induced erosion. Some small island states within the DIVA model, however, are not covered by the existing GSCD information system. Given their predisposition to be vulnerable, future iterations of the GSCD should aim to prioritize these locations. The drivers for this vulnerability stem from small economies and low per-capita GDP in conjunction with moderate sand availability. However, other impact-adaptation pathways are also likely to play a large role in these small economies. Land submergence and saline intrusion may also form large contributions to the overall vulnerability of these states.

At a global scale, the results of this study demonstrate the order of magnitude of influences that environmental and social factors contribute towards SLR-induced beach erosion. Where the environmental stressors have significant impacts on the overall expression of SLR-induced beach erosion in terms of land loss and forced migration. When comparing impacts across RCP scenarios, we note that relative to increases in radiative forcing, primary and secondary

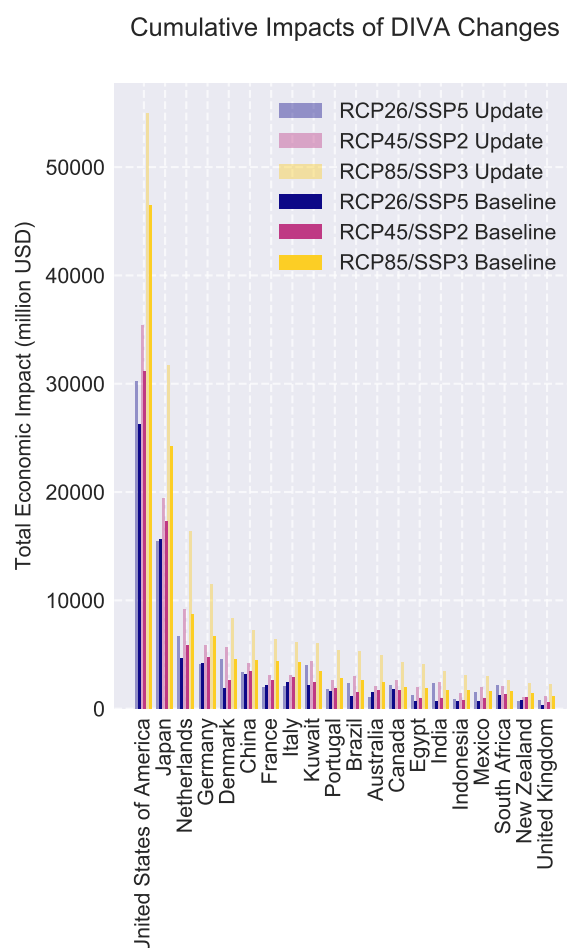


Figure 2.9: The magnitude of SLR adaptation stress is presented by resolving coastal nourishment, forced migration, and land loss at a national level.

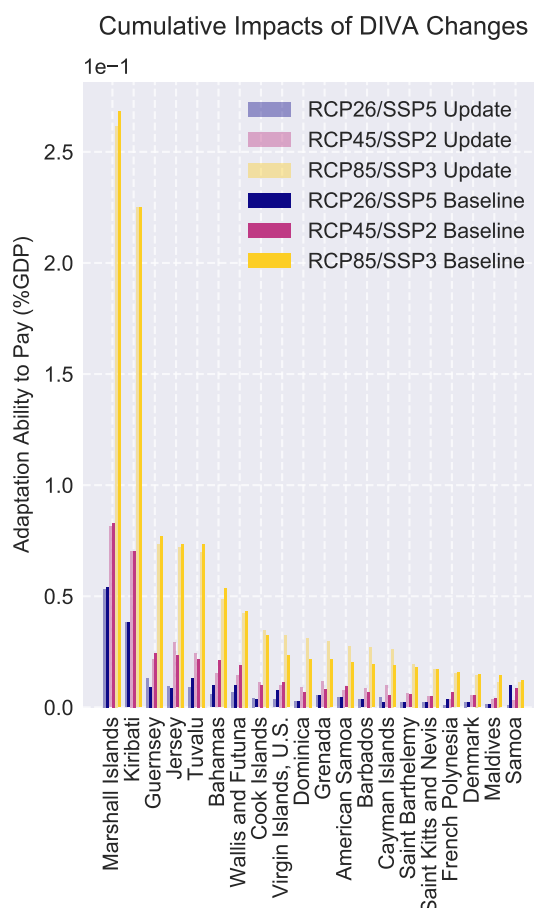


Figure 2.10: This figure demonstrates the baseline and new capacity of each country to adapt to climate change by expressing coastal nourishment, forced migration, and loss of land as a portion of the available GDP across three marker scenarios. Sorted by the 20 countries with the largest relative adaptation and impact costs

impacts from SLR-induced beach erosion rise at a lower rate between RCP 2.6 and 4.5 than between 4.5 and 8.5. However, this is representative of only a single forcing scenario. Future studies investigating the prevalence of this trend across climate models could follow the methodology presented in [Hinkel *et al.* \(2014\)](#).

DIVA's decision whether or not to nourish as a response to SLR has no direct or second order relation within DIVA to SLR or the rate of erosion. The model either opts to nourish and protect the land, or pay the social costs to abandon the land, irrespective of the rate of land loss. To some degree, these observations are echoed by real-world observations of administrative action in the Netherlands and Singapore with respect to beach nourishment and land reclamation. This information is useful because it provides planning information specific to the nourishment impact-adaptation pathway that can be de-coupled from the lack of local sediment transport information in the DIVA model (Figure 2.12). The main contributions of the physical model to the suitability of nourishment are the presence of beaches and the change in temperature used in the tourism model rather than SLR ([Hamilton *et al.*, 2005a](#)).

Given this information, we observe that a majority of the locations where nourishment is anticipated to be an effective response for SLR-induced beach erosion are already suitable for protection. Further, while DIVA does not have explicit information on local sediment conditions and there cannot truly predict if nourishment will be vital in a region. The GSCD information

that we apply in this paper does have historic trends. We compare these two datasets in Figure 2.13.

While not deterministic, these results are indicative of potential patterns in shore nourishment. Given a suitable sediment supply, the long-term protection of these properties is projected to be economical under any SLR scenario, including those driven by local transportation gradients. A substantial next step would be the development of a conceptual model to investigate the impacts of increasing sediment scarcity by developing the long-term temporal factor in the nourishment model to increase over time.

2.5. Conclusion

This paper demonstrates scale-of-impacts from advances in state-of-the-art expertise and global high resolution datasets on large-scale SLR vulnerability modelling. We provide a meaningful update to [Hinkel et al. \(2013\)](#) projections including new methodologies from [Hinkel et al. \(2014\)](#), and [Wolff et al. \(2016\)](#) to investigate global SLR-induced coastal erosion. Further, satellite-derived beach identification from [Luijendijk et al. \(2018\)](#), and integrated dredging industry knowledge contribute to develop a responsive model for long term beach nourishment costs within the DIVA segmentation.

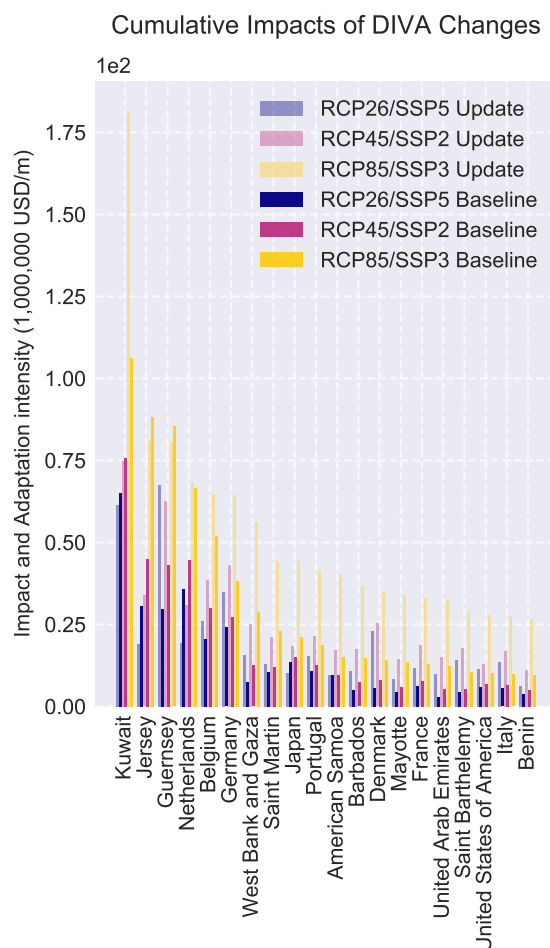


Figure 2.11: This figure demonstrates the baseline and new intensity of SLR adaptation by resolving coastal nourishment, forced migration, and loss of land per unit of coastline length across the three marker scenarios. Sorted by the 20 countries with the most intensive adaptation and impact costs

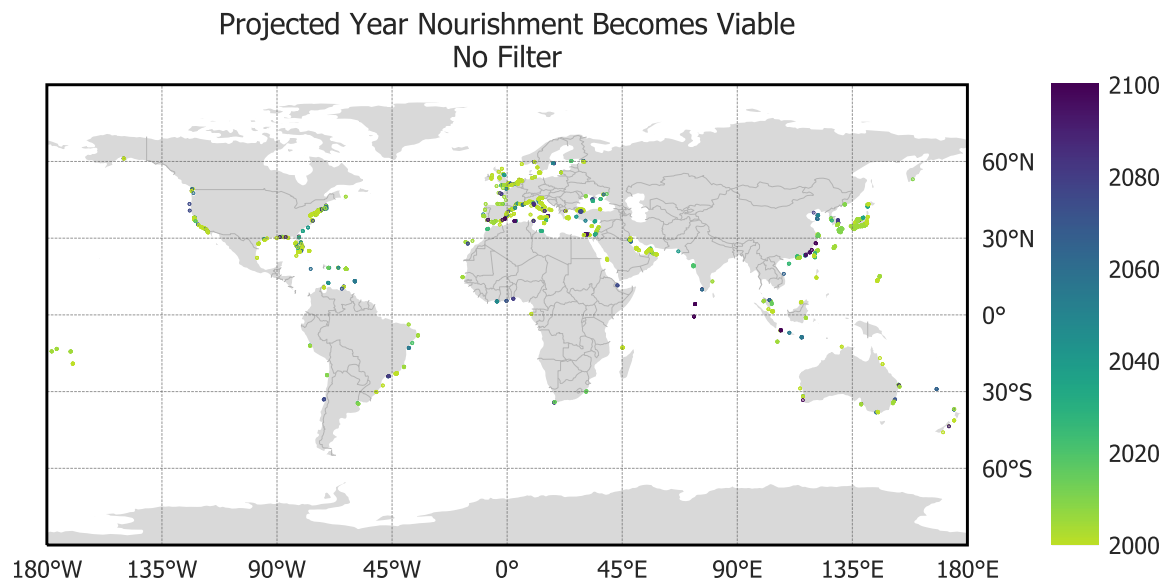


Figure 2.12: This figure outlines the year in which DIVA's Costing and Adaptation Module predicts segments become suitable targets for nourishment based on socioeconomic models. The CBA applied here balances the impacts discussed above and projected local tourism revenue using the Hamburg model. The only physical requirement considered in the selection of these sites is a CBC greater than 0

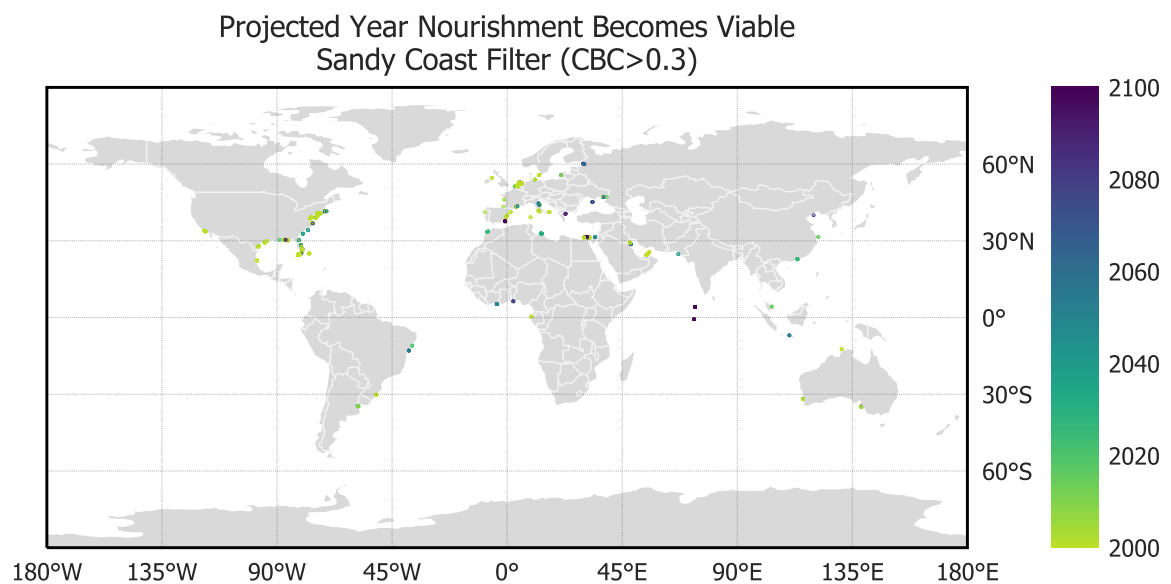


Figure 2.13: This figure outlines further resolves Figure 2.12, applying a filter which isolates segments that have a CBC greater than 3. It identifies sandy locations which will become sufficiently valuable to encourage nourishment before 2100

The inclusion of GSCD information increases DIVA's global coastal beach content from 16% to 28%, which has a direct effect on global projections and regional variations for SLR-induced beach erosion impacts. Without considering adaptation, GSCD information changes annual land-loss projections from 122 to 147, 170 to 234, and 368 to 539 km² in 2100 across RCP 2.6, 4.5, and 8.5 Scenarios respectively. Similarly, unmitigated land loss and forced migration costs in the RCP 4.5 scenario increase from 72 to 91 and 2418 to 3417 million USD per year respectively. Economically-justified adaptation reduces the size of these impacts at approximately the same relative rate with or without the GSCD data. When aggregated globally, the relative change as a percentage of the baseline is approximately 71% across all studied RCP Scenarios.

The new beach NCM adds a layer of complexity to the DIVA Model by incorporating social, environmental and economic factors likely to affect costs. This implementation improves the understanding of projected adaptation investment in developing countries. However, the global scale of the impact is smaller than that of the GSCD. After basic qualitative fitting to a small number of data points, the predictive model showed a length-normalized global nourishment price in its base year of 325\$ per nourished metre of coastline globally, which exceeds old estimates of 194. When applied to the DIVA CBA module, these prices reduce land-loss protected from beach erosion from 11.7 to 9.8 km² in the RCP 4.5 scenario. The projected monetary impacts scale approximately to the adaptation challenges faced in each scenario and the overall trend corresponds to a 5% decrease in relative beach erosion. The primary factor driving land protection against these costs is forced migration, which accounts for 97% of the protected economic impacts.

Together, the GSCD and NCM information worsen globally aggregated economic SLR-induced beach erosion projections by approximately 41%. In the RCP 4.5 scenario, our results show increases in projected land-loss from 170 to 234 km², land-loss costs from 71 to 91 million US dollars per year, forced migration from 29 to 44 thousands per year, and forced migration costs from 2.4 to 3.4 billion dollars per year. The projected adaptation of these impacts by beach nourishment increases from our baseline information under the changes presented here. Applying beach nourishment as part of DIVA's cost-benefit-analysis reduces the scale and variability of cumulative economic impacts from SLR-induced beach erosion. The largest observed economic impact of beach nourishment reduces the scale of forced migration costs from 3.4 to 2.5 billion \$/year. The reduction in land loss, conversely, has a smaller impact on the decision to nourish and follows a trend from 234 to 220 km² per year in 2100. the greatest scalar changes observed in the year 2100 occur in China, the United States, and Italy.

We find significant changes to the spatial distribution of sea level rise impacts between the baseline information and the redeveloped DIVA results. These changes are due to the many locations in the deprecated DIVA methodology which expressed no beaches. If these areas are densely populated with a high level of economic activity, the effects of the new DIVA information on projections is large. This underlines the need for ongoing development of the accuracy and validation of the physical information in the DIVA framework.

Future development of the DIVA platform will refine the results of global vulnerability analysis and frame the scientific consensus regarding potential impacts of SLR on coastal communities. The information presented here substantially sharpens the resolution of coastal information within the DIVA model used to determine SLR-induced beach erosion. The erosion model was further improved to include extended validation of the GSCD beach identification algorithm; data-driven structured development of the DIVA NCM; implementation of better-resolved tourism models; and isolation of shoreface slope parameters for the Bruun rule from measured data. Outside of beach erosion, previous studies suggest improving data resolution

for tidal basins and coastal elevation models to resolve the land-loss and forced migration projections in the DIVA model.

Key Points

1. By integrating the Delft Satellite-Derived Shoreline into the Dynamic Interactive Vulnerability Analysis platform, we demonstrate a % increase in the global economic consequences of SLR-induced beach erosion over the 21st Century.
2. A new localized cost-model for coastal nourishment practices, which incorporates environmental and social risk factors into a variable unit cost, resulting in a 21% increase in the global economic consequences of SLR-induced beach erosion.
3. Together, these changes combine for a 69% increase in projections for global economic consequences of SLR-induced beach erosion.
4. The countries most affected by these changes are ones that were identified previously as beach-deprived.
5. DIVA projects the countries most affected by SLR-induced beach erosion are economically-dense areas with high beach contents including the Jersey, Guernsey, and Belgium.
6. The countries least able to cope with or mitigate SLR are small island states including the Marshal Islands, Kiribati, and Saint Martin.
7. The use of the nourishment cost and socioeconomic models allow for secondary study of beach nourishment practices, including an approximation of the year nourishment becomes a viable protection measure for each coastal segment.

3

Discussion

Chapter Summary

This chapter discusses in detail the results of Section 2, which have lasting implications for the continued development of the DIVA erosion module. Future adaptation of the connection between the GSCD and DIVA databases has the potential to provide continuing benefits from the work presented here.

DIVA information developed in “New Developments in Global Coastal Erosion Assessment” provides unique projections with respect to beach erosion. The combination of socioeconomic and environmental models reveals information about idealized administrative behaviour which may illustrate future development in beach nourishment markets. Sensitivity analysis of the NCM and DIVA to the baseline set-price show a greater nourishment volume sensitivity to reduced nourishment prices than to movement in the other direction. The nature of the NCM could also be expanded within the DIVA framework to resolve adaptation costs in other branches of the DIVA program. The inability of the DIVA model to replicate the results of [Hinkel et al. \(2013\)](#) is a major drawback to the development of this thesis. Before publication of any results, the discrepancy between the current and deprecated model must be resolved or explained.

The scope of the DIVA package imposes further limitations on the results presented here. Large-scale validation is costly and difficult for the GSCD, and unlikely for DIVA. By ignoring process-based development through the Bruun Rule and use of ASMITA, DIVA is generally incapable of modelling morphodynamic feedback loops and mechanisms. A chronic lack of data in the coastal zone makes localization of the model outputs difficult. Finally, the nourishment cost model presented here must be optimized and validated to confirm its results and provide multifactoral sensitivity analysis.

3.1. Overview

In “New Developments in Global Coastal Erosion Assessment”, we manifest the detailed observations of the GSCD dataset within global beach erosion projections. These include a comparison of the severity of SLR-induced beach erosion with and without the application of beach nourishment. The results of this study improve the existing DIVA database at a relatively low cost given the scale of the data. This owes to the extensive availability of GSCD information and harnessed power of cloud-based geo-processing in GEE. Where previous studies have relied upon approximation through expert opinion or classification based on low-resolution data, this study is the first to incorporate the significantly improved detail of the GSCD model at a global level.

The future of the DIVA model lies in an integrated resolution of model information to improve model application at regional and finer resolutions. In parallel to work developing resolved segmentation procedures presented by in [Wolff *et al.* \(2018\)](#), our work begins to address the data scarcity needed to develop the DIVA model beyond its current capabilities.

3.2. DIVA

The DIVA model interfaces between a number of modelled scales which together allow the projection of environmental impacts and administrative behaviour beyond the scale and scope of traditional models. In this interface, a number of “external” global and national scale models identify social and economic growth in conjunction with SLR. DIVA is effectively a framework built upon these models which indicates SLR-induced beach erosion using a particular set of inputs. DIVA is therefore appropriate to predict the interactions between these external models on a limited set of physical interactions at large scales.

3.2.1. Scale

The scale and ambition of both the GSCD database and DIVA are part of a shift in scientific capability to extract information on changes affecting the entire planet. However, the issues associated with most aggregate-scale models similarly apply to the DIVA model used here. At these scales, scientists face simultaneous challenges integrating an excess of processes on one hand, and a chronic dearth of supporting information on the other. This pattern of information scarcity is similarly repeated in the socioeconomic models and the new nourishment cost model. While no silver bullet exists for these issues, studies such as this one will, over time, identify processes and develop information to improve upon this limitation.

3.2.2. Signal Strength

Where scientific consensus indicates that SLR will have an impact on beach erosion, at a local level sediment-balances have a much larger effect ([Ranasinghe *et al.*, 2013](#)). The relative strength of the background SLR signal compared to local noise means that validation of the DIVA model is, at the very least, a significant challenge. Distinguishing SLR-induced beach erosion from the shoreline position signal using the SDS database is an ongoing research topic at TU Delft ([Luijendijk *et al.*, 2018](#)), however some studies have suggested that the signal may not even be detectable under mild climate change scenarios ([Le Cozannet *et al.*, 2016](#)). Interference from human development and coastal protection also make this signal much harder to identify.

3.2.3. Nourishment Driving Rationale

DIVA is developed to respond to mitigation demands using nourishment under a pre-defined set of population, gdp, and tourism conditions. While these are suitable for most locations

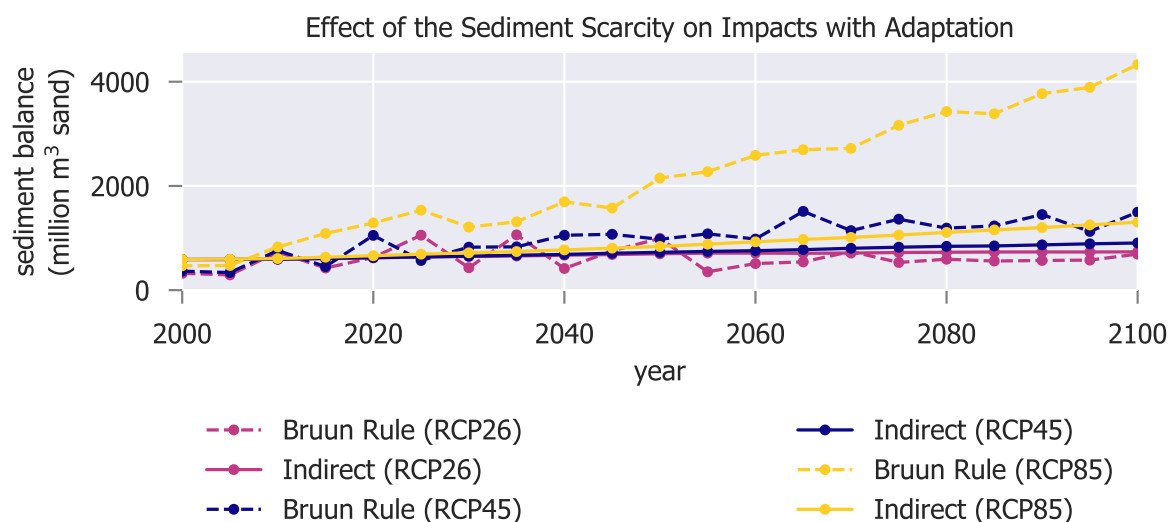


Figure 3.1: Comparison of the sediment demand from direct sea level rise, and from Tidal basins.

globally, they do not cover locations of high economic productivity such as ports or regions where nourishment is indicative of flood defense efforts such as the Netherlands. This effectively reduces the observed impacts of beach erosion below what they would be in a perfect simulation.

3.2.4. Aggregate Models

The approach carried out here is limited by the native aggregated physical models used to predict beach erosion in DIVA. these models are driven by RSLR rates, CBC information, tidal basins, uplift, beach slope, tidal range, and wave climate. Of these, tidal basins and beach slope are the least-defined at the present time. Further, the DIVA segmentation does not take into account longshore transport between coastal cells.

Coastal Erosion (Bruun Rule) The use of the Bruun Rule by the DIVA package limits computations by the program by detaching segment-level land loss from long-term sediment deprivation through longshore transport or into unidentified tidal basins. The Bruun Rule is divisive within the scientific community in this context (Stive, 2004). While some highlight it's indifference to important physical properties including sediment size, and wave conditions (Ranasinghe *et al.*, 2013; Cooper and Pilkey, 2004), others highlight the lack of apparent successor and relatively simple application across a range of categories (Zhang *et al.*, 2004). However, the basic parametrization of the Bruun Rule is likely to remain in any replacement (Ranasinghe *et al.*, 2013; Brunel and Sabatier, 2007). DIVA further simplifies the Bruun Rule, assuming a constant beach slope across all segments due to a scarcity of beach profile information.

Tidal Basins (ASMITA) While tidal basins were not explicitly part of our improvements to the DIVA model, the groundwork included a debugging phase which touched on the operation of DIVA's indirect erosion module and it's treatment of tidal basins. We do not explicitly discriminate coastal erosion due to tidal basins since no process changes were made (Figure 3.1), yet they comprise a large portion of the global sediment balance affecting the coastal zone. Hinkel *et al.* (2013) identifies that tidal inlets account for 70 percent of the total coastal mass balance.

Tidal basins within DIVA influence only single coastline segments, and therefore the decision to address the costs of nourishing those segments is dependant entirely on segment selection and its socioeconomic capacity. Given the relative size of the tidal basins within DIVA can be many times that of a segment, addressing the regional impacts of these basins could significantly alter the total volume of nourishment in developed areas. Many DIVA segments also sit within these larger tidal basins, such as the Wadden Sea in the Netherlands and DIVA does not address the implications of these inner-basin segments.

DIVA's generalized version of ASMITA assumes a consistent global dynamic equilibrium and does not consider river inflow or tidal asymmetry. Though only the 200 largest are present in DIVA, even smaller basins may have significant impacts on local coasts. Given the large implication of the 200 tidal basins covered in the DIVA model, there is a high likelihood of significant future improvements to the physical model though the examination of the indirect erosion module.

3.2.5. Baseline

Changes to the DIVA model over the past 5 years and the deprecation of key input information have had a significant and unresolved impact on DIVA erosion module results. as such, the baseline presented in "New Developments in Global Coastal Erosion Assessment" needs to be updated before publication is feasible. A comparison of results for scenario A1B is shown in Figure 3.2, which demonstrates that in it's current form, DIVA cannot replicate the results for loss of land or its derivatives. Global GDP returned in existing results is larger than in [Hinkel et al. \(2013\)](#) by a factor of approximately 3. However, annual migration and land loss costs are approximately 50% of [2013](#). Migration costs rely on both of these factors, compounding the issue. Final output information in this category is just 5% of those identified in [Hinkel et al. \(2013\)](#). Given the information available in the existing DIVA outputs, we have developed a list of potential bug-fixes which are currently under investigation:

- Adaptation measures are only applied in 2005, despite the model initializing in 1995.
- National-level GDP growth may have a discrepancy between the input information and the source code with respect to annual or 5-year growth rates.
- There may be an issue where previous versions of the model used a larger coastal zone to determine the population and GDP affected by SLR-induced beach erosion.
- There may be a final bug translating national GDP and population to the coastal zone, which is reducing coastal GDP significantly more than in past runs.

As this thesis also represents an extensive first validation of the new DIVA source code for erosion and indirect erosion. The uncovered issues are therefore under investigation and expected to be resolved in the next few months. despite this, time constraints necessitate submission and this thesis must exist outside of the stability of the greater DIVA model.

By reconstructing the deprecated input information in terms of global SLR, population, and land loss we estimate the gross economic significance of these changes to be 6 times larger than the current output. In response, we minimize the reporting of scalar quantities in this work, there is a distinct focus on relative changes to the DIVA outputs. The analysis in Figure 3.2 suggests that the current results of the model are relatively stable with respect to changes in the erosion/adaptation module. It is plausible to believe that these relative (i.e. percent difference) results will approximate new results valid once the issues in the DIVA source code

have been rectified, but in reality the likelihood is low given the large effect-interaction observed in the model. A review of the source code suggests that issues lie in a module outside of those considered here. However, due to the nature of programming errors there is no guarantee that this is the case, despite the best efforts of the authors.

Identification of the source of the discrepancy between the old DIVA results and new ones, and review of the suitability of the conclusions of this report should preclude any scientific publication of the information in Section 2.

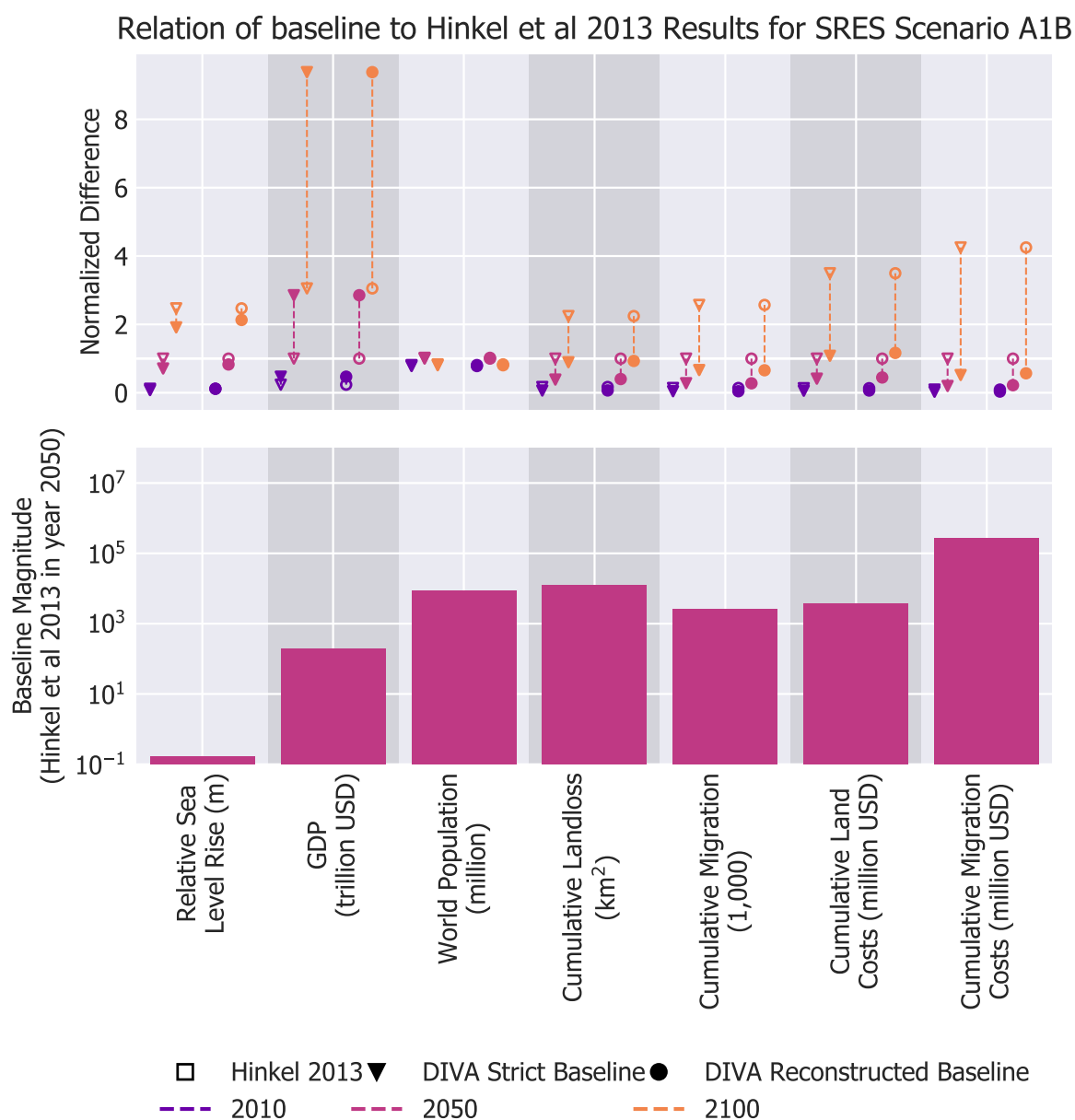


Figure 3.2: Comparison between (3) results from [Hinkel et al. \(2013\)](#), (2) DIVA baseline with reconstructed input information, and (1) reconstructed DIVA baseline with new input information across multiple outputs.

3.3. GSCD Aggregation

The new GSCD information provided to the DIVA model identifies a substantial number of countries affected by the deprecation of the old erosion matrix information. Where the matrix characterizes a large portion of the DIVA segments as non-erosive, the new GSCD information resolves beaches in these areas. A substantial number of countries see this effect, and all of the 20 most-impacted countries by this thesis foresaw no impacts due to SLR-induced beach erosion in the [Hinkel *et al.* \(2013\)](#) study. The capacity to project impacts in these countries is a substantial improvement in the resolution of SLR-induced beach erosion assessment.

3.3.1. Connection Validation

The connection between the DIVA and GSCD datasets is an exercises in data-management rather than a one-to-one relation. By using nearest-point sorting procedures, the connection is therefore vulnerable to a number of issues in it's current iteration. These include cross-connection of GSCD information, non-attribution of SDS points, and unconnected DIVA segmentation. Validation of the connection is also an issue because no prototype of the perfect connection exists and even the physical definition of the coastline can be difficult to interpret.

Our comparison of the efficacy of the sorting algorithm to manual connection develops a validation set which may be used to judge the transformation efficiency of information passing from the GSCD transect system to the DIVA database. The accuracy of this connection for the GSCD data, discussed in Section 2, shows a good correlation between manual and algorithmic connection practices.

When repeated for information included in the SDS database, which shares the same transect system as the GSCD, the connection shows a similarly low bias, but less accuracy (Figure 3.3). Developing a coastline entity within DIVA which better approximates the GSCD transect system will remove these points and improve the connection between the data-sets. However, if this shift is performed in conjunction with a resolution of the DIVA segmentation, there may be implications for the relative number of SDS points available to inform each DIVA segment.

3.3.2. GSCD Validation

The authors of this report noted some locations where the beach-detection methodology presented by the GSCD may not reliably represent the CBC used in this paper (Figures 3.4, 3.5). While these locations have been tagged as beach, visual inspection suggests this not to be the case. However, the use of the SDS dataset still addresses the scaling issues associated with the DIVA model to a higher degree than anything yet available. Therefore, several recommendations for additional validation procedures are included in Section 4. These variances, however, generally occur away from densely-inhabited populations and so are not likely to impact adaptation measures.

3.4. Nourishment Cost Model

The global-scale NCM presented here is, to our knowledge, the first academic attempt to resolve these costs at a global scale. The model provides better resolution of nourishment costs globally than existing bulk figures. The structure of the model may also be suitable to project cost information for other adaptation measures where the availability of a primary resource is a key risk factor. However, this model again suffers from the same general scarcity of baseline information.

We attempt in this paper to tie the nourishment cost model to scientific literature. However, in reality the equation is more a reflection of professional judgment and experience in the dredging industry than an applied macroeconomic formula. No public database of historical

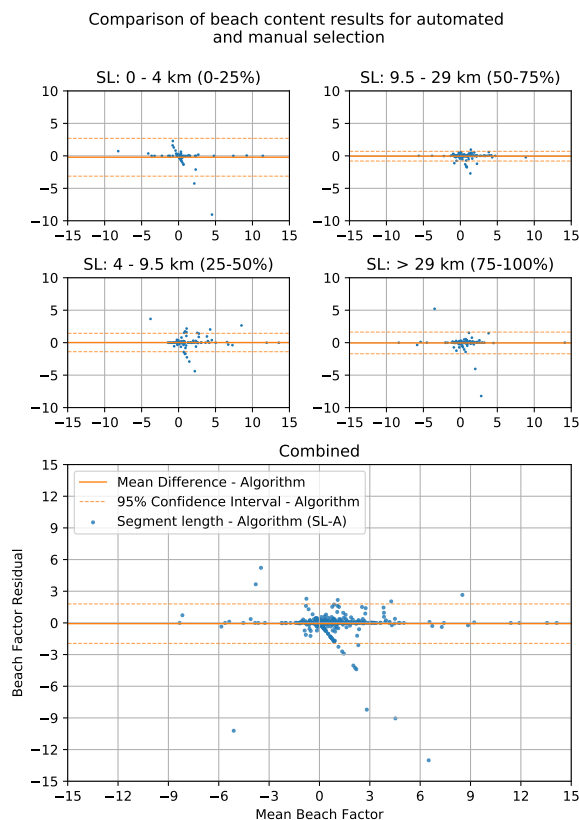


Figure 3.3: Bland-Altman diagram which compares the mean and residual between two data-sets. This diagram identifies model bias (-0.07m), a 95% confidence interval ($-1.93 - 1.80$), with an associated skill score of 0.72 when compared to an immobile coastline prediction. This diagram clearly shows a linear feature with a slope of -2 which indicates manually unconnected DIVA segments.



Figure 3.4: Satellite imagery overlain with SDS transect origins that have identified the coastline as beach (blue) and visually confirmed unconsolidated coastline. These discrepancies are common in this region, where granite cliffs and boulders dominate the littoral zone

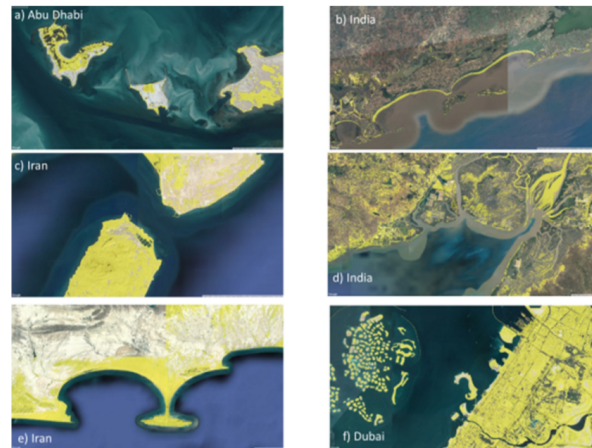


Figure 3.5: Satellite imagery used during the validation procedure presented in (Luijendijk *et al.*, 2018). Where (B) demonstrates traditional sandy beach composition, (C) and (F) show sand polygons extending far inland which may relate to physical beaches or desert sand blown-over rock or other non-erosive features (Luijendijk *et al.*, 2018)

nourishment projects covers the extent needed for the DIVA database, so a logical approach using quantified parameters was applied instead. However, there is substantial room for improvement in terms of the fit of the model and the relative importance of its parameters.

3.4.1. Nourishment Sensitivity Analysis

Sensitivity analysis of the NCM indicates the stability of the NCM to changes in prices, drives research questions, and reveals additional model details not otherwise prevalent in the model results. We perform a sensitivity analysis using the base price costs, but a more detailed analysis is discussed in Section 4. While we include sample results from this analysis in Figure F.7, bulk results from are contained within Appendix F.

We vary the base price across an interval three times greater than its minimum value. The overall percentage of the coastline protected by nourishment similarly varies by a factor of 3 across the base price uncertainty interval as shown in Figure F.7. We subsequently note that the global nourishment expenditure remains relatively constant across the same interval. This is a result of the length of nourished coastline increasing at approximately the same rate as base price.

The sensitivity analysis reveals in more detail the interaction between shore and beach nourishment in the DIVA model. The relation between the best-practice application of these adaptation measures shows an application percentage of shore nourishment between 50 and 65%. These ratios are relatively consistent at 50% below 6 USD/m³ and 65% above 8 USD/m³. These proportions show that the choice of nourishment methods heavily depends on the set base price, however this also indicates that given growing economic pressures, shore nourishment is likely to become the dominant nourishment practice over the next century.

3.4.2. Corruption

The new nourishment cost model presented here relies on a corruption parameter native to the DIVA database. This corruption information, however, is dated to 1997. While likely still relatively accurate, there are a plethora of geopolitical events since that time which may impact the distribution of those scores. As a result, we noted several countries where the corruption factors within DIVA did not match present-day expectations. For instance, where DIVA considers China and Egypt equally corrupt, the most recent global corruption index

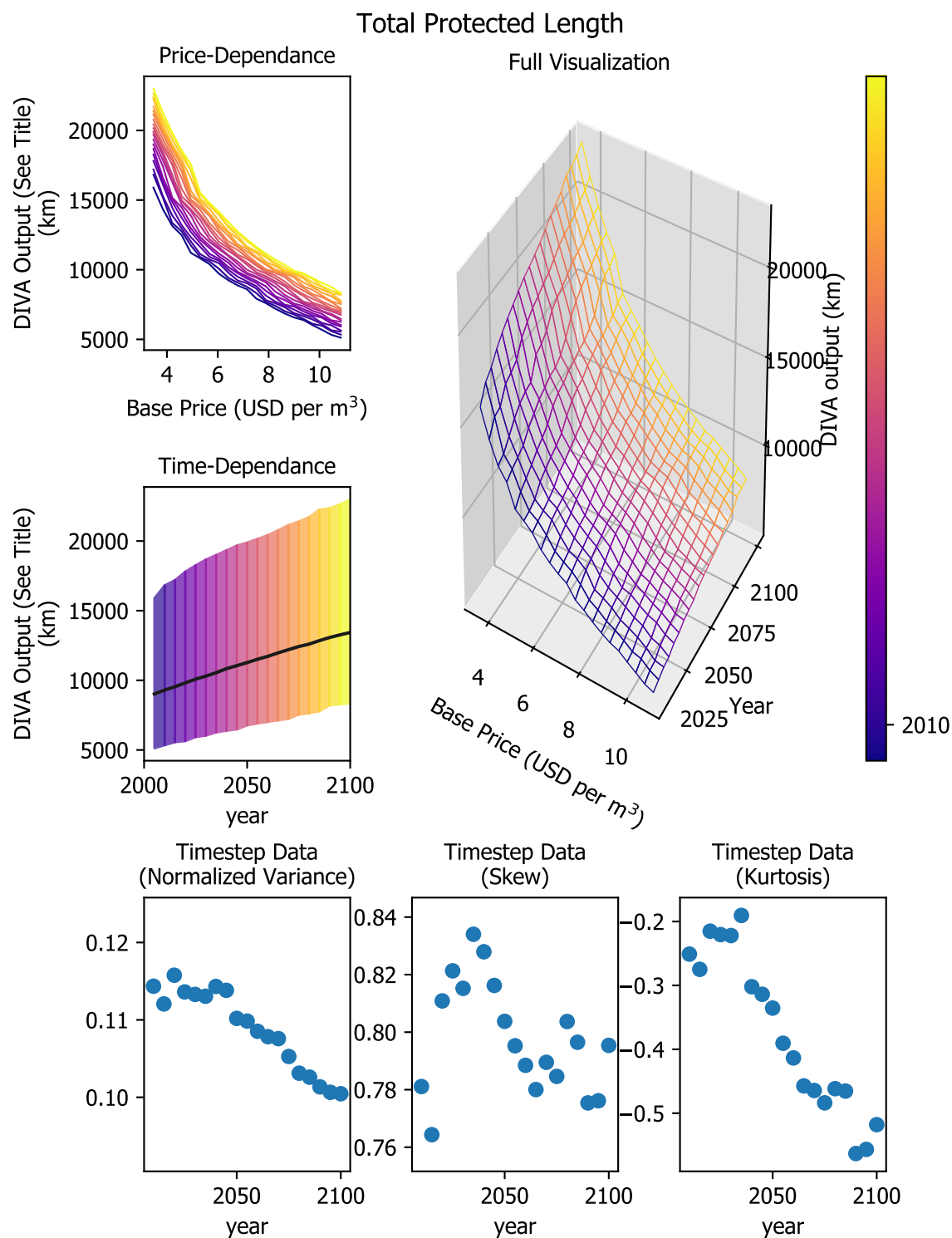


Figure 3.6: This page shows sensitivity of the total length of shore protected through beach nourishment to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties of the protected length as a time-varying parameter.

numbers indicate a moderate difference between the two countries (41 and 32 respectively [Transparency International, 2017](#)). Re-establishing a baseline corruption parameter in the DIVA database should be a relatively simple and effective way to improve the accuracy of the NCM.

3.4.3. DIVA Segmentation

The layout of DIVA administrative units can impede aggregation of GSCD information to inform NCM projections. These are most apparent in locations with large in-land water systems. An example where this has implications is the Danish Wadden sea, wherein a coastal "shell" made primarily of sand is subject to a higher modelled nourishment cost due to extensive inland areas deprived of beaches.

3.5. Impact

The most significant long-term impact of this work is the development of tools needed to further refine and study the physical and socioeconomic factors within the coastal zone that govern global civil response to SLR. As a discipline that has seen significant growth in recent years, there is no reason to believe that the GSCD and SDS techniques are the ultimate developments in the field of satellite detection and machine learning.

3.5.1. Model Integration

The elaboration of a connection algorithm between the GSCD information and DIVA segmentation is a necessary first step to encourage future studies elaborating details of the near-shore zone at a global scale. Like DIVA, the GSCD is part of an ongoing effort to develop detailed satellite-derived information in the coastal zone, and beach content information is only the "lowest-hanging-fruit" with respect to DIVA integration.

The methodology developed here is similarly effective to manual determination for GSCD information and shows promise for the interpretation of other morphological parameters. Full exploitation of this link improves real-world planning and risk management in the coastal zone by improving regional planning, identifying future markets for nourishment companies, and highlighting vulnerable populations.

Similarly one difficulty in the application of global remotely sensed datasets is in their application. While aggregation for a single site study is feasible, larger studies require assumptions of homogeneity which may not hold true or require arbitrary division of the coastline. The DIVA segmentation on it's own provides an effective tool to allow this aggregation, and further relates the information to generalized social and economic parameters.

3.5.2. Long Term Cost Models

The new NCM develops a concept and initializes a model to resolve adaptation costs on a global scale. Increased nourishment costs are anticipated where sediment scarcity, corruption, or protectionism impact construction, we improve the resolution of DIVA projections. However, we also note that the majority of the factors within the model are global risk factors essentially unrelated to nourishment. Also included in the methodology is a codification of a methodology to develop and relate GDPs throughout the extent of the simulation. A similar diversification of adaptation costs applied through other impact-adaptation pathways could provide similar alterations to the operation of other DIVA modules.

3.5.3. Nourishment Industry Forecasting

We note in “New Developments in Global Coastal Erosion” that once physical parameters determine if beach is present on a segment (i.e. the beach content is not 0), the remainder of the decision to nourish lies in the social, economic, and tourism models. This is to say that the choice of whether or not to nourish is modelled as independent of sea level rise scenario. This observation, when combined with a CBC filter identifies valuable development situated on a physically erodible coast and the year in which that land becomes valuable enough to nourish. At it's basic level this information provides a scalar indication of the ultimate potential scale of the nourishment industry. We anticipate human development to have a large and sustained signal on coastal retreat rates within the SDS. However, by applying a filter to evaluate the locations in retreat it is possible to identify potential future markets where regionalized studies may justify the future need for beach nourishment.

3.5.4. DIVA 2.0

The DIVA model is in constant evolution, and Section 4 identifies immediate next steps with respect to the DIVA model. However, a long-outlook on the ultimate future of the model is also pertinent information guiding the application of this study.

Given the likely applications of satellite imagery identifying large scale features ([Palafox et al., 2017](#)) and oceanic information ([Luijendijk et al., 2018](#); [Bondur et al., 2016](#)) we foresee a long-term expansion of the physical model and sediment balance affecting the coastal zone. While true morphodynamic inference may be difficult to apply within the existing model framework, a large-scale sediment-budget matrix could be applied at a similar contextual level to the existing indirect erosion module. In this system, each segment would constitute a single cell and remote sensing can populate information on likely longshore transport direction, sub-segment scale tidal basins. Larger tidal basins could be tied to multiple segments with distinct categories causing diverging changes to the sediment budgets of internal and external segments. A schematization of this model format is outlined in Figure 3.7. In this figure, sub-segment level basins are modelled using [Ranasinghe et al. \(2013\)](#), longshore transportation is approximated using the CERC equation, and ASMITA models larger tidal basins comprising of several segments. This methodology minimizes the computational expense required to run DIVA, but maintains the ability to treat smaller tidal basins that can have significant effects on the shoreline.

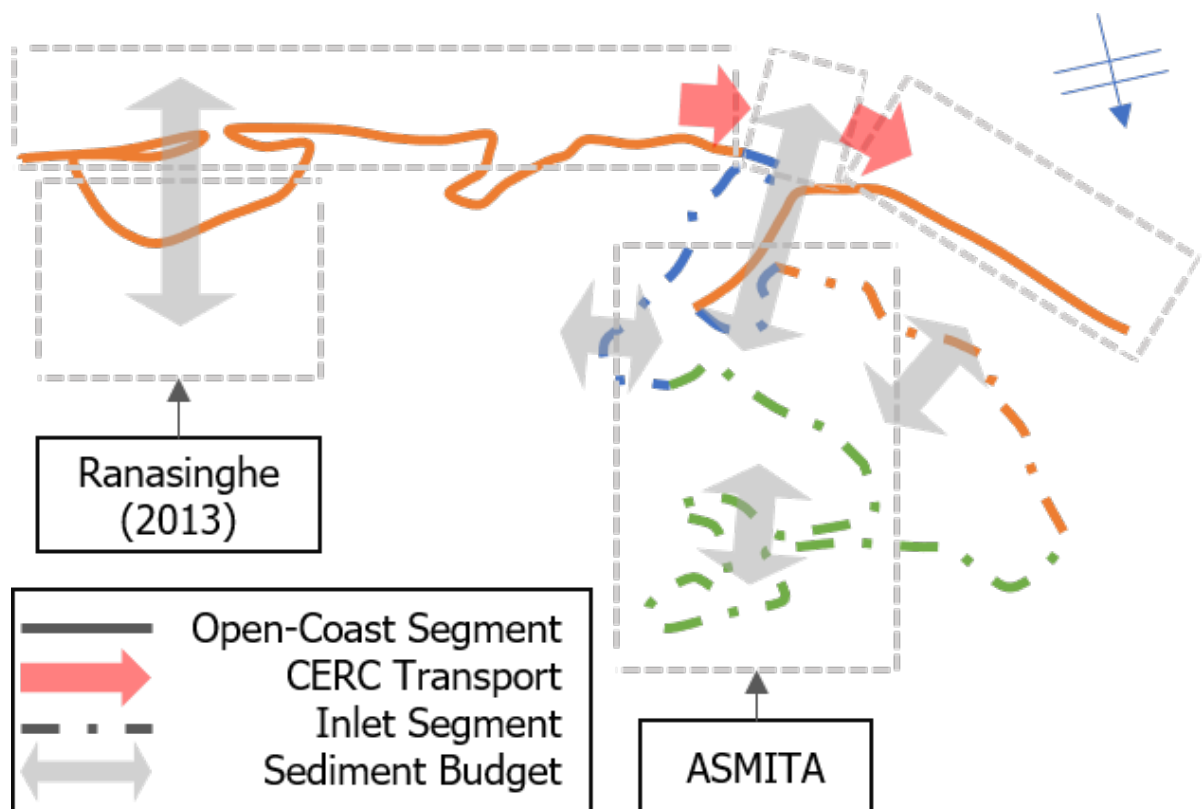


Figure 3.7: This figure indicates how DIVA could combine information from the CERC, ASMITA and information from [Ranasinghe et al. \(2013\)](#) to develop a supervised global sediment budget.

4

Next Steps

Chapter Summary

This chapter respond to the research questions posed in this paper by developing new proposals for subsequent studies, formulated as additional sets of research questions. We carry forward questions posed by [Hinkel *et al.* \(2013\)](#) and develop new questions illuminated over the course of this work:

1. Validation of GSCD beach detection and isolation of pocket beaches on open coasts
2. Remote-sensing of mean beach profiles using individual satellite images
3. The impact of remotely-sensed tidal basins on global erosion analyses through DIVA
4. Investigation of global historic erosion and significance of non-beach coastal erosion through DIVA
5. Optimizing global projections for beach nourishment costs

4.1. introduction

The research presented here outlines a strong foundation for future work using the DIVA model. Opportunities to further expand scientific knowledge regarding global coastal erosion are numerous, and only a handful are discussed in detail. In addition to the magnitude of untapped information already represented by the GSCD and parallel SDS databases, the informal connections between the DIVA team and TU Delft expertise in satellite detection techniques provides opportunities for further studies which could alter existing DIVA projections and structure substantially. We have therefore selected five “next step” research questions which further contribute to the existing body of knowledge and develop them further in this section.

4.1.1. Rocky Coastlines

The GSCD definition of beach broadly encompasses littoral compositions based on a machine learning algorithm. As discussed earlier, the algorithm responsible for the development information was calibrated in the Netherlands using open-source beach identification polygons, and validated for 50 coastal images worldwide. The results of this validation process indicate that the GSCD beach detection algorithm have approximately 90% accuracy for quartz and carbonate composed sand and gravel globally (Luijendijk *et al.*, 2018). However, to our knowledge this validation procedure specifically targets false negatives where no beach is detected while beach is present.

In our review of the data, we noted that some locations are identified as beach which are contradictory to morphological and visual inspection (See Figure 3.4). The coastline at these locations appears to vary between rocky outcroppings and boulder beaches formed from the igneous and metamorphic rocks of the Canadian continental shield, which to our knowledge do not fall within the existing validated classes. Visual estimation therefore leads to a maximum CBC of 0.13 for the location shown, which we anticipate to be representative of the region. However, the GSCD identifies almost the entire Canadian Labrador region as beach. This discrepancy, if present in other areas with a greater socioeconomic productivity could significantly impact regional vulnerabilities. At a broad scale, large coastal shields intersect coastlines on every continent (Figure 4.1) (USGS, 1997). The methodology laid out by the GSCD also neglects the possibility of inland sand deposits over an unerodable coastline. GSCD transects intersecting these inland sand polygon would then register beach where none is present.

Further, while this study treats all beach identified within the GSCD as equal, further resolution as pocket beaches or open beaches adds value to the projections by the DIVA model. Pocket beaches sit between two headlands. Catalan pocket beaches, for example, demonstrated lengths between 100 and 3000 metres (Bowman *et al.*, 2009). Erosion by unconsolidated Bruun rule erosion is restricted in pocket beaches compared to that of open coastlines (e.g. Brunel and Sabatier, 2007). Definition of these areas and mechanisms within the DIVA database and model which accommodate pocket beaches has a direct impact on the analysis presented in this paper by limiting beach erosion if pocket beaches are found.

Pocket beach algorithms could use GSCD transect reference information to evaluate adjacent points until a beach boundary is hit, which would return an approximate length for the local beach. Subsequently, a filter could apply a pocket beach flag to transects with a local beach length below a set value. However, it may be more efficient to apply a machine-learning classification to the shape of the underlying detected beach polygons. Subsequently, this information can be transferred to DIVA segmentation through the connection procedure outlined in this report.

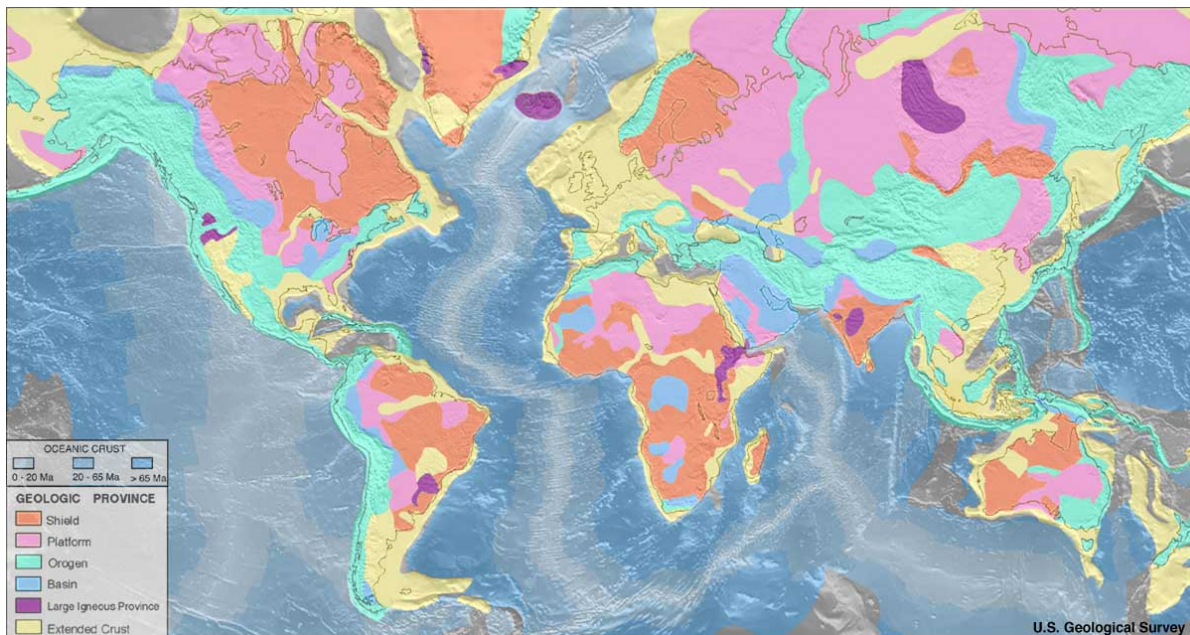


Figure 4.1: USGS publication showing the presence of Continental shields globally (USGS, 1997)

Future Research Questions - Validation of GSCD beach detection and isolation of pocket beaches on open coasts

1. From a spatial standpoint, in which areas does the information from the GSCD database disagree with traditional information in the coastal zone, including the information available in DIVA?
2. Does targeted validation in those areas with respect to false negatives and false positives indicate room for improvement?
3. Can pocket beaches be inferred using existing GSCD and DIVA datasets?
4. How can pocket beach mechanics be modelled within the DIVA framework?
5. How does nourishment affect pocket beaches? Do they require constant nourishment, or is sediment well-retained?
6. How does inclusion of pocket beaches limit global SLR-induced beach erosion projections beach erosion projections?

Similarly, other types of open-coast morphology may be obtained by means of satellite detection whose methods are not defined here which may improve DIVA projections such as mangrove forests or cliff-backed beaches.

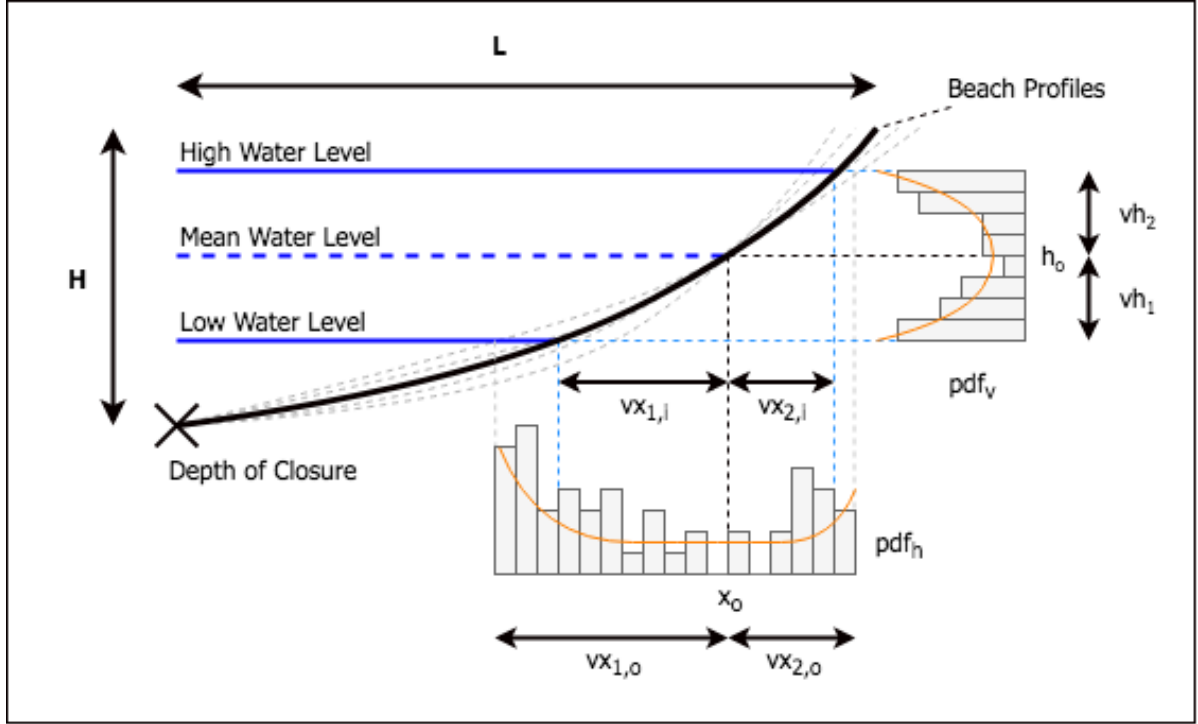


Figure 4.2: Conceptualization of beach profile identification using satellite imagery

4.1.2. Bruun Rule Slope Parameter

The current DIVA model uses a consistent slope within the Bruun rule calculation governing global beach erosion. This 1% slope is central to all previous iterations of the DIVA package and its use is argued to be suitable for large-scale studies (Zhang *et al.*, 2004). However, as DIVA is applied at finer scales, this assumption will no longer hold. It may be possible to extract a localized metric approximating coastal zone slope using techniques similar to the SDS (Sagar *et al.*, 2017). GSCD aggregates multiple point-measurements of the coastal zone to develop a mean coastline position. The frequency of occurrence of these point measurements away from the mean value reflects a probability distribution for the horizontal position of the coastline. From this distribution, it follows that an estimate of the mean horizontal tidal range for a transect can be derived from the data. The DIVA model estimates the depth of closure and vertical mean tidal range for every segment. Using this information in conjunction with a Dean's profile, which is also representative of an average coastal profile, we can estimate an average coastal slope. This adaptation could better inform the use of the Bruun rule using remote detection. A preliminary concept for this possibility is identified in Figure 4.2, and elaborated in Equation 4.1.

$$\frac{L}{DoC} = S = \sqrt{\frac{mtr^3}{(vx_{1,i}^{2/3} - vx_{2,i}^{2/3})^3 * DoC^5}} \quad (4.1)$$

To promote the development of this concept, which may have beneficial impacts, a preliminary methodology and work questions is outlined here.

- Isolate the horizontal distribution of the waterline between satellite imagery exposures.
- Perform a case study at a location with abundant data to relate physical measurements of high- and low-tide positions to the transect probability cloud and distribution moments

- Validate the relation between SDS transect information and high and low-tide marks at sites internationally
- Combine the information on the horizontal tidal range with vertical tidal range models to determine the slope of the beach in the coastal zone
- Fit a Dean profile to the points identified in previous steps using an estimated Bruun Rule function and derive a local profile slope
- Aggregate the local profile slopes for beach transects at a segment level within DIVA and
- Re-evaluate coastal erosion using the new information

Future Research Questions - Remote-sensing of mean beach profiles using individual satellite images

1. Does the existing database of historic satellite images contain sufficient resolution to develop annual probability-clouds for the horizontal position of shore-lines based on single images?
2. What is the most efficient way to aggregate this information into the SDS Transect system?
3. How does the distribution of coastal position based on single images relate to known high- and low- water marks at sites with available historical information?
4. Does this information reliably convey the length of the active shoreface?
5. How does this information upscale for global analysis, and is it feasible to perform spatial aggregation over the existing DIVA segmentation?
6. How does this new information impact global SLR-induced beach erosion projections and nourishment practices in the DIVA model?

4.1.3. Indirect Erosion Information

The DIVA model evaluates the impact of tidal basins on the coastal zone through a changing sediment demand affecting coastal segments and through the erosion of their tidal flats. 200 of the largest global basins are included in the current model which are each referenced to a single coastline segment (Hinkel *et al.*, 2013). The sufficiency of the indirect erosion module within DIVA and its associated datasets has not yet been isolated for study in scientific literature, and, given the magnitude of it's observed impacts, should be the focus of further study.

Ranasinghe *et al.* (2013) proposed a new aggregate scale model to identify the impacts of small tidal basins on a coastline, which could supplant the use of ASMITA within DIVA if sufficient baseline information can be developed. We therefore propose a number of research questions for future study:

Future Research Questions - The impact of remotely-sensed tidal basins on global erosion analyses through DIVA

1. Is the current iteration of ASMITA a suitable model for global tidal basin influence on the coastline?
 - Are the ASMITA parameters identified in the current DIVA model suitable for use at a global scale?
 - Is the aggregate scale model presented by [Ranasinghe et al. \(2013\)](#) more suitable for application within DIVA, what are its barriers to integration?
2. Is satellite detection in the coastal zone a suitable tool to identify the presence of tidal basins?
 - Is it feasible to further automate identification and approximation key parameters affecting the ASMITA model? These properties include total basin area, area of flats, inbound rivers, number of inlets, historical stability of inlets, presence and size of ebb-tidal delta, and references to DIVA segmentation.
3. Can the DIVA model support integration of the tidal basin sediment demand on multiple segments?
4. What impact does the above information have on DIVA projections for loss of land and associated economic costs?

4.1.4. Global Historic Assessment of Erosion

SDS information is not restricted to the beach identification algorithm used in this thesis. Existing studies using the SDS algorithm also identify 30-year linear trends in coastline evolution. The connection algorithm presented in this report extends to aggregate these linear (temporal) trends across each DIVA segment. We develop two datasets within the DIVA segmentation, which are not included in the existing DIVA analysis:

- An average retreat or advance rate for each segment, and
- A measure of the spatial variance of coastline morphological change rate.

The implications of these datasets are not immediately clear and merit further study. The aggregated spatial variance of historical trends is indicative of areas with high morphological activity such as basins or spits, and could eventually provide information for the classification of different types of societal vulnerability. Suitable response actions could indicate local sediment recycling schemes could be sustainable in areas with high variance. However, the relation of aggregated measurements in this way needs more study and elaboration at a local level with respect to specific landforms before it can be used extensively within the DIVA model.

Average coastline retreat rates over each segment provide more immediate benefits to the scientific community, especially when combined with the DIVA segmentation. [Burningham and French \(2017\)](#) found that aggregated position information at 100 metre intervals can be

indicative of systemic erosion or accretion. These rates of historical shoreline change are likely dominated by human development signals (Hapke *et al.*, 2013). However, the information also provides an indication of historical economic costs of unmitigated beach erosion in undeveloped areas and can be used to attempt a validation of the Bruun rule. Aggregated retreat rates on non-beach transects also contains information and the costs of erosion in non-beach environments can subsequently be developed and compared to beaches. This analysis provides an opportunity to (1) validate the proposed models with respect to actual impacts in data-dense areas, (2) quantify social and economic costs of coastal erosion in data-sparse areas (3) Identify socioeconomic impacts currently not considered in the DIVA model. For this work, we then pose the following research questions:

Future Research Questions - Investigation of global historic erosion and significance of non-beach coastal erosion through DIVA

1. Can we hindcast sufficient socioeconomic data to develop a database suitable for use within DIVA since 1984?
2. Can we develop a DIVA module which uses historical coastline retreat information to develop hindcast economic projections for the impacts of coastal erosion? How has large-scale erosion affected coastal the global population in the past 30 years?
3. Does this information reveal any under-served populations who may be feasible to protect?
4. Is the observed scale of socioeconomic impacts similar if we instead focus the analysis on non-beach segments as compared to beach segments?

4.1.5. Nourishment Cost Model Optimization

The new beach nourishment cost model presented in this report can effectively be regarded as a proof of concept and initialization for beach nourishment costing at a centennial scale. The information contained within is fit to nourishment cost data and analogues from an admittedly limited number of sources with relatively low computational power. A qualitative sensitivity analysis is provided in Appendix for this paper C. a more intensive evaluation of the model structure comes through the application of variance-based sensitivity analysis outlined in Saltelli *et al.* (2010), which requires an estimated 5000 individual DIVA runs. In perspective, a single batch of 500 DIVA runs takes approximately 24 hours and 500 GB of disk space. Optimization of program outputs for this type of analysis is recommended. Further, Developing a database of countries including statistical information on historic nourishment costs is a vital step to improve this cost model. This new system also has the potential to help study the impacts of local administrative or globally persistent factors that influence human response to sea level rise. In particular, we recommend the use of the temporal market factor to model a long-term increase in nourishment costs resulting from decreasing access to sources of beach-grade sediment. With this in mind, we propose the following research goals:

Future Research Questions - Optimizing global projections for beach nourishment costs

1. What parameters and functions optimize the fitting of the parameters of the Nourishment Cost Model?
2. How do nourishment costs and nourished areas develop spatially over the course of the simulation?
3. How do socioeconomic impact and nourishment projections of beach erosion change when we consider the shrinking availability of beach-grade sediment?

5

Closure

Conclusions

- Satellite remote sensing provides a substantial opportunity to improve the DIVA database. Spatial sorting and nearest point aggregation of these items is similarly effective to manual referencing.
- Global Sand Composition Database information impacts sea level rise information by providing a greater interface between sea level rise forcing and human actors.
- The new Nourishment Cost Model decreases society's ability to adapt to beach erosion within the original context of the DIVA model.
- Interactions between these two effects changes the expression of nourishment costs significantly.
- The modelled length of shoreline protected by means of beach nourishment is invariant to RCP forcing scenarios, and depends primarily on socioeconomic wealth.
- Adaptation favors wealthy population centres, and primarily targets forced migration as compared to loss of land.

Limitations

- DIVA cannot currently reproduce the results of [Hinkel *et al.* \(2013\)](#)
- DIVA's aggregate-scale modelling has difficulty addressing underlying processes
- DIVA is tied to the available forcing scenarios and de-coupling the impacts of various inputs is convoluted
- Limited information is available in the coastal zone to accommodate the development of a nourishment cost model
- Nourishment cost information is scarce and validation of the nourishment cost model is unlikely

This work applies newly developed remote sensing techniques and industry expertise to improve the performance of the Dynamic Interactive Vulnerability Assessment (DIVA) model with respect to beach erosion caused by Sea Level Rise (SLR). These projections support large-scale political and administrative initiatives and inform the growth of the nourishment and dredging industry.

5.1. Research Fulfillment

Section 1 identified research goals to guide this thesis and its application to the existing body of scientific knowledge. "New Developments in Global Coastal Erosion Assessment", intended for publication, provides a consequential response to these questions, presented in Section 1. Subsequent information presented in Sections 3 and 4 elaborates on this response.

5.1.1. Research Questions

How can we improve the performance of DIVA, which models large scale socio-economic impacts of SLR? Large-scale remotely sensed information directly addresses the dearth of information that afflicts large-scale models such as DIVA. A nearest-point search algorithm provides a sustainable connection between the two databases, which allows development of an improved physical model of the coastline. This development demonstrates the feasibility and validity of three dimensional nearest-point relations for integration of large point clouds of coastline information into the existing DIVA segmentation. Subsequent research can build upon this connection to improve the physical foundation for the model through the development of additional coastal characteristics. One such possibility is average beach slope, which is currently constant within the DIVA model but can vary substantially in the environment.

While pricing estimates are difficult, a set of parameters based on cultural, physical, and long term economic norms provides more information than uniform pricing. DIVA contains enough information to expand this technique to other adaptation methods, such as dike costs, given the success of an appropriate multi-factoral sensitivity analysis.

Our work specifically develops two important improvements to the performance of the DIVA Package by resolving models and datasets within the coastal zone. First, we develop a connection between the novel SDS database and DIVA segmentation. Secondly, we develop and initialize a new methodology to estimate multi-decadal beach nourishment costs. This tool improves the resolution of the DIVA mitigation response to climate change, and encourages further studies into the sensitivity of climate change adaptation to changes in base costs and administrative approach.

How do improvements to the DIVA model change global erosive patterns and the economic implications of adaptation? How do improvements to the DIVA model change the distribution of projected regional erosion? These improvements to the DIVA model have a substantial effect on unmitigated regional erosion projections. Seventy-four percent or 81,500 km more coastal beach is modelled by switching from a categorized value to an analogue CBC variable. This changes extends the limits of SLR-induced beach erosion impacts. The results of "New Developments in Global Coastal Erosion Assessment" highlight this tendency, noting that countries previously showing no impact from SLR in the DIVA model are countries most affected by converting the CBC categorized variable to a scaled value.

How do improvements to the DIVA package change the social and economic impacts of SLR-induced erosion and mitigation effectiveness predicted by [Hinkel et al.](#)

(2013)? Our update to the DIVA model develops new projections for socioeconomic impacts from SLR-induced beach erosion and the likely mitigation capacity of beach nourishment. Without adaptation, these changes amount to a 20 and 45 percent increase in cumulative land loss and forced migration respectively. We demonstrate a substantial increase in the prominence of nourishment practices resulting from both the new extents of the physically vulnerable coastline and by adapting nourishment costs locally to accommodate natural price differences. The results of these improvements show a substantial rise of 50 percent, when measuring protected length, in the application of beach nourishment on a global scale.

What do the results of the DIVA analysis reveal about the implementation of beach nourishment in the 21st Century? The DIVA analysis projects a thirty percent increase in the length of coast protected by beach nourishment practices over the 21st century. Given a simplified Cost-Benefit-Analysis, shore nourishment is more feasible than beach nourishment for 50 to 65 percent of the world's protected beaches regardless of baseline nourishment costs. Given the reliance of nourishment practice on socioeconomic conditions, nourishment will likely gain prevalence in locations with a high population, high economic density, and a primarily sandy coastal environment. Similarly most new markets will develop around major cities in developing areas. The largest concentrations of these potential markets occur in Southeast Spain, Northwest Italy, Southern Levant, and China.

5.2. Key Impacts

We develop two key alterations to the DIVA Package that have significant impacts on its projections for global beach erosion. Each of these alterations is novel scientific information, and both lead to new avenues of research for the coastal zone.

Historically, global beach erosion was elaborated using inference from secondary surveys and large scale geological criteria. However, these approaches led to drastically different pictures of the world's coastline. By tying global beach erosion evaluated using the DIVA package to remote-sensed measurement found in the GSCD dataset, we provide a meaningful update to previous studies in a novel application of existing scientific information. The link developed between these two models provides a natural aggregation pathway between data-rich remote sensing techniques and contextual DIVA database. Developing DIVA through these techniques provides substantial improvements to the basis for its physical model.

Further, we develop the first iteration of a method to quantify the costs of shore-erosion mitigation via beach nourishment at a regional level. This model elaborates existing information on resource scarcity, corruption and local economic factors to approximate market conditions within the dredging industry. The application of this model in the DIVA program is a first-step to model the impact of global sediment scarcity on beach nourishment practices.

5.3. Key Limitations

The inability to recreate existing work is the largest barrier to the appropriate interpretation of this study. Without an appropriately modelled baseline, the gross outputs are likely lower than 50 percent of those using a functioning DIVA distribution. The attempt by this study to evaluate impacts primarily by means of percentages relative to the baseline reduces the likelihood that significant changes will affect the ultimate submission of the paper "New Developments in Global Coastal Erosion Assessment". This study also highlights also a number of limitations when dealing with large scales and datasets. Most importantly, more baseline information and validation data is needed. Subsequently, the large-scale application of aggregated models such as ASMITA and the Bruun rule is technically feasible, but there are limitations to its application

at more local scales which may prevent successful down-scaling of DIVA results for regional and local application. Other Limitations include:

- Validation of the economic models used in DIVA is not considered.
- There are only a limited number of datapoints available for the inference of nourishment costs.
- A large number of outputs in [Hinkel *et al.* \(2013\)](#) makes comparison of baseline results overwhelming, resulting in simplified outputs.
- Regional analysis is difficult to quantify using the DIVA segmentation system.

5.4. Recommendations

While Section 4 outlines specific research proposals pursuant the present work, a larger set of next steps is feasible:

Computational Optimization The DIVA model should be reviewed and debugged so that the discrepancy between the baseline here and the baseline in the [Hinkel *et al.* \(2013\)](#) report is removed or suitably explained.

Develop DIVA outputs to minimize computational expense More efficient outputs from DIVA showing both baseline conditions and adaptation would improve the operability of the model. Currently, two runs of the model are needed to illustrate the impacts of adaptation, this same process is feasible in a single run with limited additional computational expense. This greatly reduces the ultimate computational costs of analysis and simplifies interpretation of model results.

Align DIVA to the OpenStreetMap 2016 coastline Re-projection of the DIVA coastline is a large task which may require re-development of DIVA segmentation as well. However, matching the DIVA coastline to the OpenStreetMap 2016 coastline in the anticipation of future remotely sensed information will further serve to reduce error developed during the connection of the two databases.

Expand and validate the GSCD database to include small islands and high latitudes Currently, the GSCD database does not include every segment for which DIVA develops information due to a lack of suitable imagery to develop the parallel SDS database. However, the GSCD requires only a single cloud and ice free image, and this database can be expanded in these areas.

Validate the GSCD database against false positives The validation of the GSCD was undertaken to determine if false negatives affected the data. As outlined in our discussion, there are several locations where measurements appear to be false-positives. Since the GSCD detects all sand and gravel along a set line perpendicular to the coast, it also detects sand and gravel deposits a short distance away from the ocean which do not represent beach. A validation of the prevalence of this occurrence might better inform the GSCD processing algorithm and improve accuracy.

Continue to develop and integrate coastal zone information using remote sensing techniques We demonstrate here the added value of remote sensing for the DIVA model, but much more is feasible given the current applications of remote sensing in academia. The integration of these large-scale datasets directly addresses a fundamental need within the DIVA program.

Improve DIVA's interpretation of the coastal sediment balance DIVA's interpretation of the coastal sediment balance shows particular promise for development using satellite imagery. Where current tidal basins impact the sediment balance in a single segment, ultimately, large basins should be regionally prominent features with expression across multiple features. By adding tidal basins and improving their relation to the DIVA segment system, a better indication of the dominant driver of the coastal sediment balance is achieved. Rudimentary longshore transport information between segments and basic input information from cliff retreat and river output could also be included in this development as the model begins to approximate a large scale Sediment Budget and Analysis system.

5.5. Closing Remarks

The fundamental quest for knowledge at the core of this work is one for a safer world, which complicates its answering. The two models presented here are unique, and their authority to speak to global vulnerability in the coastal zone is arguably unrivalled if imperfect. This thesis only grazes a portion of the capability of either work, but lays out promising next steps which we hope will develop clarity. The knowledge presented here helps us to anticipate how society might react to natural processes that we do not fully understand yet, hoping to ease the human costs of climate change and sea level rise. We started this thesis with four questions, and finished with five. While that math might not add up, we hope it lights the path a little farther in a search for a safer world.

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Extended Context

The context for our thesis takes three parts. First, we review the relation of the physical properties studied. Second, we review the theoretical basis for the aggregation and analysis of physical information. Finally, we review existing work which inform the development of the link and subsequent validation steps.

A.1. Physical Aspects

A.1.1. Scale

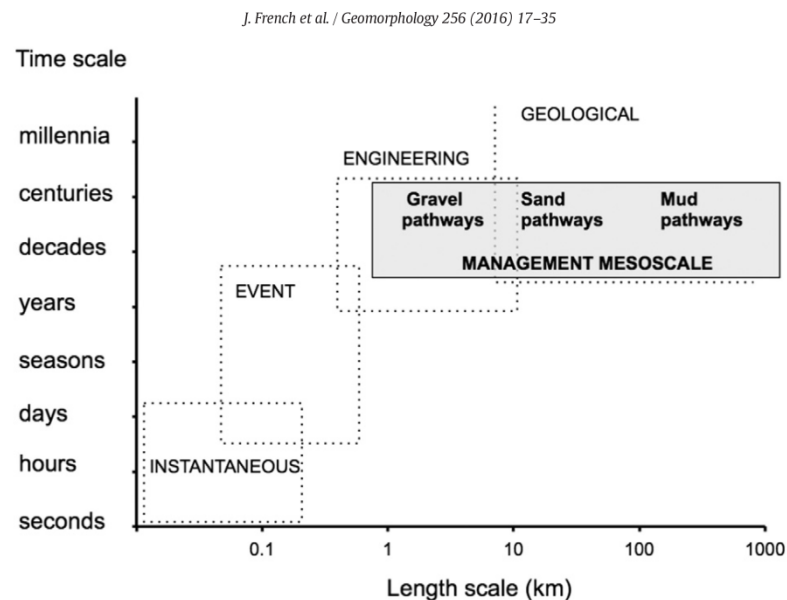
As discussed in Section 1.1, SLR extends beyond traditional engineering timescales. Human interventions in the coastal zone typically encompass time scales ranging from years to decades whereas the GMSL may change over decades to millenia ([French et al., 2016](#); [Cowell et al., 2003b](#)). [Cowell et al. \(2003b\)](#) identified a nested-scale structure called the coastal-tract which attempted to relate the temporal and spatial scales of processes in the coastal zone (See Table A.1).

Many of the processes illuminated by research in the past 50 years belong to third and fourth order systems identified in [Cowell et al. \(2003b\)](#). These scales relate to initial sedimentation-erosion (ISE) or medium-term morphodynamic (MTM) models. However, these models are not suited to modelling sea level rise. ISE models are scaled to match instantaneous events and do not update bathymetry. They are therefore unsuitable to model morphological changes. In comparison, MTM models model event and engineering scales, but are subject to a complex interplay between boundary conditions and numerical limitations which destabilize their predictive power over time ([Cowell et al., 2003a](#)).

Instead, Aggregate-Scale Models (ASM) are used to estimate long-term trends in coastal behaviour. These models directly address the second- and third-order systems of interest, but do not resolve finer-scale behaviours. The forcing on these models is dictated by aggregated properties known as Sloss variables ([Sloss, 1962](#)). This class of conceptual model was formalized in [Cowell et al. \(2003a\)](#). In particular, [Cowell et al. \(2003a\)](#) identify accommodation space as a key morphological parameter, which changes due to shifts in hydraulic forcing caused by sea level rise. In a basin this parameter may take the form of a tidal basin where it may take the form of direct water level on an open coast. ASM then codify the creation of accommodation space and the concept of dynamic equilibrium to predict large-scale trends.

Table 1. *Coastal-tract systems and system scales.*

System	System-scale	Time Scale	Space Scale
zero order	meta-scale	Quaternary Period ($\geq 10^4$ yrs)	tract environment
first order	meta-scale	Holocene Epoch ($10^2 - 10^3$ yrs)	coastal tract
second order	macro-scale	late Holocene Age ($10^1 - 10^3$ yrs)	morphological complex
third order	meso-scale	years to decades	morphological unit
fourth order	meso-scale	seasons to years	morphological element
fifth order	micro-scale	days to seasons	sub-grid phenomena
$\geq$ fifth order	micro-scale	seconds to days	sub-grid phenomena

Figure A.1: Description of the spatial and temporal scales affecting the coastal Tract (French *et al.*, 2016)Figure A.2: Comparison of scales affecting processes in the coastal zone (French *et al.*, 2016)

Aggregated Scale Morphological Interaction between a Tidal basin and the Adjacent coast (ASMITA)

ASMITA models long-term aggregate morphological behaviour of tidal basins and their adjacent coast. ASMITA does not model variations over a single tidal period. Instead, the model addresses residual transport patterns between large morphological features (Wang *et al.*, 2007). The aggregate volume of the tidal channel, tidal flats, ebb-tidal delta, and external environment form an interconnected set of elements representing the morphological complex of the basin. An equilibrium state, or volume, for each element is defined on the basis of empirically derived constants relating each element to hydraulic forcing, or tidal prism; and morphometric constants, or the area of the basin (van Goor *et al.*, 2003). These relations follow the general format outlined in A.1.

$$\begin{aligned}
V_{flats} &= f_1(A_b, H) \\
V_{channel} &= f_2(P) \\
V_{ebb\ delta} &= f_3(P)
\end{aligned}
\tag{A.1}$$

Where:

- V is the equilibrium concentration for a particular element n (later identified as V_{ne}).
- A_b is the total horizontal area of the basin.
- H is the basin's effective tidal range.
- P is the basin's tidal prism.

Following the above equations, ASMITA assumes an equilibrium state at which sediment availability in each element equals the external sediment availability. At this point, no further morphological change is expected to occur in a stationary system. deviating from this equilibrium state, ASMITA employs the power law identified in Equation A.2 which relates local sediment demand to a measure of the mean flow velocity. This measure is calculated by comparing the present state of the element to its equilibrium state (Wang *et al.*, 2007).

$$c_{ne} = c_E * (V_{ne}/V_n)^r \tag{A.2}$$

Where:

- c_E Represents sediment concentration external to the tidal basin, and therefore the equilibrium concentration of each element if the basin has reached equilibrium.
- c_{ne} is the local equilibrium concentration, at which the present system will exchange no sediment with local morphological features. Also identified as a local scarcity or surplus of sediment.
- V_{ne} is the equilibrium volume of the local element from the equations identified in Equation A.1.
- V_n is the volume of the element in its current timestep.
- Since the volume of an element will relate to the available space through which the tidal prism passes, (V_{ne}/V_n) becomes a representation of the mean flow velocity in the element.
- r is a constant relating the mean flow velocity to a sediment transport formulation.

Once the local sediment demand has been determined, ASMITA begins to compare this with the availability of sediment and it's transition between each of the elements. Equation A.3 shows a mass balance for a single element which includes changes local to an element and diffusion into other elements. ASMITA solves this equation for each element as part of a matrix such that the state of one element influences the others (Wang *et al.*, 2007).

$$\sum_m \underbrace{\delta_{nm}(c_n - c_m)}_1 = \underbrace{A_n w_s (c_{ne} - c_n)}_2 \tag{A.3}$$

Where:

1. A diffusion term representing the exchange of sediment between the an element and it's neighbours:
 - c_n and c_m are sediment concentrations represent locally available sediment in elements n and m.
 - δ_{nm} determines the rate of excahnge of sediment between the two elements.
2. Represents the exchange of sediment with morphology local to the element, this effectively indicates the rate of change in the volume of the local element:
 - A_n is the area of element n.
 - w_s is the rate of local erosion.

ASMITA in DIVA Modifications to the basic model outlined above allow ASMITA to accommodate sea level rise, or changes to the layout and number of elements. The DIVA erosion module includes a paired-down version of ASMITA, which relates the impacts of a tidal basin to a single coastal segment. The model retains information on the area of the tidal basin and the number of inlets that connect the tidal basin to the adjacent ocean ([Hinkel et al., 2013](#)). The model considers the number of tidal inlets by dividing the basin into identical equally-forced models. This model does not into account whether or not the basin is ebb or flood dominant, and neglects the presence of inflowing rivers or the shape of the external tidal signal, both of which are significant to the comportsment of the basin ([Ranasinghe et al., 2013](#)).

Bruun Rule

The use of the Bruun Rule to predict changes in coastal morphology is the subject of a long-standing debate within the coastal engineering community (e.g. [Zhang et al., 2004](#); [Le Cozannet et al., 2016](#); [Cooper and Pilkey, 2004](#)). The bruun rule reflects a mass balance along the cross-shore profile of a beach which shifts landwards and upwards to maintain an equilibrium position with respect to the waterline. The profile, which follows the form in equation A.4, has two constants A and m. In this formulation, m is generally equated to 2/3 while A relates to the steepness of the profile ([Bruun, 1988](#)). This empirical profile was subsequently supported by theoretical development of wave dissipation across the surf zone ([Dean, 1991](#))

$$y = A * (x')^m \quad (\text{A.4})$$

Detractors posit that the rule's negligence of antecedant topology, sediment characteristics, and hydrodynamic conditions result in gross oversimplifications at any single location ([Cooper and Pilkey, 2004](#)). However, [Zhang et al. \(2004\)](#) found, in a study of the American Eastern Seaboard, that the rule provided a good fit when considering aggregated properties of large scale geomorphic units. However, more recent work posits the bruun rule as a key component to any proposed solution, since at it's base it remains a sediment balance issue ([Ranasinghe et al., 2012](#)). Further, work by [Le Cozannet et al. \(2016\)](#) developed a methodology which could be used to validate or invalidate the Bruun Rule by the middle of the 21st Century.

Bruun Rule in DIVA DIVA applies the Bruun Rule to determine direct erosion on sandy coasts. The total erosion module simplifies the Bruun Rule further so that the term representing the nearshore slope is set to 0.01. This bruun rule is combined with depth of closure calculations based on wave classifications and tidal ranges using ([Hallermeier, 1978](#); [FAO GEONETWORK, 1995](#)) ([Hinkel et al., 2013](#)).

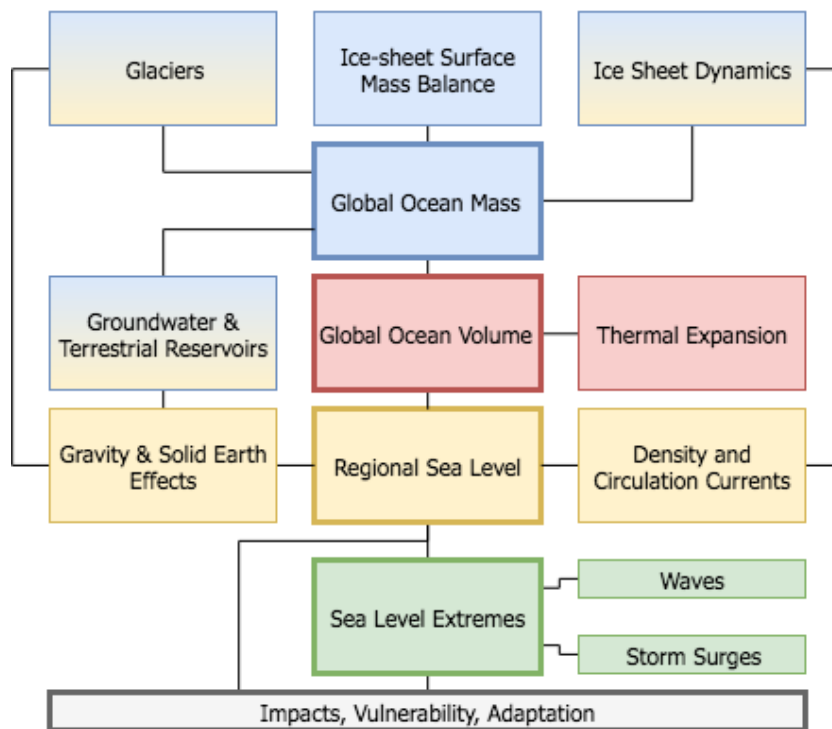


Figure A.3: Summary of factors influencing SLR at global and regional scales as related to their key effects on ocean levels - adapted from Church *et al.* (2013)

A.1.2. Sea Level Rise

SLR itself is a complex phenomenon which is the result of interactions at many levels. While these interactions can be broken down in any number of ways. Generally these can be categorized into factors affecting the mass of water in the oceans, volume of water in the oceans, regional mean sea levels, and extreme water levels (A.3). With respect to beach erosion, DIVA considers the impacts associated with the first three of these categories, but not those due to extreme events. In theory, more frequent storms could impact average shoreline positions as beaches spend more time in a dissipative state (Wright and Short, 1984), but the authors were unable to find academic publication supporting this inference and ultimately this factor is likely small compared to centennial rates of SLR-induced erosion or local sediment transport gradients.

The most uncertainty in the above model stems from the reaction of the Greenland and Antarctic ice shelves to warming temperatures. Information in these regions is historically sparse, although some recent studies have identified accelerations in melting of the antarctic ice sheet which indicate that melt rates are faster than previously thought (The IMBIE team, 2018).

A.2. Technical Aspects

A.2.1. Satellite Imagery and Remote Sensing (RS)

Satellite imagery has found consistent application since its first introduction in NASA's pre-Apollo Mercury and Gemini missions. prior to this, aerial photography was the predominant remote sensing technique, and was employed primarily for military and clandestine activities. However, the use of this information in civilian applications soon became apparent and the resulting National Aeronautics and Space Administration (NASA) mission to document the resources of the earth launched in 1972 with Landsat 1. Since that time, 7 more satellites in the Landsat series alone have been launched and taken millions of geo-referenced images

across the planet. In addition to Landsat, the Sentinel missions operated by the European Space Agency (ESA) are of particular importance to this thesis ([Emery and Camps, 2017](#)).

Modern satellite imagery refers to much more than simple image acquisition. Active or passive systems can be employed to image any number of important phenomena. In active sensing, the device emits an electromagnetic signal and measures the response of the environment to that signal. Passive sensing, however, relies on reflected solar or surface generated sources to generate the measured spectrum. Many terrestrial features reflect visible light in distinct patterns, and passive systems are better able to record these patterns. Therefore we focus on passive satellite imagery to support the development of the theoretical basis for the SDS technique ([Emery and Camps, 2017](#)).

Passive satellites measure the intensity and wavelength of light reflected or emitted from the earth's surface and atmosphere. Each pixel relates to the number of photons within a particular wavelength band that hit the sensor and is stored as a single number between 0 and 255. The number of bins in which wavelength is measured differs from sensor to sensor, but information the visible light bandwidth is typically included. The need for visible light information stems from the reflectance properties of many terrestrial features, which are particularly distinguishable in that range. Landsat 5, launched in 1984, was the first high-resolution satellite mission with multispectral sensors. As a result, the current database available for remote sensing using optical satellite imagery has a 34 year time frame ([Emery and Camps, 2017](#)).

A Multispectral image contains multiple layers of pixelated images representing bandwidth measurements of radiance values for each pixel. This value can be later combined with visual representations of other spectra to form a color composite image. Standard imagery relates the intensity of a band with it's associated color in the display medium so that images look real. However, many permutations and combinations is possible. One advantage of this technique is that modification and re-ordering of the various spectra can produce images which highlight particular physical properties ([Ose et al., 2016](#)).

preprocessing Before a satellite image is ready for processing using remote sensing algorithms, it must be pre-processed with various corrections applied to the imagery to improve its accuracy and the consistency of the underlying data. These corrections are generally grouped into geometric, radiometric, and projection-related categories and can address random and systematic errors ([Fragkopoulos, 2016](#)).

The instrumentation of the satellite itself applies the first correction factor to account for systematic radiance interference due to the position of the earth in relation to the sun. The instrument measures the distance from the sun and solar zenith in order to immediately apply a radiance correction to the measured values. These values are stored in terrestrial infrastructure as a Top of Atmosphere (TOA) radiance value. from the TOA value, random radiometric error includes atmospheric effects from aerosols known as haze effect. These disruptions can be evaluated by measuring radiance parameters over dark areas where no radiance is anticipated. At these locations, the only measured information can be attributed to haze disruption, which can subsequently be filtered from the remaining pixels ([Fragkopoulos, 2016](#)).

Similarly, random geometric error can be caused by atmospheric distortion or the stability of the sensing platform. Callibration of this error occurs ground-side by comparing the satellite imagery with known reference locations and applying a correction to the position of each pixel within the image ([Fragkopoulos, 2016](#)).

Systematic geometric error includes the rotation of the earth as the satellite passes overhead.

this rotation skews the accuracy of sampled material to fit a parallelogram unless corrected. Similarly, the slight differences in perspective will skew the geometry of information at the edges of the photo. These sources of error are corrected through the application of algorithms which stretch, manipulate, and resample the information (Fragkopoulos, 2016).

Random errors affecting geometry and radiance are generated by the interaction of light with aerosols in the atmosphere. These effects are filtered out of satellite imagery by comparing radiance values of known pixels to measured values and applying a correction to the image. Geometry corrections can be applied by comparing the location of known pixels and applying a correction based on the linear interpolation of interference between known points (Fragkopoulos, 2016).

Finally, orthorectification accommodates changes in relief and elevation which distort satellite imagery. Processors use a digital elevation model to re-sample each pixel and project its information onto the underlying ellipsoid.

Remote sensing is a process by which the properties of an object, area, or phenomenon are inferred by an object or device which is not in contact with its subject (Lillesand and Kiefer, 2000). Due to their relatively long history and wide availability, Landsat images are one of the most common sources of remotely sensed terrestrial information (Feyisa *et al.*, 2014). With respect to the derivation of a global shoreline, remote sensing is extremely advantageous compared to physical survey techniques when large scales are concerned. The added manpower and equipment required to perform large scale surveys often far outweigh any minor bias or accuracy issues associated with RS. Further, RS can be calibrated and validated extensively to ensure its accuracy (Hagenaars *et al.*, 2018).

A.2.2. Satellite Derived Shoreline (SDS)

One of newest sources of globally relevant shoreline information is the SDS dataset created in a partnership between TU Delft and Deltares. SDS is a technique for extracting shoreline information in vector format from satellite imagery which also includes a module for determining a 500 metres mesh indicating the presence of beach in the imagery (Luijendijk *et al.*, 2018).

The SDS uses pre-processed images from Google Earth Engine (GEE) in 20km square boxes which are selected on the basis of their intersection with the coastline defined in the Open-StreetMap 2016 dataset. After pre-processing, the SDS algorithm applies a pan-sharpening algorithm to images from Landsat 7 and Sentinel 2. This process uses the results of the panchromatic band measurement available on these instruments to sharpen the resolution of these images to a 15 metre pixel size. Pansharpening is effective because the panchromatic band receives a greater amount of light than any of the specific bands, and is therefore less susceptible to noise in each pixel (Fragkopoulos, 2016).

Composite Images Image processing in the coastal zone may be subject to error when applied to single satellite images due to differences between the instantaneous water level and mean sea level, recent precipitation events, or the presence of clouds. In order to accommodate these issues, current SDS algorithms monitoring longterm changes use composite images based on a moving average of 192 days. In order to obtain these images, first, radiance values for each pixel are collected and sorted into a histogram. Subsequently, the first and last portions of the histogram are removed from the dataset. These values generally represent either cloudcover or shaded measurements, which are not suitable for the remainder of the algorithm. The final image is a clear composite image representative the average state of the covered area (Luijendijk *et al.*, 2018).

Beach Identification Beach identification within the SDS is governed by a machine learning algorithm based on a Classification and Regression Tree (CART) classifier. which fits a basic decision tree analysis to the test data. The authors of the SDS used test information available for the dutch coastline, and validated at 50 sites worldwide. They found that the CART methods returned true positives in 97% of pixels in the test data set. In order to reduce processing times, calculations are limited to a 500m buffer around the OSM 2016 shoreline. This method subsequently return a global dataset of sandy beach polygons ([Luijendijk et al., 2018](#)).

SDS - Shoreline the SDS process then develops a Normalized Difference Water Index (NDWI) for each pixel as shown in Equation A.5. NDWI is a composite image processing technique which performs operations on the radiance values measured in each band of the satellite image. The NDWI is commonly used to differentiate aquatic and terrestrial pixels in imagery. In this classification, more negative values are associated with water, while more positive values are associated with land ([Hagenaars et al., 2017](#)).

$$NDWI = \frac{(\lambda_{NIR} - \lambda_{green})}{(\lambda_{NIR} + \lambda_{green})} \quad (A.5)$$

The threshold NDWI which differentiates between water pixels and land pixels is set following an unsupervised technique outlined by [Otsu \(1979\)](#). Where supervised thresholds require manual input to identify a NDWI value which differentiates between land and water, unsupervised methods use an algorithm to search for a similarly effective threshold. The mean and variance of the NDWI histogram within a single satellite image are used to develop this threshold, which maximizes η in A.6

$$\eta(k) = \frac{\sigma_B^2(k)}{\sigma_T^2} \quad (A.6)$$

Where:

- η is the discriminant criterion which the algorithm maximizes
- $\sigma_B^2(k)$ is the variance between the classes on either side of the threshold k , calculated as the product of the zero-order moments in each bin multiplied by the square of the difference between the first order moments.
- σ_T^2 is the total variance of the histogram

This methodology operates within each frame of the satellite image to develop an optimal threshold factor which maximizes the variance between the data on either side of the threshold. This methodology, however is only viable for images which contain approximately eq From this threshold, a binary image identifies land and water ([Otsu, 1979](#)).

The SDS further applies an unsupervised region-growing algorithm to the binary land/water image, which searches for large contiguous water regions within the image. Following the definition of the water and land regions, the SDS algorithm searches for the most seaward contiguous region in order to define the shoreline. This shoreline runs along the edges of the boundary water and land pixels. One disadvantage of this search method is that it neglects harbours and bays with entrances smaller than one pixel from the final dataset ([Luijendijk et al., 2018](#); [Hagenaars et al., 2018](#)).

The SDS algorithm subsequently applies a smoothing algorithm around the derived water-line by using a moving 7x7 pixel search window in which a polynomial surface is fit to the previously-calculated NDWI values using a least-squares method. the method defines the

shoreline at locations where the Laplacian of the NDWI surface is zero and the gradient is maximum, which corresponds to the water level. This process is repeated such that each measurement will occur in 7 search windows, and an average shoreline position can then be extracted (Hagenaars *et al.*, 2017).

SDS - Spatial Resolution The above methodologies provide detailed global information on the presence and erosion of sandy beaches, but post-processing of the data is still required to shape the available information into technically useful data. Theoretically, this information is available at a sub-pixel scale which equates to approximately 30 metres. However, the authors instead measure the shoreline at 500 metre transects, which are developed on the OSM 2016 shoreline. If these transects locally intersect a sandy polygon, they are flagged as sandy beach. Subsequently, shoreline measurements are loaded into the datafile as an array, and a linear regression on the datapoints over time provides a measure of the average regression or accretion between 1984 and 2016. These points are then stored along with relevant statistical information for further use (Luijendijk *et al.*, 2018).

A.2.3. Google Earth Engine (GEE)

A substantial drawback to the above-outlined SDS methodology is the high computational cost to analyze each image. Traditional computing infrastructure would be pressed to efficiently run the required algorithms on the scale that we require for a global vulnerability assessment. However, recent advances in cloud computing technology have made new infrastructure available to the public which changes the feasibility of the SDS algorithm (Luijendijk *et al.*, 2018).

Google Earth Engine (GEE) is a novel cloud computing resource combining extensive access to a petabyte of Landsat and Sentinel imagery in conjunction built-in computing capacity. By moving this capacity to the cloud, GEE allows efficient application of image processing techniques on the large scales required to implement vulnerability assessments on a global scale. In addition to providing the computational power, GEE negates bandwidth requirements by applying algorithms to images in the cloud rather than forcing the user to download each datafile.

A.2.4. SRES and RCP

The IPCC Special Report on Emissions Scenarios (SRES's) and Representative Concentration Pathways (RCP's) are two tools which identify the breadth of scientific knowledge with respect to future socio-economic and climate conditions. The presence of these scenarios facilitate scientific research into the impacts of climate change by providing a unified set of conditions under which new information can be coordinated and evaluated (IPCC, 2000) Since the SRES's were developed first, and led directly to the development of the RCP's, they are considered first.

SRES

SRES scenarios illustrate the range of driving forces and emissions as understood in the scientific literature in 2000. The space in which these scenarios make predictions is highly uncertain, and all are considered equally probable by the IPCC. While 80 such scenarios exist, generally they are split into four main storylines, which are outlined in Figures A.4. These scenarios exclude the development of specific climate legislation. These storylines A1, A2, B1, and B2 represent significantly different development patterns over the next 100 years. Storyline A1 is further broken down into three sub-categories, which indicate the primary mode of technological development. While scenario A1T indicates a developing world that embraces green

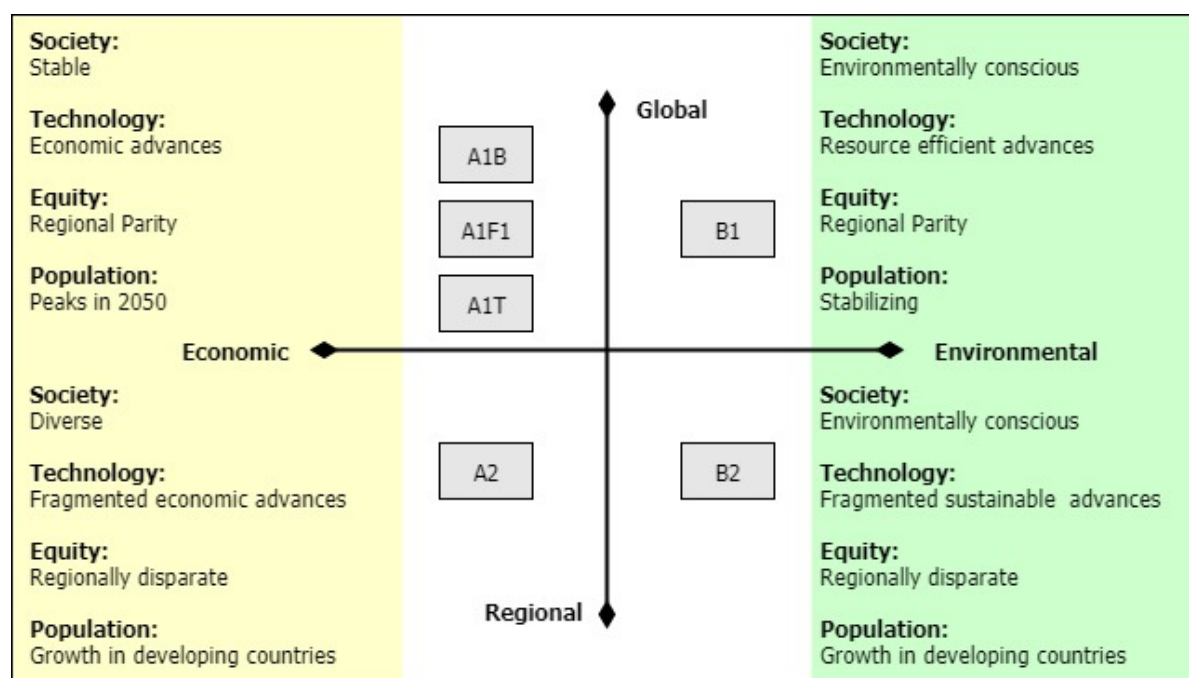


Figure A.4: Identification of key attributes associated with IPCC SRES storylines

technology, Scenario A1FI represents a world in which growth is driven by fossil fuels and Scenario A1B represents a balance between energy sources.

Prior to the release of the updated RCP's in 2014, the IPCC recommended that scientists use a number of marker scenarios to analyse and present data over the long term. These marker scenarios are no more likely than the other scenarios in each timeline, but are considered representative of the narrative presented by the IPCC in its 2000 report. Further, the IPCC recommended the analysis of A1T and A1FI scenarios, which are considered illustrative of the range of possibilities within the basic A1 scenario. These marker scenarios are highlighted Figure A.4.

We find the SRES scenarios significant due to their inclusion in the 2013 analysis by [Hinkel et al. \(2013\)](#) studied here. However, these scenarios do not address any explicit attempt to limit carbon emissions, which provided a basis for their eventual replacement.

Representative Concentration Pathways (RCPs)

In response to criticisms about the SRES scenarios, the IPCC encouraged the development of a new set of scenarios for the Fifth Assessment Report in 2014a. These scenarios, termed Representative Concentration Pathways (RCP's), are projections of forcing parameters such that they are realistic representations of a number of different socioeconomic conditions ([van Vuuren et al., 2011](#)). The forcing identified in the RCP scenarios, or radiative forcing, is a general measure of the retention of radiative heat by the atmosphere. These are named to approximately represent a multiplicative factor of radiative forcing over pre-industrial levels ([IPCC, 2014a](#)).

Newer studies typically use RCP scenarios to align with the body of existing research. Any work developing the DIVA model should thus attempt resolve discrepancies between the existing academic work in [Hinkel et al. \(2013\)](#) and the current state of research using RCPs before moving forward.

A.2.5. Vulnerability Assessment

Füssel and Klein (2006) identify two overarching responses to risks stemming from climate change: mitigation and adaptation. Mitigation attempts to stymie climate change by reducing greenhouse gas emissions and promoting the health and development of CO_2 sinks. Adaptation aims to moderate adverse affects through actions targeted at vulnerable systems. Where mitigation is broadly applicable in both it's methods and benefits, adaptation occurs at a regional scale. However, adaptation is significantly beneficial in that its use is less dependant on other actors than mitigation.

To be effective, adaptation strategies must build on a foundation of information about what to adapt and how to adapt. The IPCC reports, particularly those of Working Group II, and other global vulnerability assessments are part of a framework of information informing these important decisions. from Füssel and Klein (2006), three major decision contexts are outlined with respect to vulnerability assessment:

1. Specification of long-term targets for the mitigation of global climate change.
2. Identification of particularly vulnerable regions and/or groups in society to prioritize resource allocation for research and for adaptation (both internationally and nationally).
3. Recommendation of adaptation measures for specific regions and sectors.

Of the above items, we focus most on the second context, in which vulnerable regions are identified. However, there are also some components of the DIVA framework which touch upon the first and third points. Historically, global assessments in the coastal zone have fallen under the first two categories:

First Global Vulnerability Assessment The first Global Vulnerability Assessment for SLR was completed in 1992 and was subsequently updated in 1993 (Hoozemans *et al.*, 1993). The assessment provided a basic first look at changes to flood risk and response costs, losses in coastal wetlands, and changes to rice production. This study applied a global 1 metre sea level rise and calculated a static population density in coastal regions. As outlined in Füssel and Klein (2006), the first global vulnerability assessment would fall primarily under the Impact Assessment category of vulnerability assessments.

Second Global Vulnerability Assessment The Second Global Vulnerability Assessment, by Klein *et al.* (1999), improved upon the first to integrate variable impact algorithms. These define alternative sea lever rise scenarios, and changes to the valuation of the coastal zone over time. This change reflects globally improving standards of living and migration patterns towards the coastal zone. The second assessment also improves the prediction of impacts on coastal wetlands due to SLR. Following from Füssel and Klein (2006), this Second Global Vulnerability Analysis best represents a first order vulnerability assessment.

However, neither of the above Global Vulnerability Assessments considered structural erosion in their scope of work. The Global Vulnerability Assessments stressed relative impacts as an important measure to assess the vulnerability. and treated the coastline at a relatively coarse scale (Klein *et al.*, 1999).

A.2.6. Dynamic Interactive Vulnerability Assessment (DIVA)

DIVA was originally established to supplant the global vulnerability assessment which provided the first global estimates of the impacts of sea level rise. It is an established tool for vulnerability assessment within the coastal zone. The coastal zone is traditionally a broad swath of

land and ocean that abut the physical interface between water and land [Stive *et al.* \(2002\)](#). DIVA distills important information related to the entirety of the coastal onto a single linear coastal structure [Vafeidis *et al.* \(2004\)](#).

Segmentation

The basis for segmentation dictates how new information can be interpreted in DIVA. Segmentation refers to a decomposition of the singular global coastline into continuous homogeneous units for vulnerability analysis. These segments form the basic geographic unit within DIVA and govern the resolution of information produced by the model. Pre-processing the database in this way establishes units that are close to homogeneous over their entire length. Therefore each property is represented by a single value. Homogeneity is heavily dependant on the scale of the database ([Wolff *et al.*, 2016](#)), and DIVA segments it's coastline on the basis of four overarching factors outlined in [McFadden *et al.* \(2007\)](#):

- Physical subsystem:
 - Administrative Units
 - Socio-Economic Environment (Population Density Classes)
- Socioeconomic Subsystem:
 - Geomorphic classification of Coastal Landforms ([McGill, 1958](#))
 - Landform evolution given coastal morphology

Using this methodology, the DIVA database represents the coast as a global linear entity made up of 12,148 coastline segments. Each segment is selected so that a single dimensional array of properties approximately models an area homogeneous with respect to large-scale vulnerability to sea level rise. Segments are referenced to a geometric shapefile, such that the final database can be represented in a GIS-based GUI ([Vafeidis *et al.*, 2004](#)).

A.2.7. DIVA Model

The DIVA Database contains extensive information on the coastal zone, but does not enable vulnerability analysis on its own; instead, the DIVA Model provides this analytic and interactive capacity. [Hinkel and Klein \(2009\)](#) identified 10 modules within the DIVA framework. We are primarily concerned with modules related to beach erosion as discussed in [Hinkel *et al.* \(2013\)](#). These modules are outlined in Figure [A.5 Hinkel and Klein \(2009\)](#).

Indirect Erosion

DIVA includes 200 tidal basins which are linked to individual segments. for these segments, indirect erosion is also estimated. A simplified form of the ASMITA model provides this information. The tidal basin is broken down into three key components which exchange sediment ([Hinkel *et al.*, 2013](#)).

Total Erosion

Total erosion in DIVA is comprised of three parts: direct erosion, indirect erosion, and nourishment volumes. The total erosion module in DIVA calculates the direct erosion of sandy beaches caused by SLR using the Bruun rule. In doing so, the model assumes a cross-beach slope of 1% ([Hinkel *et al.*, 2013](#)).

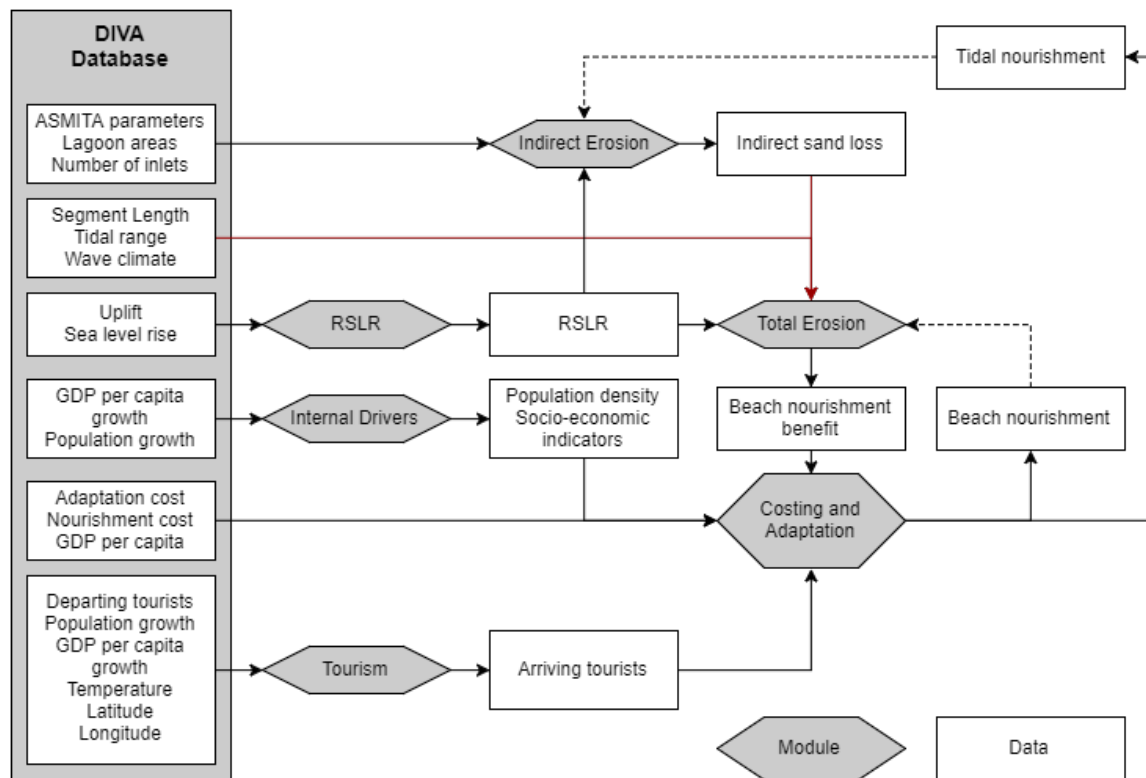


Figure A.5: Schematic diagram of DIVA modules included in the 2013 analysis by Hinkel *et al.* on sandy beach erosion Hinkel *et al.* (2013)

Internal Drivers

Socio-economic growth is based on the IMAGE 2.2 model, which is a global implementation of the IPCC SRES for socio-economic growth and climate impacts between 1995 and 2100. Socio-economic growth patterns affect the erosion module through the Tourism and Costing and Adaptation Models. Essentially, the internal drivers modulates the damages and adaptation costs of sea level rise. IMAGE is a dynamic model which incorporates complex feedback mechanisms. However, DIVA only uses results from the first two tiers of the IMAGE Model, schematized in Figure A.6.

IMAGE 2.2 is a spatially explicit assessment framework which resolves key interactions between the human use of energy, land, and water in relation to key environmental processes. The model incorporates complex feedback mechanisms to explore long-term dynamics of human development.

IMAGE 2.2 draws upon the Phoenix population model and the Worldscan general equilibrium economy model to provide population and economic growth patterns (Strengers *et al.*, 2004). Since its implementation in Hinkel *et al.* (2013), IMAGE has gone through a number of iterations, but we neglect these new iterations to better resolve the impacts of changes to the DIVA Erosion module. Similarly, a full description of IMAGE is beyond our scope, but we find an understanding of the processes it considers valuable context to the DIVA model. IMAGE 2.2 is comprised of 5 Stages, which each contain a number of significant Modules. The socio-economic stage of the IMAGE model is a key interface between the SRES scenarios and DIVA and are treated in greater detail.

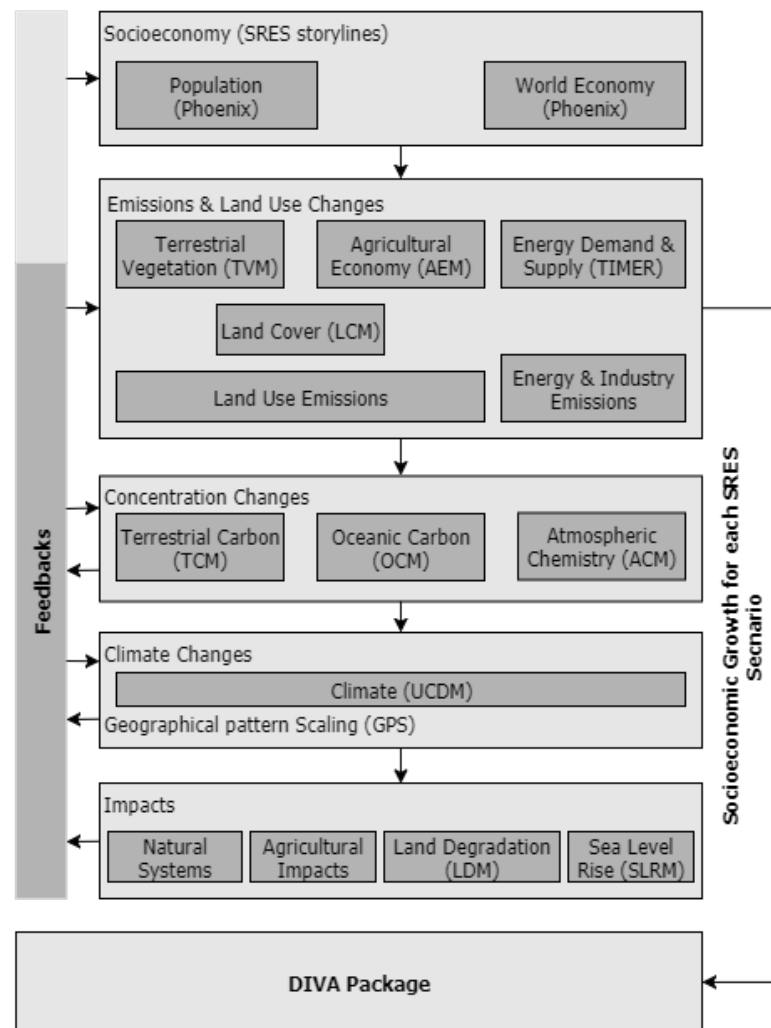


Figure A.6: Schematization of the IMAGE 2.2 model for socioeconomic growth and climate change, adapted from [Strengers et al. \(2004\)](#)

Socio-economy: WorldScan The WorldScan model is essentially a geographically resolved implementation of the neoclassical theory of growth. In this theory, three distinct factors govern changes in production: physical capital, labour and technology. Other applied general equilibrium models attempt to describe the dynamic impacts of singular changes to the economic sphere, which is generally referred to as the neoclassical theory of growth. However, WorldScan instead focuses on structural changes including the “rise and decline of regions, demographic dynamics; shifts in patterns of consumption, trade, and capital flows; and the changing distribution of income” (CPB, 1999). To achieve this, WorldScan models regions as consumer markets, production firms, labour markets, and capital markets (CPB, 1999).

WorldScan makes three changes to the neoclassical theory of growth which allow its growth scenarios to better capture these dynamics. First, WorldScan allows technology to differ between each region. In this way the model can incorporate the sharing of ideas as developing countries catch-up to more advanced countries. Second, the model incorporates high-skilled labor and low-skilled labor rather than a single labour pool. Finally, WorldScan incorporates a low-productivity sector in developing countries in which the workers have no access to capital or technology. These three factors relate to the manner in which developing countries perform

economically in relation to developed countries (CPB, 1999).

The model has thus been arranged such that these countries are able to catch-up to developed nations under the appropriate circumstances (CPB, 1999). The core principles of the WorldScan model, including the neoclassical theory of growth follow these broad categories:

- an Armington Trade Specification, which uses relative market power to determine medium-term trade patterns, while a Heckscher-Ohlin model based on the regional disparity of production factors governs long-term trade patterns;
- imperfect financial capital mobility;
- consumptive patterns based on a per-capita income, converging to a unified pattern of consumption as income increases;
- The inclusion of a low-productivity sector in developing regions. At a regional level, transferring labour from the low-productivity sector to high productivity sectors allows for short-term elevated growth patterns; and
- A division of labour between high-skilled labour and low-skilled labour (CPB, 1999).

Socio-economy: PHOENIX Model The PHOENIX model resolves regional populations into demographic age-groups and applies environment-based fertility and mortality rates in each group to determine long-term population growth. The model further resolves gender into male and female categories is comprised of four subsystems for population, fertility, mortality, and migration and can take climatic and economic parameters into account.

Population forms the core of the PHOENIX model and is governed by a principle of conservation following Equation A.7. Fertility rates determine the number of births in each year and take as an input parameter the per-capita income derived from the WorldScan model. Subsequently PHOENIX derives the number of deaths for each age and sex category rates. Mortality takes into account external factors not explicit in the PHOENIX model, but which are present in the rest of IMAGE 2.2. Both environmental and economic factors influence the rate of births and deaths within the PHOENIX model. Finally, intra- and inter-regional Migration patterns are derived. Intra-regional patterns are modelled primarily as migration between rural and urban area. Inter-regional patterns are governed by labour markets and disruption, however these follow complex patterns not implicitly modelled in the PHOENIX package. Both intra- and inter-regional net migration are therefore based on historical data according to age and sex.

$$P_a(t) = \begin{cases} B(t-1) - D_0(t-1) + M_0 & a = 0 \\ P_{a-1}(t-1) - D_{a-1} + M_{a-1} & 0 < a \leq 99 \\ P_{99}(t-1) - D_{99} + M_{99} + P_{100+}(t-1) - D_{100+} + M_{100+} & 99 < a \end{cases} \quad (\text{A.7})$$

Where:

- $P_a(t)$ is the population in age category a at time t
- B_{age} is the births in a given year
- D_{age} is the number of deaths in a given year
- M_{age} is the migration of people into a region in a given year

Land Use Land use information for the DIVA model is extracted from the IMAGE project. In addition to its use within the internal drivers module, land use is used as a switch to determine the cost of the land lost. DIVA relates land loss costs to the lowest-value land in each segment. This relation assumes that SLR-induced beach erosion is a slow process by which assets are allowed to fully depreciate and owners move landward before any damage occurs. However, as with forced migration [Yohe et al. \(2011\)](#) posits that this form of planned retreat may be unlikely. Land loss is thus calculated using Equation A.11, which relates land costs to agricultural land costs where this is the least valuable land in any segment. If the loss of land occurs in a segment with un-tilled land, these land costs are then halved [Hinkel et al. \(2013\)](#); [Hinkel and Klein \(2009\)](#).

$$V = \alpha * (d * GDP_c)^\beta \quad (\text{A.8})$$

Where:

- V is the cost of agricultural land
- α is an empirical factor equal to 180.4
- β is an empirical factor equal to 0.53
- d is the population density in the coastal zone
- GDP_c is the per-capita GDP converted 1995 USD

Relative Sea Level Rise

DIVA approaches SLR as a two part problem. While SLR in SRES scenarios is tied to the output from CLIMBER 2, which provides climate predictions based on the capacity of the environment to absorb CO_2 , more recent work is capable of using a range of global circulation models to develop global SLR projections. This report focuses on the Hadley Centre Global Environment Model version 2 (HADGEM2), which provides information on sea level changes due to temperature and salinity ([Collins et al., 2011](#)). This is supplemented with Land-ice contributions from glaciers, and the Greenland and the Antarctic ice sheets are developed as part of the GSLR model [Hinkel et al. \(2014\)](#); [Bamber and Riva \(2010\)](#); [Marzeion et al. \(2012\)](#); [Fettweis et al. \(2013\)](#); [Levermann et al. \(2012\)](#). This information is stored in DIVA separately from local uplift information as a result of isostatic adjustments. These are superimposed onto the model on a segment-by-segment basis including a 2mm per year subsidence at deltas ([Hinkel et al., 2013](#); [Peltier, 1999](#)).

Tourism

Tourism is directly affected by erosion as the loss of beach is tied to a loss of tourist revenues. In the DIVA model, tourism also plays a role in the Costing and Adaptation Module as an input for the optimized cost-benefit analysis for beach nourishment programs. Tourist revenues in DIVA are based on the Hamburg Tourism Model (HTM) presented in [Hamilton et al. 2005a](#). The HTM models the flow of tourism between countries at a national scale. DIVA assumes that 16 percent of National Tourism Revenues, which accounts for tourism profits in the coastal zone [Hinkel et al. \(2013\)](#).

Hamburg Tourism Model The HTM models global flows of tourists at a national level with two matrices indicating the number of tourists entering and leaving a country. Known arrival and departure information forms the initial conditions for this model. Where data is unavailable, initial conditions are estimated using a best-fit procedure, outlined in Equations

A.9 and **A.10**. Equation **A.9** approximates the arrival of tourists by country. Here, **Ar** is the number of arriving tourists in a year, **A** is the total area of the country, **T** is the average annual temperature, **L** is the length of coastline, and **Y** is the per capita income of the country (Hamilton *et al.*, 2005a). Equation **A.10** approximates the number of tourists generated in a country. Here, **Pop** is the country's population, **D** is the number of departures, and **B** is the number of countries sharing borders with the country in question.

$$\ln(\mathbf{Ar}) = 5.97 + 2.05 * 10^{-7} * \mathbf{A} + 0.22 * \mathbf{T} - 7.91 * 10^{-3} * \mathbf{T}^2 + 7.15 * 10^{-5} * \mathbf{L} + 0.80 \ln(\mathbf{Y}) + \mathbf{K}_a \quad (\text{A.9})$$

$$\ln(\mathbf{D/Pop}) = \mathbf{K}_d * (1.51 - 0.18 * \mathbf{T} + 4.83 * \mathbf{T}^2 - 5.56 * 10^{-2} * \mathbf{B} + 0.86 \ln(\mathbf{Y}) - 0.23 \ln(\mathbf{A})) \quad (\text{A.10})$$

The aggregation of the above data results in a 17% disparity between total global arrivals and departures. Information on departures is therefore uniformly scaled with $\mathbf{K}_d$ to match the arrivals and ensure a conservative model. Initial information is subsequently used to calibrate the general attractiveness of each country using $\mathbf{K}_a$, to define the portion of global tourism attributed to each country. Calibrating the matrix in this way allows the model to vary other inputs, such as population, average temperature, and average per capita income, for Equations **A.9** and **A.10**. As such, tourism is modelled in relation to climate change and socio-economic development.

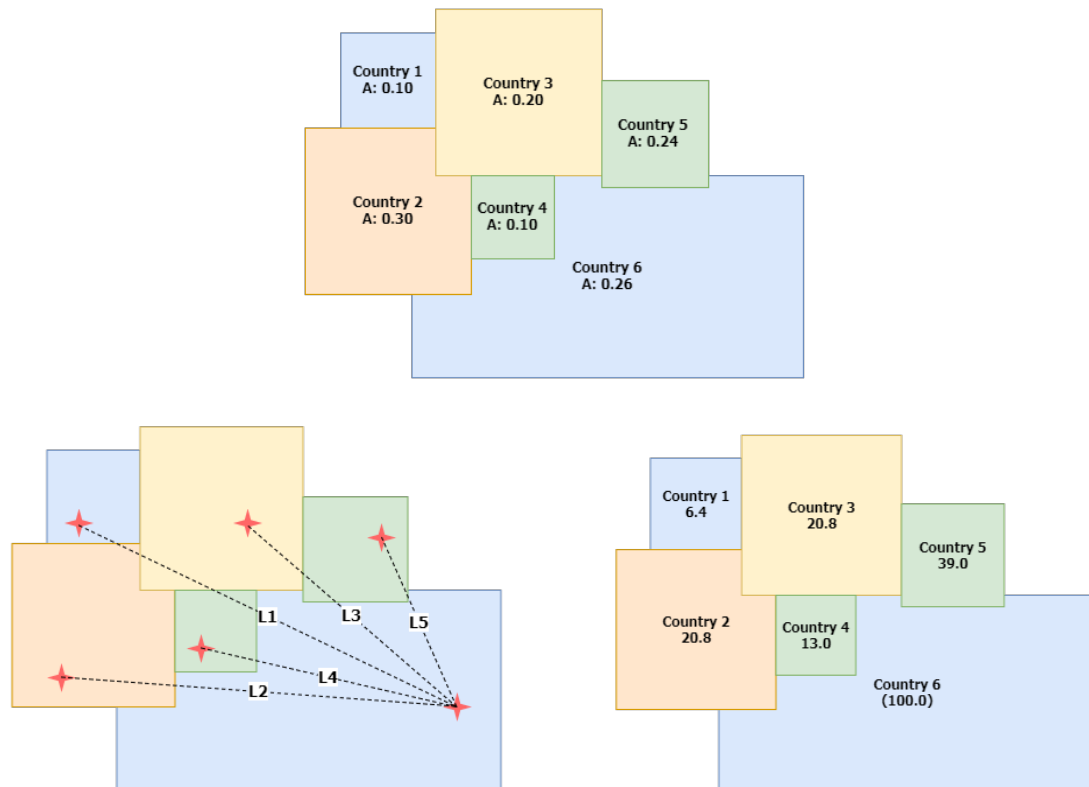
Once calibrated, future tourism projections are driven primarily by the development of departing tourist projections developed through Equation **A.10**. General Attractiveness indices are also modified to suit climate change and socioeconomic scenarios by means of Equation **A.9**. For a single country of origin, tourists are divided among destination countries by weighting the General Attractiveness Index for each recipient and the distance between origin and destination capitals. This process is visualized in Figure **A.7**, which demonstrates the HTM portioning procedure for 100 tourists from a single origin country.

This initial data is used to populate a bi-lateral chart of tourism flows

Costing and Adaptation

Costing and Adaptation (CA) is one of the most complex modules in the DIVA package in terms of input and outputs parameters. Indeed, the capacity of DIVA to assess costs from a broad range of impacts is one of the strengths of the package. Taking inspiration from earlier attempts to quantify the impacts of climate change (e.g. Yohe *et al.*, 2011, 1996; Tol, 1995) the CA interacts with modules for tourism, flooding, wetland valuation, internal drivers, and total erosion. However, we are only interested in those factors impacting the erosion model, so flooding and wetland protection are not expanded upon here. Costs can be split in two dimensions. First the distinction between damages and adaptation costs is developed, and secondly costs can be impacts into tangible and intangible costs. At this time, generalized costs for land loss, forced migration, and beach nourishment interact within the DIVA erosion suite.

Land Loss The most tangible impact of beach erosion within the DIVA Model is the physical loss of land due to the regression of the shoreline. Loss of land is based on a sediment balance



Country	G.A.	Distance (L)	R.A.	R.A Portion	tourism
1	0.1	20	0.005	0.064	6.4
2	0.3	18	0.016	0.208	20.8
3	0.2	12	0.016	0.208	20.8
4	0.1	10	0.010	0.130	13.0
5	0.24	8	0.030	0.390	39.0
Total			0.077	1.000	100

Figure A.7: A simplified application of the HTM for a single origin country. In the above model, socio-economic and climate change models alter the General Attractiveness index (G.A.) and the generation of total tourists from each country. In this way, a simplified pattern governing tourism revenues can be modelled at a coarse level (Hamilton *et al.*, 2005a)

using the Bruun Rule and ASMITA results. Total volume is derived using a depth of closure equation which relies on wave climate classifications (Hinkel *et al.*, 2013; Hallermeier, 1978; FAO GEONETWORK, 1995) and tidal ranges (Pickering *et al.*, 2017). This information is fed into a basic sediment balance which includes volumes of sediment diverted from the coastal zone to local tidal basins to determine a remaining sediment balance, which is distributed over the length of each segment to determine the total land lost (Hinkel *et al.*, 2013).

Predicted areas of land lost due to beach erosion is passed from the Total Erosion module to the CA module along with information on the dominant land-use class for each segment. Hinkel *et al.* (2013) noted that this class is usually graded agricultural or lower. Due to the slow speed of change, DIVA assumes that the land-use classes lost to erosion will re-locate elsewhere. This leads to a cascading shift ending at low-value and abundant land-use classes which are lost. The general form of the land-loss calculation is shown in Equation A.11.

$$'Cost' = 'ErodedLandArea'(ha) \times 'ValueofDominantLandUse' (\$/ha) \quad (A.11)$$

Forced Migration DIVA also considers the intangible costs forced migration as a part of damages resulting from beach erosion. The number of people displaced due to erosion is generalized using the eroded land area and average segment population density information passed from the Internal Drivers module and the IMAGE 2.2 model for socioeconomic growth. There are a number of complex factors which influence the intangible cost of migration including the socioeconomic circumstances of the migrants, the reason for the migration. Forced migration is valued in DIVA at 300% of the per-capita income to represent their hardship (Hinkel *et al.*, 2013; Tol, 1995)

$$'Cost' = 3 \times 'ErodedLandArea'(ha) \times 'PopulationDensity'(c/ha) \times 'PerCapitaIncome' (\$/c/year) \quad (A.12)$$

The DIVA package assumes that owners act with “perfect foresight” and that infrastructure depreciates over time until it is abandoned in reference to work by Yohe *et al.* (2011). As such, no tangible costs are associated with forced migration. However, a second scenario posited by Yohe *et al.* argued that a “no-foresight” scenario in which owners maintain properties until catastrophic failure due to misplaced confidence in governing bodies is more realistic. However, the implications of this difference on the DIVA package are relegated here for the subject of future research (Hinkel and Klein, 2009).

Nourishment Nourishment refers to the application of foreign beach-grade materials of a suitable quality to the nearshore zone to provide protection from erosion and flooding. The secondary benefits of this protection, such as the provision of open beach space which in turn generates tourism revenues, further encourage the implementation of this adaptation methodology. Nourishment traditionally takes place directly on the beach, which immediately improves flood protection and the space available for tourism (Hinkel *et al.*, 2013). Recent advancements have introduced the concept of shore nourishment, which places material beyond the near-shore zone with the understanding that long-term natural processes will drive the sediment on-shore over time. Shore nourishment is less intensive than beach nourishment and comes at a lower cost, but does not immediately provide the secondary benefits provided by beach nourishment (Hinkel *et al.*, 2013). Nourishment volumes are selected to offset the loss of sediment outlined in the total erosion module.

A basic model for nourishment uses expert judgment to establish the cost matrix shown in Table A.1. The model assumes that regional disparities have no direct impact on the unit costs of nourishment, but instead distinguishes classes of sediment availability inferred from the Erosion Factor. The factor, taken directly from the Total Erosion module, is the proportion of coastline occupied by sandy beaches. This relation between sediment availability and beach composition is tenuous, since beach-dense segments can reside in larger regions with poor marine sediment availability (e.g. Indonesia, UAE). However, the DIVA package had few alternatives in the pre-existing data-sparse environment.

The indifference of the DIVA nourishment cost model to the local economy reflects the large and global character of major dredging companies, but neglects some market factors which may affect long-term costs. Instead, the highly regional availability of suitable material provides greater detail for dredging costs. The costing model categorizes nourishment alternatives as either beach or shoreface as shown in A.1 (Hinkel *et al.*, 2013).

Table A.1: DIVA nourishment cost model (Hinkel *et al.*, 2013)

Erosion Factor	Shore Nourishment (US\$/m ²)	Beach Nourishment (US\$/m ²)
>0.5 (sand supply abundant)	3	6
0.2 to 0.5	6	9
<0.2 (sand supply limited)	9	12

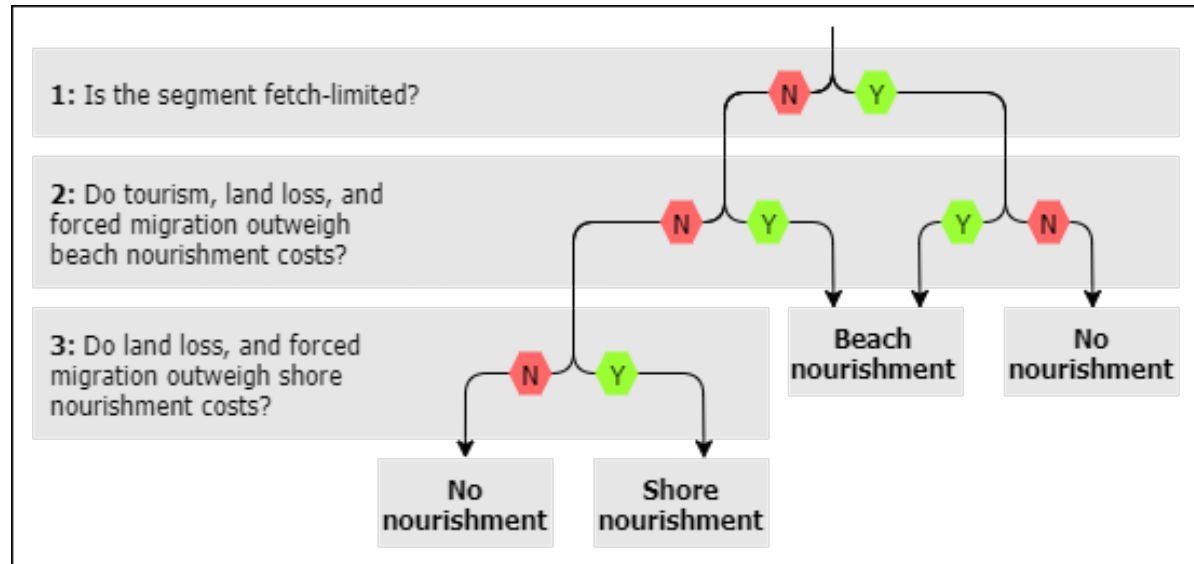


Figure A.8: Decision tree identifying beach and shore nourishment options in the existing DIVA model 2010.

Tourism The implications of SLR on tourism are not explicit in the DIVA CA module, and changes to tourism revenues are not reported as damages or adaptation costs. However, tourism revenues are applied within the CA module as part of the cost-benefits analysis for nourishment practices. The impact of tourism on each segment is taken directly from DIVAs Tourism module in 1995 US Dollars

Cost Benefit Analysis The costs and impacts in the CA model are modelled as linear functions of the area protected. As such, beach nourishment either protects against all erosion or is entirely neglected. The CA module applies a basic decision-tree cost-benefit-analysis, outlined in Figure A.8. Since secondary benefits of tourism are only applicable in the case of direct beach nourishment, beaches affected by the Tourism module exhibit a strong preference towards beach nourishment. Similarly, processes on the lower shore-face require relatively large waves to push sediment onshore, such that shore nourishment is not suitable in fetch-limited areas which only experience low-energy-waves REFERENCE.

A.2.8. Spatial Relation

Spatial relation of two datasets on a global scale is difficult because measurements do not align. Further, any flat-planed projection of information will contain artefacts near the edges of the reference plane in which the actual location of the point may vary. Coordinates for each dataset considered in this report are stored as latitude and longitude coordinates. This coordinate system is a spatial representation of data on a grid in which distances between points changes the further from the equator those points sit. Generally, any "equal distance" projection can be expected to have locations where the projection does not work as intended.

Earth-Centered, Earth-Fixed (ECEF) coordinate systems sit in space with the equator as the x-plane and bisecting y and z planes. Data presented in this form can be related directly, but these distances may not cover arc-length.

KD-Tree Analysis

Spatial KD-Tree analysis is a methodology by which a spatial dataset is developed into a structured binary search tree. By passing through this tree, an input point can be related to the nearest point in the tree by passing through a series of “branches” which bi-sect the space occupied by the tree. These planes are orthogonal to each other such that three subsequent branches will represent planes bisecting x, y, and z space before repeating. Every branch isolates approximately half of the remaining points so that the search time is logarithmically faster than a point-by-point search pattern. In this way a large dataset can be tested in a relatively small amount of time to determine the closest point. While the initial formulation of the tree takes some time, it represents a fast method to relate two large datasets such as those represented by the DIVA and SDS databases without searching point-by-point ([Maneewongvatana and Mount, 2001](#)).

A.3. Recent Analysis

The DIVA package has been developed over the course of almost two decades in increments. The trend in published papers regarding development has generally gone from descriptive papers outlining the techniques supporting the model; to limited application of the model across specific regions or modules; to global analyses; and more recently to refined application of the model basis to develop better-resolved information. Much of the information presented above relates to the techniques supporting the development of the model. Here, we go into more detail on the published DIVA applications and the placement of our thesis within the current body of work on global vulnerability analyses.

A.3.1. Hinkel 2010

One of the first published applications of the DIVA model by its founding partners is [Hinkel et al. \(2010\)](#). Here, [Hinkel et al.](#) applied the DIVA Package to countries within the European Union to assess adaptation strategies by country and region. SRES scenarios A2 and B1 develop the predicted risk and adaptation patterns for European coastal countries. This study included adaptation strategies and policies associated with flood protection, salinization of rivers, and erosion. The combination of these modules is a full application of the DIVA Costing and Adaptation module at a regional scale.

[Hinkel et al. \(2010\)](#) breaks the costs associated with sea level rise into adaptation costs and damage costs. Adaptation refers to planned measures such as beach nourishment or dike adjustment whereas damages are physical costs associated with the loss of land, forced migration, and flooding events. The study found that extreme storm surge and flooding events worsened by rising sea levels account for most of the foreseen damages. [Hinkel et al.](#) posits that established adaptation methods will effectively manage the risk from SLR in the EU so long as per-capita GDP continues to grow and adaptation becomes routine ([Hinkel et al., 2010](#)).

However, this study does not explicitly address the erosion module that acts as a focal point for our thesis. Therefore, the quantitative results from [Hinkel et al. \(2010\)](#) cannot be employed as a benchmark for the updates proposed by our thesis, but serves as contextual information given the magnitude of the impacts of erosion when compared to inundation.

A.3.2. Nicholls, 2011

The benefits of impact assessment and adaptation planning are long-standing and well-documented in the coastal zone (e.g. [IPCC, 2014a](#); [Klein et al., 1999](#); [Nicholls and Hoozemans, 2000](#)). More recently, [Nicholls et al. \(2011\)](#) used the DIVA model to quantify and highlight the potential differences between a planned management approach and an unplanned approach in the context of extreme SLR. This study is a first global application of the DIVA program with a current cost and adaptation module, but similarly to [Hinkel et al. \(2010\)](#) includes modules not addressed by our thesis and so cannot be used as a baseline. However, the low-probability, high consequence scenarios such as these are important contextualization which motivates improvements to DIVA.

The IPCC reports are purposefully neglected of these scenarios, yet they still require study as part of an effective global vulnerability assessment. [Nicholls et al.](#) used two approaches contrasting adaptation to CC and management of CC impacts. In adaptation, flood protection is improved to keep pace with SLR, while management of CC implies flood protection is maintained at current elevations.

The paper evaluated 0.5 and 2.0 metre SLR scenarios, finding that the cost of adaptation to climate change is much less than the cost of consequences with no adaptation. From a conceptual standpoint, the DIVA model is a fundamental part of the adaptation approach. The package provides context for management decisions and at a large scale identifies vulnerable regions for further study.

A.3.3. Hinkel, 2012

[Hinkel et al. \(2012\)](#) further expanded the number of scenarios considered in DIVA in a regional study which considered the impacts of Sea level rise on Africa. This study, motivated by the apparent social vulnerability of the continent to SLR, demonstrated the DIVA's suitability to operate in regions characterized by a scarcity of information. This report also highlights areas where this scarcity of information can be addressed by future studies, specifically with respect to existing flood protection measures on the African coast, which are difficult to qualify.

A.3.4. Hinkel, 2013

Of the studies outlined here, [Hinkel et al. \(2013\)](#) is the first to explicitly address the erosion module within DIVA. [Hinkel et al.](#) used the DIVA module to show significant socioeconomic impacts of erosive patterns resulting from predicted rates of sea level rise in the 21st century at a global level. The paper builds on work from [Hinkel et al. \(2012\)](#), [Nicholls et al. \(2011\)](#), and [Hinkel et al. \(2010\)](#) using similar methodologies but synthesizing information specifically related to the DIVA erosion module. As such, the [Hinkel et al. \(2013\)](#) paper is of specific interest to our work.

The [Hinkel et al. \(2013\)](#) study is also notable because it considers a far greater breadth of climate change and administrative response scenarios than previous studies. Sensitivity analysis across climate change and sea level rise scenarios at a global scale form the work's core, explicitly considering the impacts of modern beach nourishment programs. The extent of the climatic considerations and spatial scope of the study, combined with a focus on coastal erosion make this paper an ideal baseline for contrasting our new information with historic analysis. We therefore re-develop the results from [Hinkel et al.](#) as a foil to highlight important changes to DIVA applied in this thesis [Hinkel et al. \(2013\)](#).

Scenarios

[Hinkel et al. \(2013\)](#) models 8 scenarios in their assessment using the IMAGE 2.2 and CLIMBER

2 projections outlined in 2. Apart from emission scenario A1B, all scenarios assume a medium climate sensitivity developed in the CLIMBER 2 model. Emission scenario A1B is modelled with all climate sensitivities to better evaluate the stability of the DIVA model in this dimension.

The [Hinkel et al. \(2013\)](#) paper assesses beach nourishment policy by repeating each scenario with and without human intervention through beach nourishment. When modelled, nourishment occurs using cost-benefit analysis to optimize nourished volumes against projected tourism revenues, land-loss, and the economic equivalent costs of forced migration. When the cost of damages exceeds the cost of adaptation through nourishment, DIVA assumes that segment is then protected entirely. In areas where tourism is significant, this protection is almost always afforded in terms of beach nourishment. Beach nourishment is also assumed for fetch-limited seas such as the Baltic where shore nourishment does not provide timely protection due to reduced wave energy([Hinkel et al., 2013](#)). [Hinkel et al.](#) further assumes no lack of available sediment for beach grade materials

[Hinkel et al. \(2013\)](#) evaluate the impacts of sea level rise in the DIVA model through two mechanisms: Physical land-loss and forced migration. Physical land loss is a direct impact of SLR, whereas forced migration is indirect. These calculations are carried out following the standard DIVA methodology in which the predominant land-use category estimates the cost of the lost land and forced migration amounts to three times the per capita income of the displaced persons. [Hinkel et al. \(2013\)](#) observed that the majority of the land-lost is agricultural or lower in value, and posited that as humans move away from eroding regions in a knock-on pattern, the ultimate loss of land will be equivalent to the lowest value land not replaced. There are other costs associated with the migration of people and industry away from the coast which are currently integrated into the damages caused by forced migration.

Quantification

[Hinkel et al. \(2013\)](#) quantifies the predictions made by DIVA in multiple stages. First, Hinkel establishes a global aggregated baseline for each scenario in terms of population, GDP, SLR, number of people forced to migrate, and migration cost without the implementation of nourishment practice. This information is presented in a number of timelines demonstrating development over the next 100 years. This information specifically excludes the consideration of current programs such as the Dutch Delta Plan or the Thames Estuary Plan. [Hinkel et al.](#) subsequently develops country-by-country information in terms of gross costs and as a percentage of GDP for land lost and forced migration. Finally, [Hinkel et al. \(2013\)](#) finds the global aggregated impact of the beach nourishment adaptation strategy in terms of percent reduction in land loss and forced migration and contrasts this against the nourishment cost under each scenario. Together, these form a minimum-set of relevant output parameters. Any analysis building upon [Hinkel et al. \(2013\)](#) should address these figures and how they change in relation to the studied material.

Nourishment Impact

[Hinkel et al.](#) finds that the global share of nourished erodible coast increases from 3% in 2000 to 18-33% in 2100. At a simplified level, this is a minimum 600% increase in nourished coast which relates directly to nourished volumes and capital expenditure. However, multiple factors compound the impacts of this increase. The DIVA model predicts that increasing affluence and climate change will tip the balance of the cost benefit analysis in many regions towards beach nourishment rather than shore nourishment, which will further increase capital expenditure. However, [Hinkel et al.](#) also identified numerous factors affecting the comportment of the erosion modules within DIVA. Improving the available information in these domains will refine the DIVA results and better nourishment cost projections:

- Improve the description of coastal erosion via the Bruun rule or other method
- Improve the resolution of the length of sandy coast in each DIVA segment
- Improve the resolution of the tourism module within DIVA
- Improve the information available and implementation procedures for tidal basins, which greatly affect secondary coastal erosion

While this thesis addresses an update to the DIVA model by addressing direct coastal erosion, secondary erosion due to the presence of additional tidal basins is not treated, and likely represents a suitable topic for another thesis.

A.3.5. [Spencer, 2016](#)

Following the paper by [Hinkel *et al.* \(2013\)](#), [Spencer *et al.* \(2016\)](#) published work which expanded DIVA's scope to include substantial implementation of a global Wetland Change Model to refine the impacts of SLR and coastal squeeze from an environmental sense. This new module is not discussed at length in our work here. Wetland ecosystem services valuations are more likely to have an effect on the DIVA inundation and flood protection modules than those related to coastal erosion, but are important considerations for future work.

A.3.6. [Wolff, 2016](#)

Most recently, [Wolff *et al.*](#) implemented the same methodology behind the global DIVA model in a Mediterranean database with a refined segmentation process. The study identifies 4 dimensions of uncertainty which impact the results of flooding vulnerability analyses including elevation, population, vertical land movement, and scale and resolution.

This resolution of DIVA segmentation improves the scale at which the aggregation of information becomes useful. Studies by Deltares in conjunction with the RISES AM program have similarly attempted to validate DIVA as a potential source for boundary condition information for local projects ([Deltares, 2013](#)). This trend in analysis patterns suggest a future demand for finer DIVA segmentation in conjunction with more detailed data development capable of supporting studies at scales finer than a national setting.

[Wolff *et al.*](#) evaluated the Emilia-Romana Region of the Italian coast found that the resolution of the input data for the DIVA information can have a significant impact on the results of coastal flood vulnerability assessment. This study uses three sea level rise scenarios to demonstrate the full range of uncertainty covered by [Hinkel *et al.* \(2014\)](#), and presents streamlined information on the impacts of these changes. [Wolff *et al.*](#) demonstrates significant differences between Lower bound, mid-range, and upper bound SLR. Specifically, the study finds differences between segmentation scales for the emilia-romagna region show fluctuations of 28% for the predicted portion of the total population flooded annually. This information does not relate to the DIVA erosion module, but the approach demonstrates a method for the analysis of changes to the DIVA framework.

A.3.7. [Wolff, 2018](#)

in 2018, [Wolff *et al.*](#) presented a new segmentation methodology for the Mediterranean Sea which was derived from the DIVA methodology. This segmentation uses different administrative boundaries and physical factors as well as a coastline with more detailed information to develop a segmentation with approximately 20 times more segments than the global DIVA database. The information contained in this new database represents a significant departure from that available in the global database, and as such cannot be compared to the global work

presented in this thesis. However, the new segmentation information represents a significant step towards a fine-resolution model and comparing the SDS-DIVA and SDS-DIVA-med connections is a useful analytical tool to discuss the impact of this thesis as DIVA continues to evolve.

B

Database Methods

The methodology presented in this report is split into 3 parts to clarify its processes and techniques. Appendix B outlines a technical methodology to relate the GSCD point information to the DIVA segmentation. Appendix C outlines the development of the Nourishment Cost Model (NCM) and the relevant parameters therein. Finally, Appendix D identifies the overall procedure taken when developing the first two methodologies within the DIVA framework.

While the technical methodology does not address the core practice of coastal engineering, the proper administrative and technical support is vital to the future success of the model including validation, updates, and improvements. The technical methodology delivers quantitative measures of the suitability of the new and old beach information with reference to benchmark and baseline scenarios developed by students within the Coastal and Marine Engineering and Management Erasmus program.

B.1. Technical Methodology

Determining the link between DIVA and GSCD is theoretically simple, yet technically difficult. From a theoretical standpoint, the databases relate to the same coastal entity. However, each database stores information in a different way and the entities do not exactly align. There are also elements resolved at a smaller scale in GSCD which do not relate to DIVA. These include some significant morphological features such as spits, barrier islands, and small tidal basins. The selection of a connection methodology between the two databases inherently addresses the relevance of these features in one way or another, and is discussed in some length here. The link is further complicated by the relatively large size of each database and a preference for computational efficiency.

B.1.1. Process

The purpose of this technical methodology is to elucidate the transfer of information from the GSCD database to the DIVA database. Information regarding the storage of information within the two databases is summarized in Table B.1. DIVA relates data as an array to a single-dimensional set of coastline segments, which is stored as a shapefile with multiline geometry types. GSCD information, however, is referenced to points at 500 metre intervals.

There are three overarching processes that govern the transition of information between the two databases. The first references GSCD information to unique DIVA coastal segments. Second we develop modules capable of transmitting information from one database to the other. Finally, a validation process identifies the suitability of the connection compared to a manual digitization of the connection.

Database	Storage Type	Base Coastline Information	Spatial Information	Number of Spatial Entities
DIVA	Shapefile	Open Earth 2016	Multi-line	Approximately 10^4
SDS	Geojson	Digital Chart of the World	Point	Approximately 10^8

Table B.1: Information on the representation of the SDS/GSCD and DIVA databases in electronic information systems.

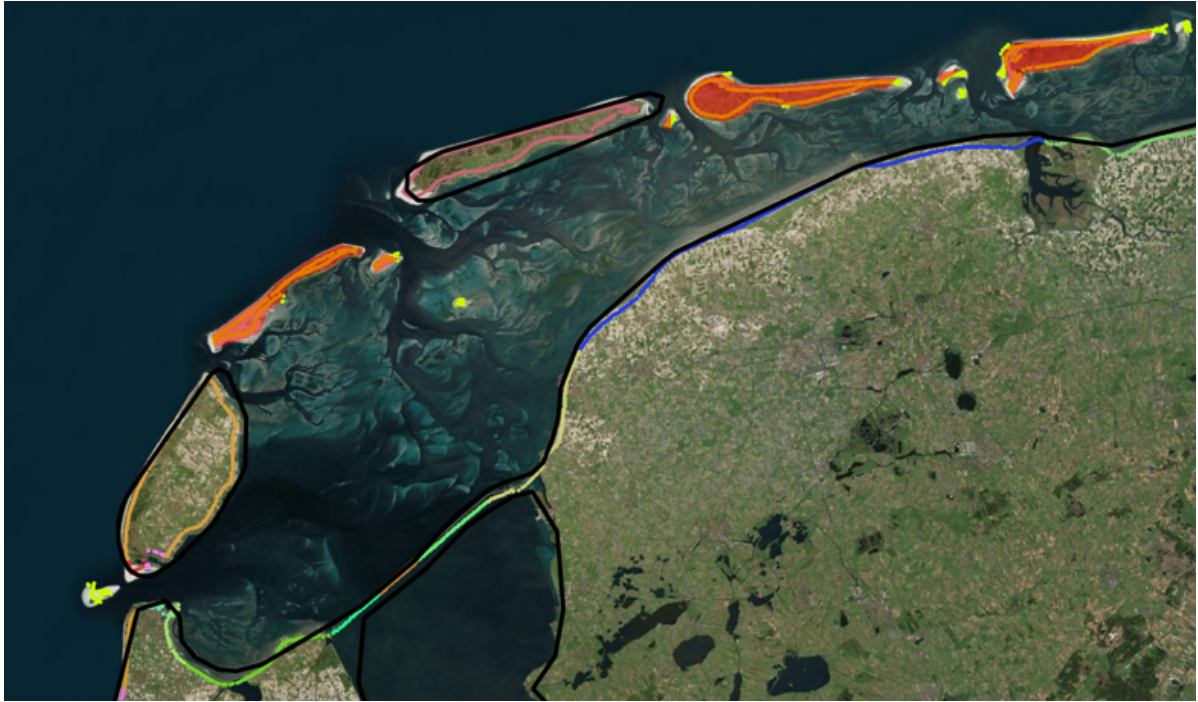


Figure B.1: Map of the Wadden Sea demonstrating differences between the GSCD and DIVA data-sets. Some islands included in the GSCD are not reflected in DIVA, while some basins identified in DIVA are not included in the GSCD.

B.1.2. Reasoning

A successful methodology connecting the DIVA and GSCD framework is heavily dependant on the overall frame of reference and intended development pattern for the existing DIVA package. Current applications of the DIVA package use multiple levels of aggregated information. At it's most basic level, the DIVA database is an aggregation of select 2 and 3 dimensional properties at the interface between land and water. Subsequently, large-scale applications of the DIVA model aggregate key information for each country or region of interest. The information available in the SDS shoreline represents a significant modification to the first level of aggregation within DIVA, and this thesis will estimate bias introduced by this measure compared to a manual interpretation of the shoreline. Finally users of the DIVA model analyze and aggregate the results of the package into information for presentation or publication.

An initial comparison of the two coastlines demonstrates some of the difficulties expected for the connection, as shown in Figure B.1. The two coastlines, contrary to expectation, express significantly different versions of the physical entity, particularly in areas of complex morphologies such as archipelagos, tidal basins, and river deltas. In particular:

- The DIVA coastline occasionally omits barrier islands, such that the Dutch Wadden Sea is represented only by Terschelling and Texel. These predominantly beach environments are therefore underrepresented in the current DIVA information.

- The DIVA coastline occasionally includes inland waterbodies which have been separated from the ocean by permanent engineering works, such as the IJsselmeer and the Markermeer
- The GSCD information is developed in such a way that data segments can “cross”, which may increase the number of point measurements around headlands or complex morphology
- The GSCD information is presented in such a way that complex landforms, such as river deltas are not continuous and may represent multiple seaward-facing shorelines and incomplete bar formations.
- The GSCD information does not include information on a large number of atoll and small islands which are explicitly included in the DIVA segmentation to address vulnerability.
- The GSCD information does not include information on the northern coast of the world.

The above discrepancies result in two data-sets that are difficult to relate with complete accuracy; even manually. Further, the best data available to test the accuracy of the DIVA segments is the GSCD information itself. To overcome these hurdles we propose that a manual connection be undertaken for a select number of regions representing just under one tenth of the total DIVA segmentation. This connection will then be compared and contrasted to the results obtained by the algorithm outlined in the next section. The results of this validation methodology will help to indicate the suitability of the connection methodology and the anticipated error introduced into DIVA results through the connection.

B.1.3. Database Connection

The final GSCD-DIVA connection projects information from both models into an Earth-Centred-Earth-Fixed 3 dimensional coordinate system, and uses a nearest-point query between the two neighbouring data-sets in 3D space. A filter is then applied to the GSCD information to remove the 99th percentile of S GSCD points from the connection, which approximately represents the extent of the coastal zone. Finally, development of relevant information takes place in DIVA modules, which is aggregated and appended to the DIVA database. Intermediate steps govern data translation methods and module calculations as outlined in Figure B.2. The essential goal of this methodology is to succeed in applying a reference identifier from the DIVA segments to each point in the GSCD model, and determine a procedural methodology to sort, filter, and aggregate data points which provides a “good” connection at a given location. This process is schematized in Figures B.2, B.3, and B.4.

Pre-processing

The intent behind pre-processing is to develop a data-structure that can be used to model and relate the two databases. Since calculation methodologies to link points with linear features are not yet widely available in 3D space, we opt to split the DIVA information into point features. These points are developed from the linear coastline feature at 100 metre intervals. The decision to split DIVA at this interval is somewhat arbitrary. A 100 metre spacing limits the error in the link due to point spacing to 50 metres, which is approximately 0.03% of the median distance between the data-sets, but this variable was not optimized. The initial estimate here was kept since the impact to the database and computer resources required for the connection was minimal.

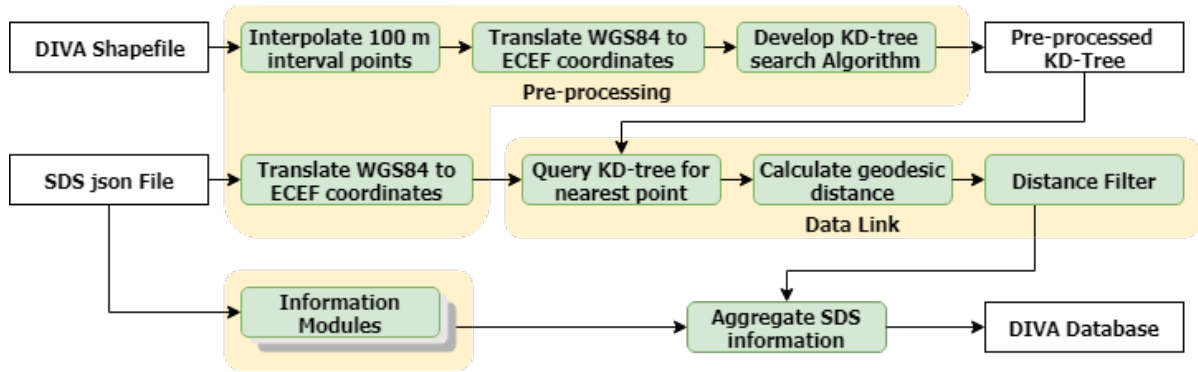


Figure B.2: Process flowchart identifying the methodology and steps for the link between the DIVA and SDS databases

Pre-processing: Projection The format of both databases in WGS84 lat/lon coordinates is significant because the physical distance represented by the WGS84 grid changes varies with latitude. These issues develop because maps place 3 dimensional information onto a 2 dimensional plane, which necessarily generates error in some map properties. Some projections attempt to allow equidistant calculations, however, these are most often applicable for certain portions or points of the map (e.g. Werner, Simple Conical, Cassini). To remedy this issue, many global applications of mapping software re-project information for each region to complete calculations, but this methodology can be unwieldy and computationally expensive with large data sets. While the GSCD technique relies on the use of efficient cloud computing infrastructure to provide this capability, our goal is to limit the effort required to maintain and update the data link (Tang and Feng, 2017).

Converting the geographic projection WGS84 to spherical coordinates will preserve the nearest-point calculations needed for the proposed methodology for relatively small distances. On a perfect spheroid, the order of distance calculations is preserved for linear distances smaller than the chord length between the pole and equator. We approximate the earth here as a spheroid, which reduces the distance over which order is preserved, however, we found the mean distance separating the two data-sets to be approximately 2 km, which is less than 0.1% of the chord distance. We therefore hold the preservation-of order assumption as valid for our data. The ECEF approach to nearest-point calculations however, also needs special consideration as the 3 dimensional nearest-point calculations are more expensive than in 2 dimensions (Karney and Deakin, 2010).

Pre-processing: KD Tree In order to speed nearest-point selection, a spatial KD-tree search algorithm is used. A spatial KD Tree reduces computational time by sorting information in the DIVA data-set into an ordered set of bin-pairs. Rather than calculate the distances between each point, we calculate the distance to the centroid of each bin and compare to remove approximately half of the data-set from consideration with each iteration. This increases the pre-processing required for the target data-set, but greatly improves the speed of the sorting process.

Data Link

Once the KD-tree has been developed, it may be saved to reduce future computational time. the tree is subsequently queried for each of the points in the SDS data-set, and a single file is written including the coordinates of each point and unique references in each data-set which govern the aggregation of GSCD information within DIVA.

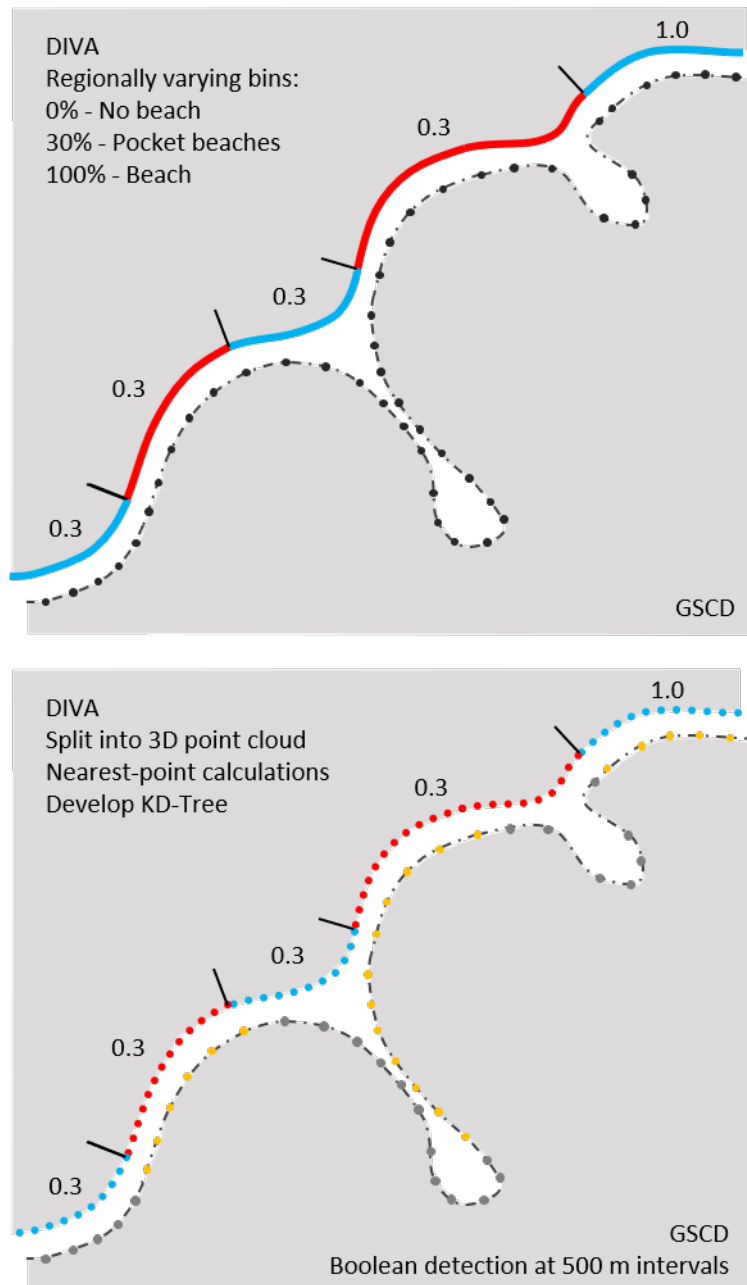


Figure B.3: (Part 1 of 2) The first two stages of the SDS-DIVA connection relating to pre-processing of the information, splitting of DIVA multilines into points, and projection into 3D-space.

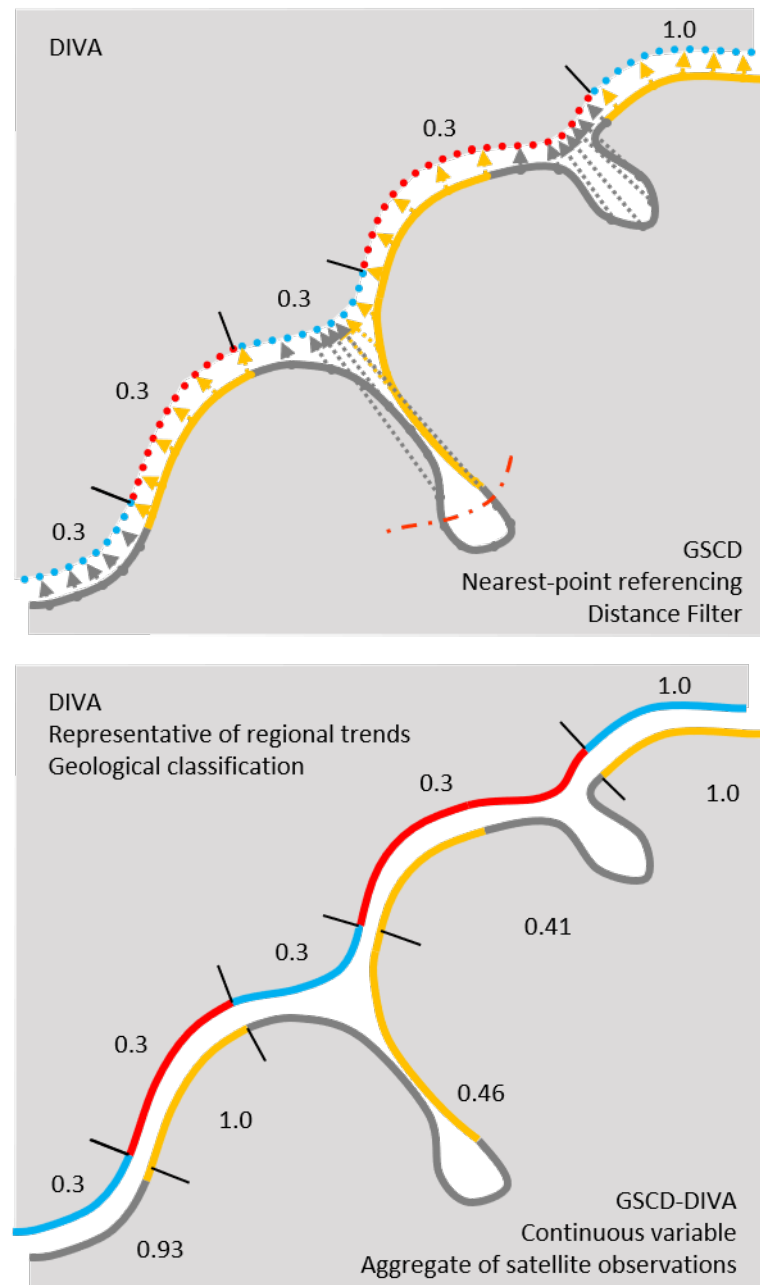
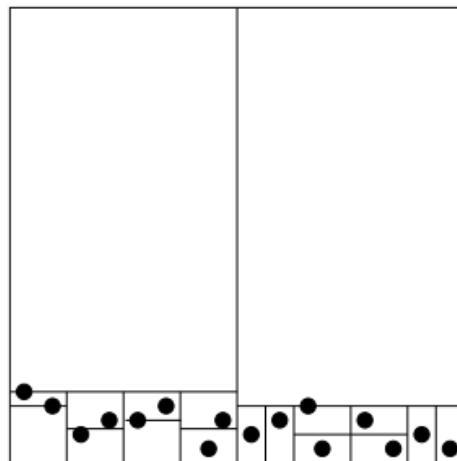


Figure B.4: (Part 2 of 2) The Second two stages of the GSCD-DIVA connection, showing the spatial relation of the two datasets, filter application, and aggregation.



Sliding-midpoint split

Figure B.5: Schematic of a KD-tree search algorithm similar to the nearest-point queries between the SDS and DIVA coastlines (Maneewongvatana and Mount, 2001)

Data Link: Filter In this technical methodology, manual post-processing of the information relates the information back to physical separation parameters and defines limits and traits used in the rest of the process. An initial iteration of the model is run with arbitrary set-points, at which point their impact on the link as a whole is evaluated. This approach allows the data link to be explored without a-priori information regarding the similarities between the two databases.

We consider islands as one of two different classes within the GSCD-DIVA connection. First, we consider some islands as off-shore islands which do not relate to the coastal zone or any DIVA segment. second, we consider some islands to be a part of the coastal zone represented by the DIVA segmentation. For example, we consider barrier islands an integral part of the coastline which may not be directly represented in DIVA. Therefore, we develop a uniform distance filter based on qualitative analysis of the 10 validation locations identified in Table B.2. In particular, the green islands highlighted in Figure B.6 were determined to be fall into this first category, while red islands were qualitatively sorted into the second category. The filter is based on a the cumulative distribution of the nearest-point distance between the GSCD and DIVA databases. as such, the filter takes 99.7% of the SDS-DIVA connection points with a maximum acceptable distance of 12.7 km. Interestingly, this number corresponds relatively closely to the observed and modelled changes in morphology observed by Roy *et al.* (1995) and Stive and de Vriend (1995).

B.1.4. Modules

To facilitate integration of future research efforts into this technical methodology, interpretation of physical information at any GSCD point is relegated to GSCD modules, which apply statistical measures to aggregate information stored in the GSCD database. These modules can be added or deleted as desired by the user.

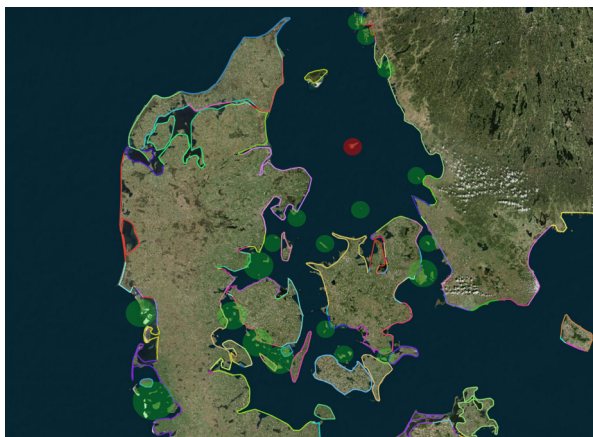


Figure B.6: The above figure illustrates the difference between the DIVA segmented coastline. green-highlighted islands are tied to the DIVA segmentation while the red island is considered too far offshore.

Coastal Beach Content (CBC) Module

DIVA applies a factor to each coastal segment which determines the portion of that segment which is vulnerable to beach erosion. Where the original DIVA database relied upon expert judgment and large-scale geological classifications to classify the portion of areas as either 0, 0.3, or 1, the new GSCD information encourages development of a new fraction system without predefined values. The CBC module essentially counts the portion of GSCD points referenced to a particular DIVA segment and passes that information to the DIVA database.

Retreat and Morphological Dynamics

These modules take the 30 year linear trend at each GSCD point and aggregates them into the DIVA segmentation. [Burningham and French \(2017\)](#) notes that aggregation in this way provides insight into structural erosion at a regional scale. As a result, two pieces of information are available to include in the DIVA database. By first filtering the SDS information to represent only beaches, we develop retreat mean and variance information that is directly relevant to the DIVA erosion module. First, overall linear retreat rates measured from the SDS at beaches are aggregated onto the DIVA segmentation, which provides a snapshot of large-scale structural trends in the past 30 years.

Second, the along-shore variance of the linear shore movement trend is taken, which provides an indication of the strength of the morphodynamic regime for each segment. This is distinct from the first information passed by this module as a coastline showing uniform patterns of retreat may have a low variance, while a coastline which is both retreating and advancing in locations will have a high one. This is significant because higher morphological variance in the alongshore morphological trends also indicates greater uncertainty with regards to climate change impacts, and may have administrative consequences for property setbacks and insurance.

Overall Retreat and Morphological Dynamics In addition to the beach retreat model, there is an opportunity to gather further information with regards to the coastline without filtering for beach segments. When compared to the beach retreat dynamics, this factor will indicate the local significance of beach morphodynamics within each DIVA segment.

B.1.5. GSCD-Independent Updates

While some information from the GSCD is immediately applicable to the DIVA package, the simplification of nourishment costs within the DIVA model create unintended consequences

stemming from the above changes. Currently the GSCD, which has a regional resolution, is also used to determine the local sediment availability used in nourishment cost calculations. This connection uses an assumption that the percentage of beaches on a given segment is inherently dependent on the amount of sediment available in a region. However, by resolving the CBC from a regional resolution to individual segments, we decouple these two pieces of information.

Duplication First, in order to better identify the impacts of the new CBCs in DIVA, an exact duplicate of the existing information is made. This information is used only when comparing the immediate impact of the updates presented in this thesis. This information is then normalized by segment length and aggregated across administrative units within DIVA's Database for later use (Appendix C).

Validation We propose a selection of 9 locations to evaluate the suitability of the SDS-DIVA connection measures. The locations are selected manually to represent multiple coastal morphologies which may affect the connection between the databases. Approximately 100 coastal segments are contained at each location. Since the only information needed for this analysis is the two databases themselves, there is no restriction on the selection of these locations outside of utility and variety. An list of locations is outlined in Table B.2.

Classification of the validation areas is provided on the basis of two separate classification systems. A tectonic classification by [Inman and Nordstrom \(1971\)](#) provides information on the processes responsible for the formation of the coastal morphologies. Supplementary information regarding the typology of the coastline is indicated through classification outlined in [Dürr et al. \(2011\)](#).

Each of the above locations represents approximately 100 DIVA segments such that the entire set comprises 8% of the total DIVA segmentation. A connection at these locations is digitized manually by graduate engineering students familiar with coastal morphology. These students attempted to digitize the connection of the SDS and DIVA as a "single coastline", neglecting offshore features such as barrier islands.

The manual connection is conceptualized as the ideal connection between the two databases. By this we imply that the students would be capable of predicting the connection with 100 percent accuracy if the SDS points and DIVA segmentation align perfectly. As such, we treat the manual connection as a theoretical baseline for subsequent statistical tests to isolate the error created during the connection procedure. In particular, we attempt to compare the bias, accuracy, and skill between the new and old beach composition information in the DIVA database.

The Bias and Accuracy of the SDS-DIVA link are compared to the theoretical data link by means of a Bland and Altman (BA) diagram and scatter plot ([Watson and Petrie, 2010](#)), which both provide information on the agreement of the two data-sets. The BA diagram graphs the average against the difference between two data-sets, and includes information on the bandwidth which contains 95% of the measurements for the differences between the two sets. The BA diagram contains more information than the scatter plot. However, the scatter plot, which compares the results of each data-set is more intuitive and provides information on the correlation of each model to the "ideal" model (See Figures B.7 and B.8).

The skill of each method is evaluated within the validation areas by comparing the accuracy of each measurement to a baseline prediction method. To provide an efficient comparison, the baseline prediction method should contain as little information as possible. As such, since the original GSCD shoreline found 31% of the world's beaches to be sandy, we use a global

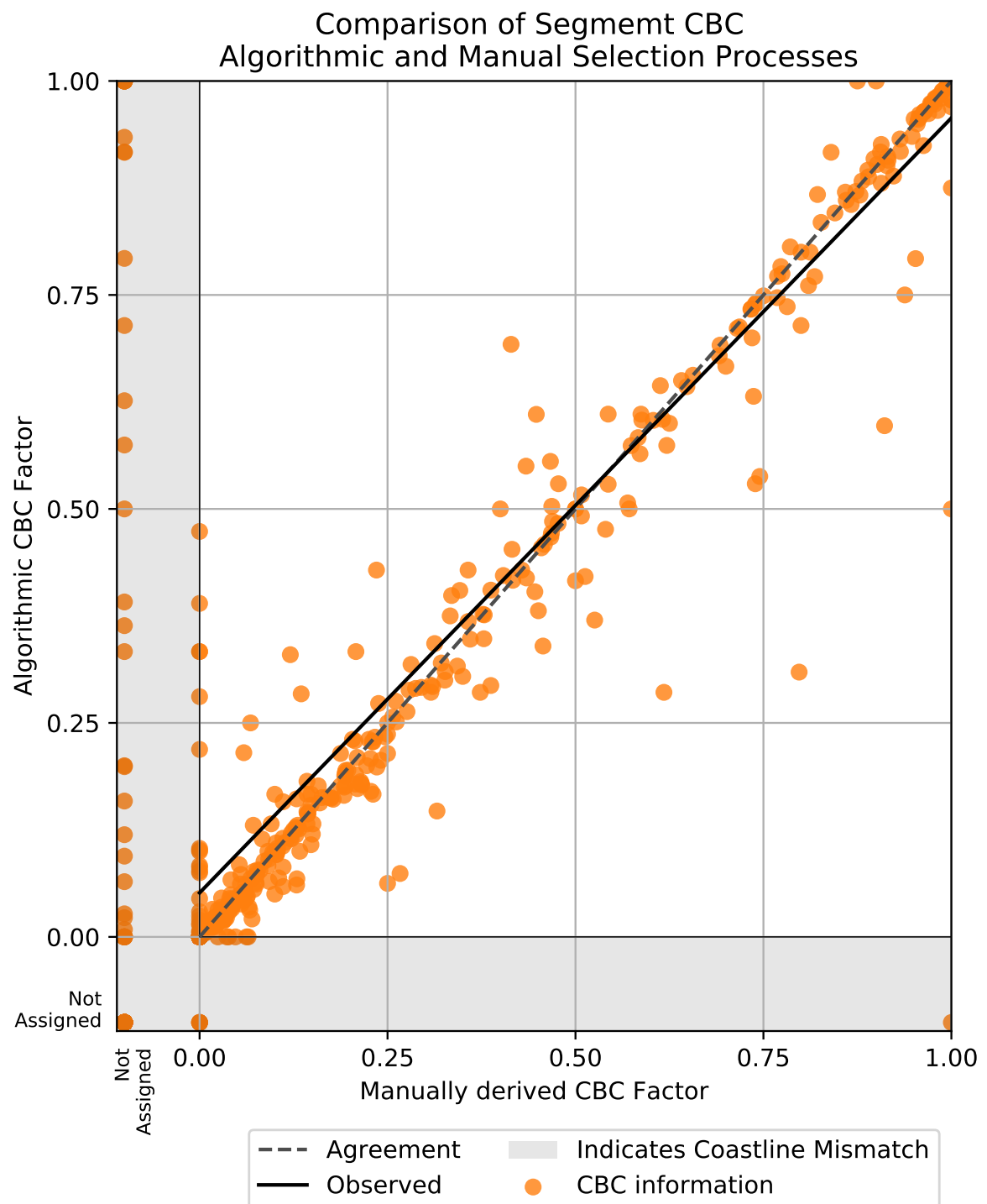


Figure B.7: Scatter plot showing the agreement between manual and algorithmic methodologies interpreting the CBC factor at a segment level. Note the unassigned values.

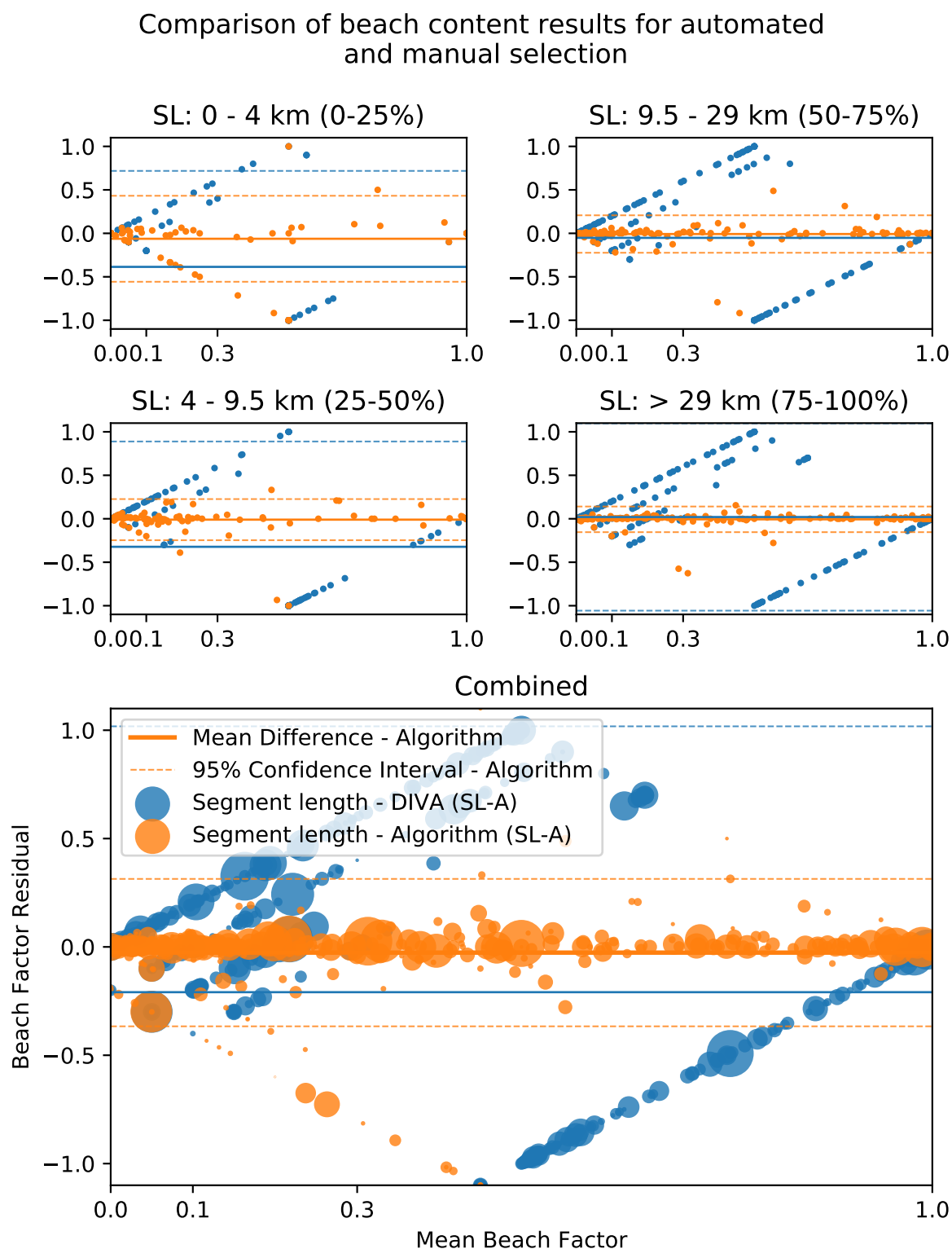


Figure B.8: Bland and Altman diagram identifying the mean and residual between the two datasets. In this graph, bias and accuracy are also shown as the horizontal colored lines.

Table B.2: Locations in which the validation process for the SDS-DIVA connection model are completer

Reference Country	Name	Tectonic Classification (Inman and Nordstrom, 1971)	Typology Classification (Dürr et al., 2011)
Denmark	Danish Straights	Amero-trailing	Fjords & fjards
Australia	New South Wales	Marginal sea	Tidal systems & Lagoons
Nigeria	Gulf of Guinea	Glaciated	Tidal systems
St. Kitts and Nevis	Caribbean	continental-leading	Karst
Nether-lands	Wadden Sea	Amero-trailing	Tidal Basin & Tidal Systems
Canada	Juan de Fuca Strait	Continental-leading	Fjords & fjards
Iran	Persian Guld	Island arc-leading & Neo-trailing	Arheic
Korea	Korea Straight	Island arc-leading & Marginal sea	Tidal systems, Lagoons & Small deltas
Guinea	Gulf of Guinea	Afro-trailing	Tidal Basin & Tidal Systems

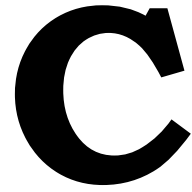
CBC of 0.31 to compare the skill of the two data-sets. The skill score is generated using the Root Mean Square Error (RMSE) for the prediction method over the RMSE for the baseline measurement method as shown in Equation B.1 (Fawcett, 2008).

$$SS = 1 - \frac{RMSE_p}{RMSE_b} \quad (B.1)$$

$$RMSE = \sum (obs.i - pred.i)^2$$

Where:

- SS is the score used to evaluate the skill of the model at making predictions compared to the baseline. This measure has a maximum value of 1, with scores closer to 1 better at predicting reality than lower scores,
- $RMSE_p$ is the RMSE measurement for the methodology used to predict Shoreline Beach Factor with respect to observations, and
- $RMSE_b$ is the RMSE measurement for a constant baseline with respect to the observations.



Nourishment Cost Model Methodology

The nourishment cost model was initially developed with the support of thesis committee members at a brainstorming meeting on 29-05-2018, in which a number of other proposed models were turned down. Ultimately, it is believed that a reasoned approach with quantifiable parameters plus a calibration for known deviations is more suitable than an arbitrary set of country-specific factors based on industry experience. Initial data for nourishment costs is taken from a number of disparate sources ranging from academic to NGO reports to industry expertise (Table [C.1](#)).

The Netherlands is thought to be a natural baseline for the above model. Due to a history of government-supervised coastal protection, there is a higher likelihood that baseline changes to the model can be captured in recent nourishment costs should the model be updated in the future.

Taking the average and range of Netherlands nourishment cost information provides a baseline cost of 7.16 2014 USD per cubic metre. The committee also felt that the range of average-price-per-cubic-metre values available in the literature is indicative of a suitable 95% confidence bound for the Netherlands.

subsequent discussion led to an elaboration of a number of factors which have an impact on nourishment costs. Three factors were identified to have significant impacts on individual projects, but limited impact across multiple decades as established in the DIVA model. These factors include market fluctuations, the size of individual projects, and the depth of sediment for individual projects.

However, we posit 5 factors that do have an impact on long term nourishment costs. First, the availability of sediment has a direct impact on the cost of nourishment since it relates to the time and resources required to transport sediment from it's source to the beach in question. Second, corruption and graft is identified as a factor which has a major impact on the cost of a project. Third, the committee identified the costs of local labor, specifically with reference to conditions in China and the USA, as another factor that can influence the cost of dredging and nourishment projects. These factors are only applied when national regulation prevents the competition of the international dredging market from affecting local prices. We also note that the mode of sediment placement can have a large impact on the costs of beach nourishment. Finally, we note that the generalization of the model is likely to create some circumstances which are far from indicative of reality. In these areas, a calibration factor applied on a country

Location	Source	Nourishment Type	Original Cost		2014 USD
			Currency	Cost	Cost
AU (Gold Coast)	(Langedijk, 2008)	Beach	2008 AUD	\$ 6.54	\$ 6.13
BE	(NSCMG, 2000)	Beach	2000 EUR	€ 7.50	\$ 9.50
DE	(NSCMG, 2000)	Beach	2000 EUR	€ 4.40	\$ 5.57
DK	(NSCMG, 2000)	Beach	2000 EUR	€ 4.20	\$ 5.32
DK	(NSCMG, 2000)	Beach	2008 AUD	\$ 5.36	\$ 5.03
DK	(NSCMG, 2000)	Shore	2000 EUR	€ 2.60	\$ 3.29
NL	(NSCMG, 2000)	Beach	2000 EUR	€ 3.85	\$ 4.88
NL	(Hillen et al., 2010)	Beach	2010 EUR	€ 5.05	\$ 7.25
NL	(Langedijk, 2008)	Shore	2008 AUD	\$ 2.57	\$ 2.41
NL	(NSCMG, 2000)	Shore	2000 EUR	€ 1.20	\$ 1.52
NL	(Hillen et al., 2010)	Shore	2010 EUR	€ 2.42	\$ 3.47
UK	(NSCMG, 2000)	Beach	2000 EUR	€ 14.00	\$ 17.73
US (California)	(Flick and Ewing, 2007)	Beach	2009 USD	\$ 10.00	\$ 10.99
US (East Coast)	(Trembanis et al., 1999)	Beach	1996 USD	\$ 6.54	\$ 9.84
US (Great Lakes)	(Trembanis et al., 1999)	Beach	1996 USD	\$ 9.15	\$ 13.77
US (Gulf)	(Trembanis et al., 1999)	Beach	1996 USD	\$ 7.84	\$ 11.80
US (New England)	(Trembanis et al., 1999)	Beach	1996 USD	\$ 16.99	\$ 25.57
NL	(Kok et al., 2008)	Beach	2010 EUR	€ 3.00	\$ 4.31
NL	(Hillen et al., 2010)	Beach	2010 EUR	€ 7.55	\$ 10.84
NL	(Hillen et al., 2010)	Shore	2010 EUR	€ 3.72	\$ 5.34
SA	(Hillen et al., 2010)	Beach	2010 EUR	€ 11.00	\$ 15.80

Table C.1: This table summarizes nourishment costs per metre cubed used to develop the cost model.

basis can be used in cases with significant and justified discrepancies to the model. These factors are summarized in Figure C.1.

Sediment Availability In order to determine the impact of sediment availability, we aggregate the GSCD parameters as an indicator of local sediment availability. There is significant discussion on the appropriate scale of this aggregation to best represent local sediment supply across an entire segment. Given the small size of some densely populated, and therefore likely-to-be-nourished coastal segments, the administrative unit is thought to provide a balanced approach. We use the geometric average sediment factor within an administrative unit as a variable to fit a function which determine this parameter. Of the parameters, this has the most physically-direct relation to nourishment cost, and multiple relations were tested to try to accommodate a best fit. We compared results for the variable to average costs in known countries at a qualitative level to determine an exponential relationship fitting the Netherlands to a factor of 1.0 and a theoretical country with no beaches to a factor of 3.0. The initial loss in efficiency which drives costs will likely not have an effect until sediment is relatively uncommon on the coastal segment, we approximate that 20% of the total effect of the factor will occur at an aggregated CBC parameter of 0.5.

Corruption Fortunately, DIVA contains corruption information on a simplified scale at a country level ([Kaufmann et al., 1999](#)). This information has a base year of 1997 and 1998, with interpolated values based on per-capita GDP in that year. [Locatelli et al. \(2017\)](#) estimated the impact of corruption between the Netherlands and Italy on the order of 19-20% for basic infrastructure projects. We expect a similar range between the two countries for nourishment projects, and therefore apply a linear fit using 1.0 and 1.2 for the Netherlands and Italy to establish a relation between the [Kaufmann et al.](#) factor and a nourishment corruption factor.

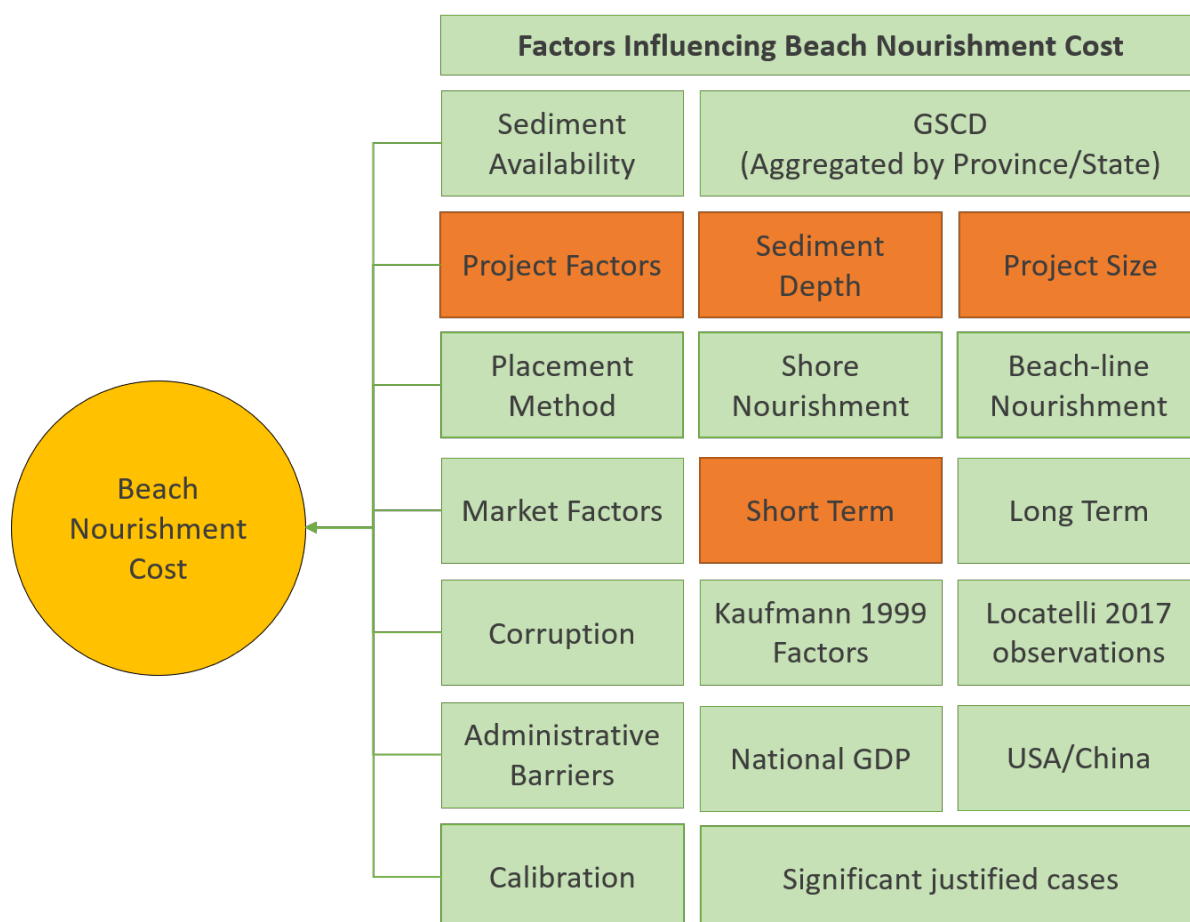


Figure C.1: This figure identifies characteristics which can determine the cost of nourishment, including those that have no impact on the long-term cost of nourishment outlined in this thesis.

Per Capita GDP The intent of incorporating per capita GDP into the model is to apply a factor to account for local prices of labor or fuel. This factor was specifically incorporated to accommodate difference in prices in China and the USA. In fitting the model, however, we found that the prices better-conformed to expectation in almost all countries without inclusion of local per-capita GDP. The two countries which notably perform better with the inclusion of a GDP factor are China and the United States, which are both party to strong administrative barriers to external competition and local nourishment industry. Reliable information on the portion of a project which can be applied to labor costs is scarce, but industry guides and expertise indicate that 30% of a project can be factored as labor. Since dredging equipment is generally constructed in large worldwide ports and prices are not likely to vary significantly, we propose a GDP nourishment factor which accounts for this 30% of project costs. We fit this information using GDP between the Netherlands and Liberia, where *gdpc* is lowest and labor is likely to be cheapest. This factor, however, is only applied to countries like China and the United States with strong home-grown dredging industry. At the current time, these countries include the United States, China, and the Netherlands, however these countries could be expanded to include the UK, Belgium, South Korea, Malaysia, and the United Arab Emirates given the size of their dredging industry.

Segment Calibration Constant In order to prevent a calibration factor from defeating the initial purpose of developing and fitting a model based on logic and reasoning. We only

Factor	Range	Description	Country	Analogue
F_{nm}	0.47, 1.0	$F_{n,beach} = 1.0$ $F_{n,shore} = 0.47$	NL	
$F_{le,i}$	0.7 - 1.0	$F_{le,i} = 0.00000723 * pcGDP_i + 0.749$	NL	(Okoye <i>et al.</i> , 2018)
$F_{s,i}$	1.0 - 5.0	$F_{s,i} = 0.558 + 4.442 * e^{-2.609 * CBC_{ave,i}}$	NL	
$F_{c,i}$	0.94 - 1.71	$F_{c,i} = -0.154 * CORR + 1.323$	NL, IT	(Locatelli <i>et al.</i> , 2017; Kaufmann <i>et al.</i> , 1999)
$F_{c,i}$	1.0	varies by country (further study)	N/A	
$F_{ma,t}$	1.0	varies slowly over time (further study)	N/A	

Table C.2: Description of the parameters which develop the proposed coastal nourishment cost model.

apply this factor in extreme cases where it is possible to define a quantifiable and significant issue with a logical explanation outside of the factors considered here. We apply this factor only once in our model, in Singapore. Singapore has an unexpectedly high CBC parameter as derived from the GSCD information. Upon closer inspection, we note that there are a significant number of points flagged as sand in areas of new development. We surmise that these areas are properly flagged as sand, but include sand imported for the expansion of the country. Therefore, we apply a calibration factor which pushes the cost of nourishment to 50 USD per cubic metre.

C.1. results

The cost model evaluation changes the overall value and distribution of nourishment cost on a global scale. We find that this information drives nourishment costs much higher in sediment starved areas, while dropping these costs in areas rich in sediment. We evaluate the results of this model at a preliminary level in the model base year to compare it qualitatively to the deprecated information (Figures C.3, C.2, C.4). Overall, we find that the average price to nourish the global coastline increases from XX to XX USD (geometric average of all coastline segments). We note that these costs do not necessarily reflect the actual average spend on nourishment, but the theoretical cost of nourishing for each segment of coast. Actual costs are discussed more in detail at a later time.

C.2. Sensitivity Analysis

We perform a sensitivity analysis on results from the above cost model under a condition of a changing baseline cost in the Netherlands. The results of this analysis indicate the sensitivity of the model to large scale shifts in costs. Changes in the model are measured over time and include information on variance, skew, and kurtosis of the global output parameters for a number of relevant parameters. These results are presented in Appendix F

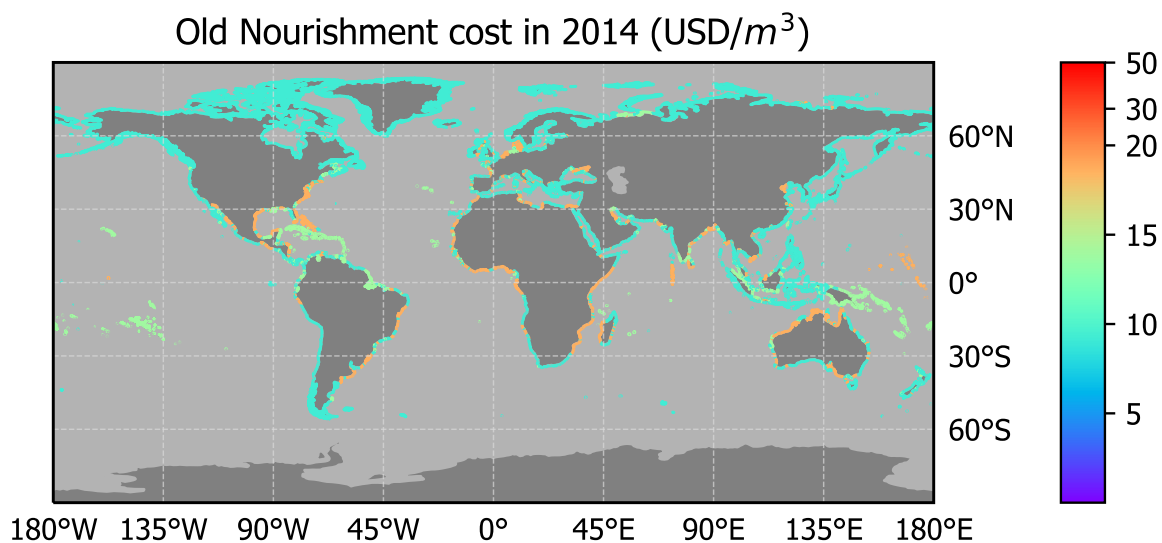


Figure C.2: Nourishment price per theoretical metre cube for each segment using old cost model information. Note this differs from actual expenditure on nourishment

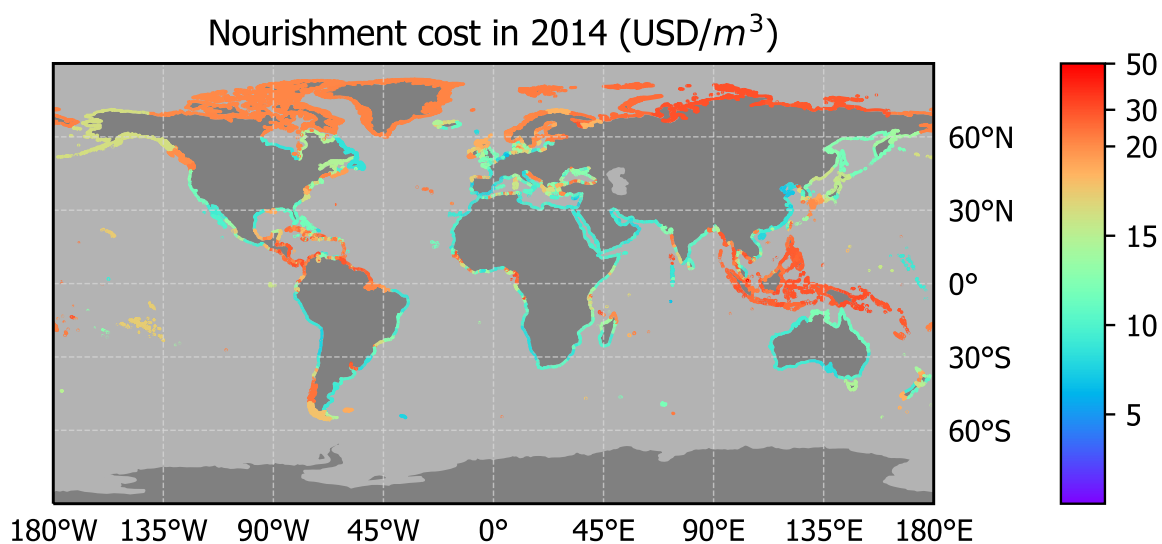


Figure C.3: Nourishment price per theoretical metre cube for each segment using new cost model information. Note this differs from actual expenditure on nourishment

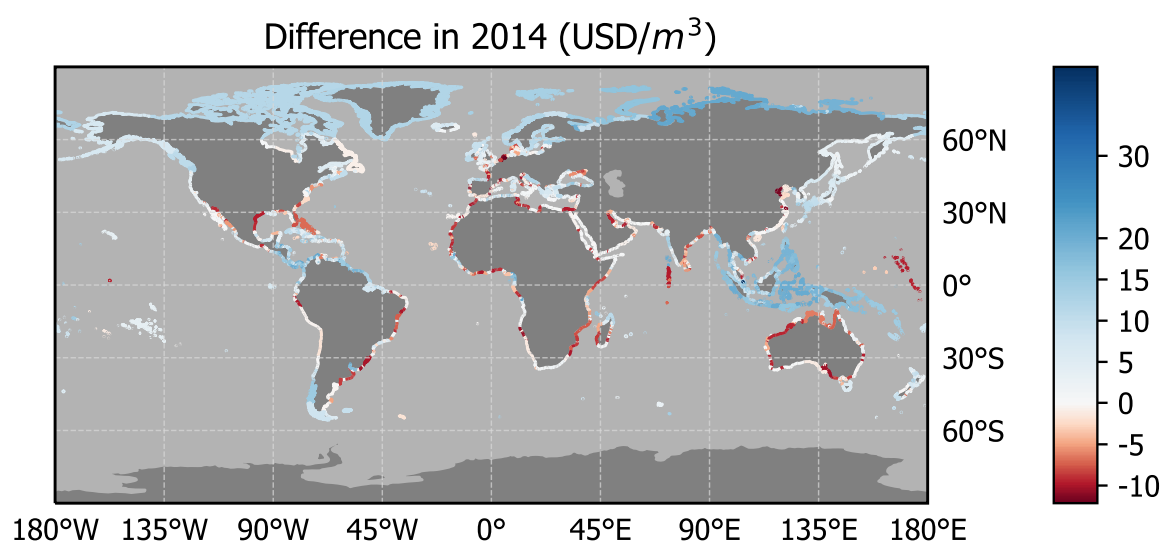


Figure C.4: The difference in nourishment price per theoretical metre cube for each segment using new and old cost model information. Note this differs from actual expenditure on nourishment

D

DIVA Methodology

Second, a contextual methodology develops new information in relation to the approach taken by [Hinkel *et al.* 2013](#). The contextual methodology underpins the assumptions and interpretation of the original paper and provides a basis for the integration of the new information into the body of existing scientific knowledge. subsequently, the new results are compared and contrasted with new information developed in Section A. By tying the advances to the data into existing literature, we demonstrate it's value and identify potential avenues for future work.

D.1. Recreate existing data

Prior to the implementation of the new information in the results from DIVA, we must either demonstrate an ability to duplicate the [2013](#) results by [Hinkel *et al.*](#) or develop a strong argument supporting our results if they differ. The information contained in Section A define the development of this information. This model run acts as a baseline for changes to the work and a basis for the comparison of the impacts of different changes.

For this thesis, recreation of the exact results from [Hinkel *et al.* \(2013\)](#) was problematic due to a number of changes made to the DIVA model since 2012. Troubleshooting these issues took substantial effort given the complexity of the model. Included in the efforts to rectify the divergence between the old and new baseline were modifications to the Erosion Module, Indirect Erosion Module, Erosion Adaptation Module, Socioeconomic Drivers Module, as well as changes to the input files at a segment, administrative, and country level. The changes to each dataset is outlined below.

- The Hadley Global Environment Model2 - Earth System (HADGEM2-ES) physical circulation model is kept, though other models are now available ([Collins *et al.*, 2011](#))
- The administrative classification system within DIVA has changed, and some overseas departments of traditional colonial powers are now updated such that they are treated as separate entities.
- We keep the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) for the coastal zone, however it can be replaced by the Global Land One-Kilometer Base Elevation (GLOBE) in the most recent DIVA release
- DIVA is now capable of replacing the Global Rural-Urban Mapping Project (GRUMP) information for population densities in the coastal zones with the LandScan (LS) global population dataset

- A new geo-spatial re-projection of the coastline has reduced it's total recorded length by 40%
- New tidal ranges for each segment improve depth of closure prediction and impact local sediment balances (Pickering *et al.*, 2017)
- Improved uplift information develops a more accurate picture of relative sea level rise
- Redeveloped per capita GDP and population drives a much larger economy, which affects both societal vulnerability and mitigation capacity (Hinkel *et al.*, 2013)

Despite an analysis of the impact of these changes through the redevelopment of deprecated datasets, the re-established baseline could not be made to match the Hinkel *et al.* (2013) report. Reasonable fitting is observed for GDP, Population, and SLR when using deprecated datasets. However, loss of land, land-loss cost, forced migration, and forced migration cost result are all approximately 3 times greater than results made with the new distribution.

Since the basic physical parameters between the two runs show identical results, the nature of the outputs is investigated. In runs using the new model, a superposition of indirect (back-barrier) and direct erosion gives results closest to those obtained by Hinkel *et al.*. In the 2013 paper, Hinkel *et al.* states that indirect erosion is responsible for approximately 70% of the land lost.

In an investigation of the source code for the DIVA package, we discovered that the current distribution takes multiple outputs from the Indirect Erosion Module. One such output is labelled "Erosion_indirect", while coastal erosion is labelled "Erosion_total". Hinkel *et al.* (2013) notes that indirect erosion accounts for 70% of the total projected erosion. While this statement should refer to the ratio of volumes owing to direct and indirect sources in the coastal sediment balance, it appears that this may refer instead to the ratio of tidal basin erosion to a combined total of indirect erosion and beach erosion.

When we combine total beach erosion and indirect erosion in this manner, the DIVA results show an improved fit to the existing results. In the current distribution of DIVA, the indirect erosion parameter is not carried forward to the economic considerations in the remainder of the model. However, given the discrepancies between each parameter is consistent to the others, we posit that this superposition was carried forward in the original paper. Therefore, by matching DIVA outputs to the land loss parameters using direct and indirect erosion, we demonstrate that the model presented here corresponds to known improvements from previous work.

D.2. Alteration of individual Elements

Second, the modules outlined in the technological methodology which have an impact on the erosion predicted by the DIVA model are isolated so that their impact can be delineated and compared. Specifically, we consider:

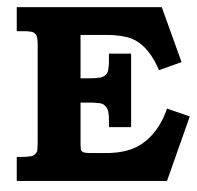
- Updated bruun rule factor with the Beach Nourishment Cost Analysis information altered to duplicate the process presented by Hinkel *et al.* (2013).
- Updated Beach Nourishment Cost module, but retain the historical BRF within the DIVA segmentation

D.2.1. Cumulative DIVA alterations

Once the individual impacts caused by each change to the database are delineated, we apply all of the changes to determine cumulative impacts and complex interaction effects that may present themselves in the final results. At this stage, the full scope of results from [Hinkel et al. \(2013\)](#) will be redeveloped in full and contrasted to the original across all 8 scenarios presented in the original work.

D.3. External Evaluation

Finally, we will evaluate the performance of the DIVA erosion module if it were applied over the last 35 years. Socioeconomic information regarding the impacts of SLR is not available over the lifetime of the SDS data. Instead Historic records of SLR and coastal retreat from the SDS information is compared to the results that would have been predicted by the DIVA model. Here, statistical aggregates from the SDS information are applied to DIVA results to compare the significance of Sea Level rise to erosion caused by local transportation gradients.



Impact Timelines

Baseline Information

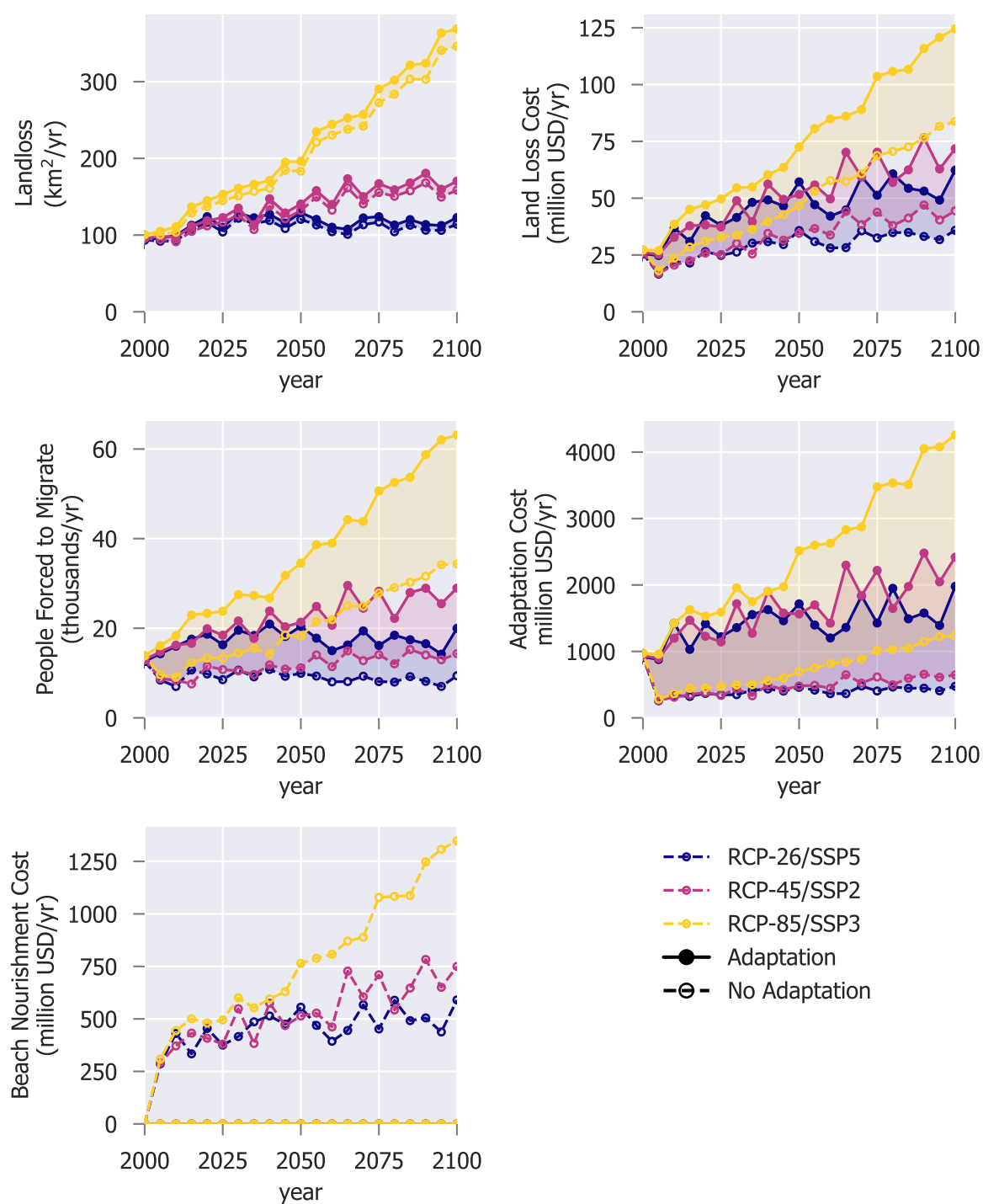


Figure E.1: The baseline timeline presented in Section 2 including both no-adaptation and adaptation, repeated here to facilitate comparison. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

Effect of the GSCD on Impacts without Adaptation

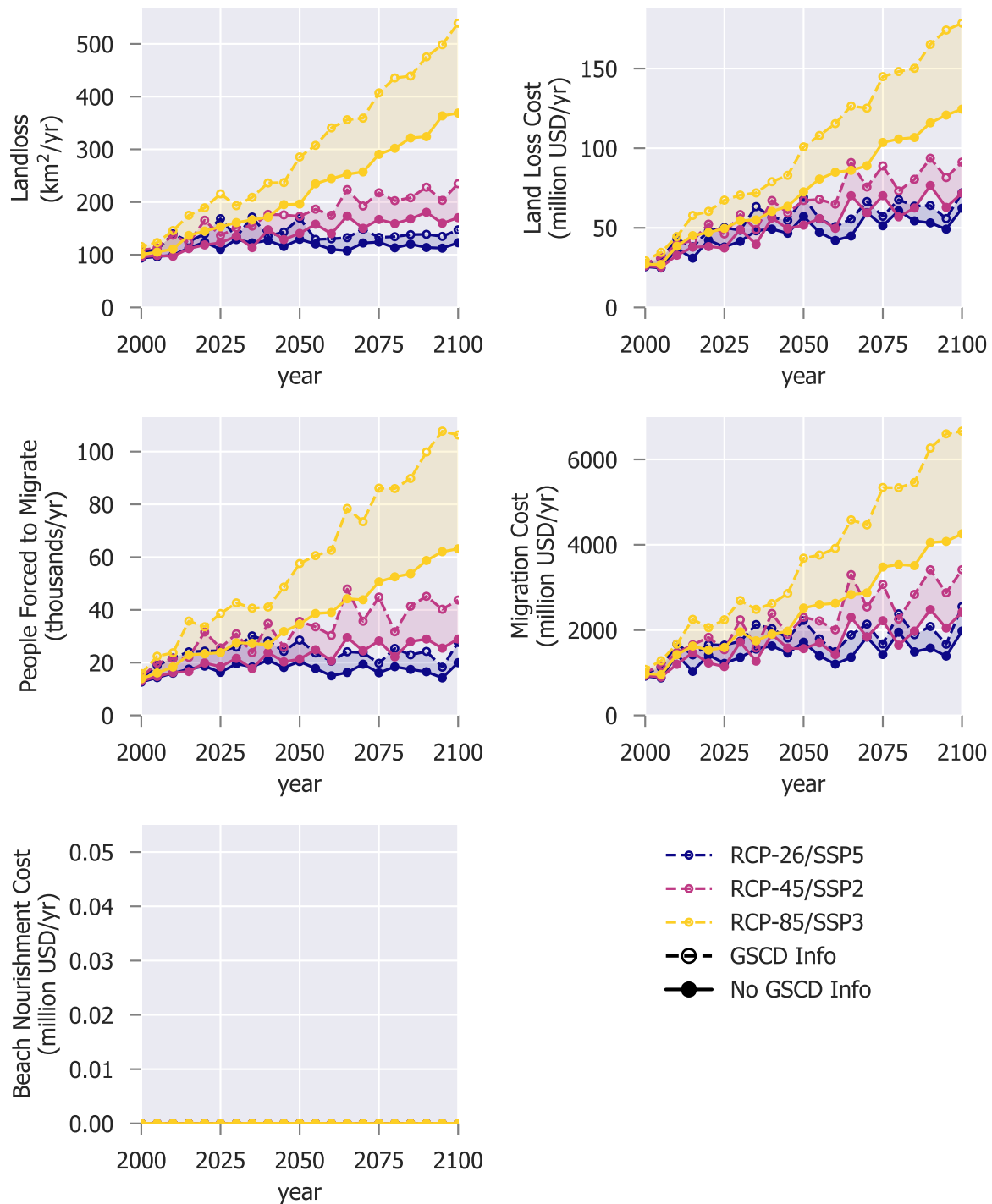


Figure E.2: The implication of the GSCD information on the DIVA Model without adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

Effect of the GSCD on Impacts with Adaptation

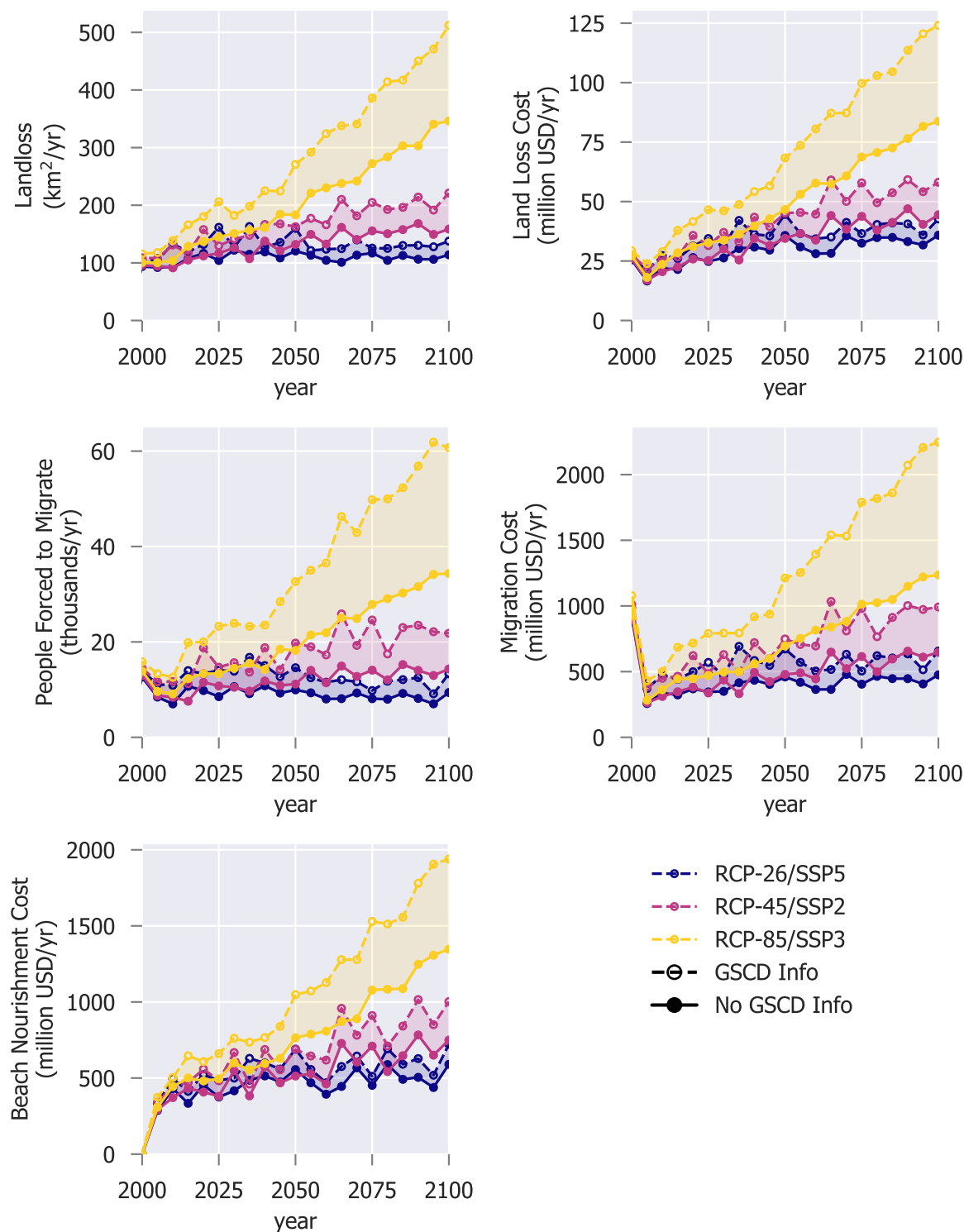


Figure E.3: The implication of the GSCD information on the DIVA Model with adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

Effect of the NCM on Impacts with Adaptation

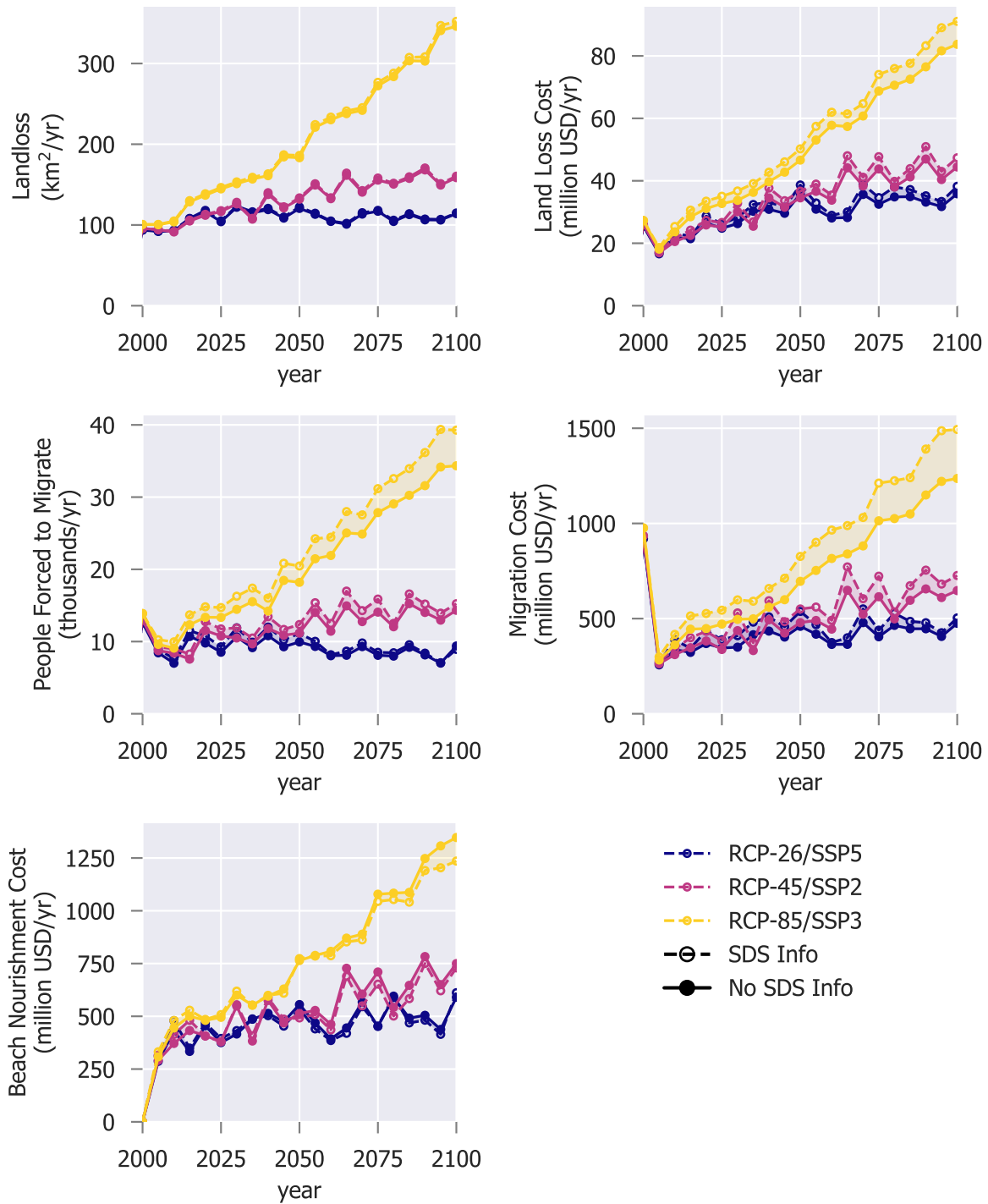


Figure E.4: The implication of the NCM on the DIVA Model without adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

Effect of NCM on Impacts with no adaptation

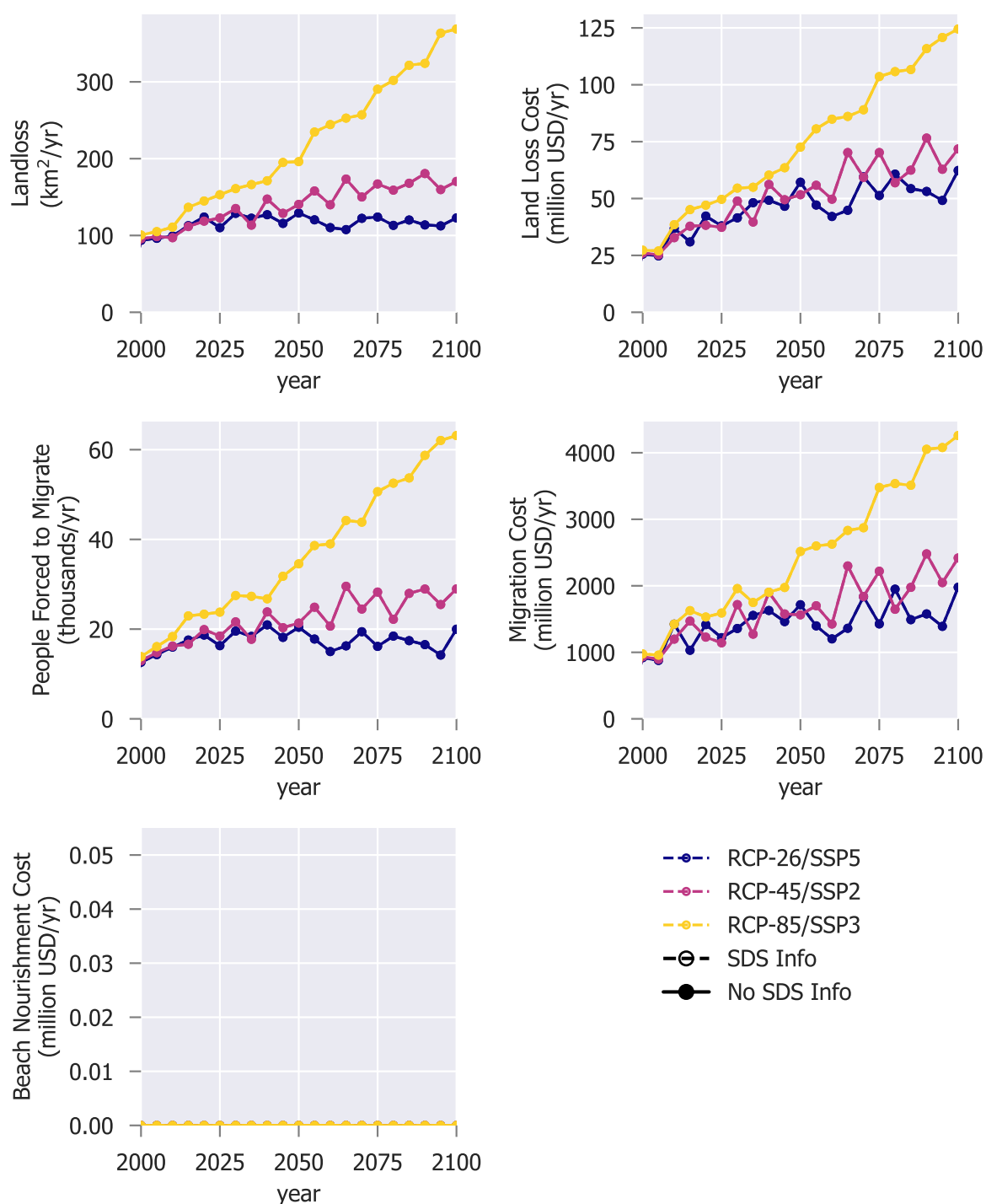


Figure E.5: The implication of the NCM on the DIVA Model with adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

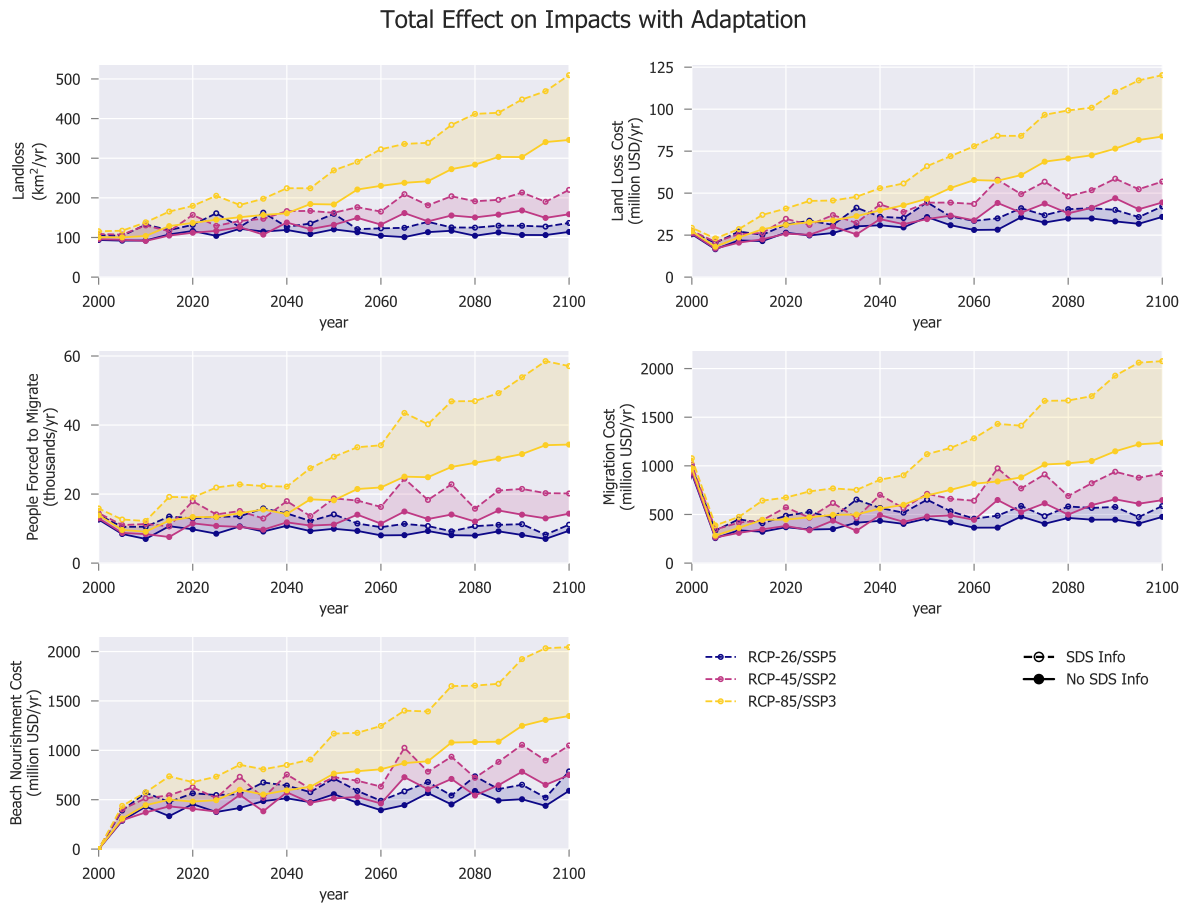


Figure E.6: The implication of the both GSCD and NCM on the DIVA Model with adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).

Total Effect on Impacts without Adaptation

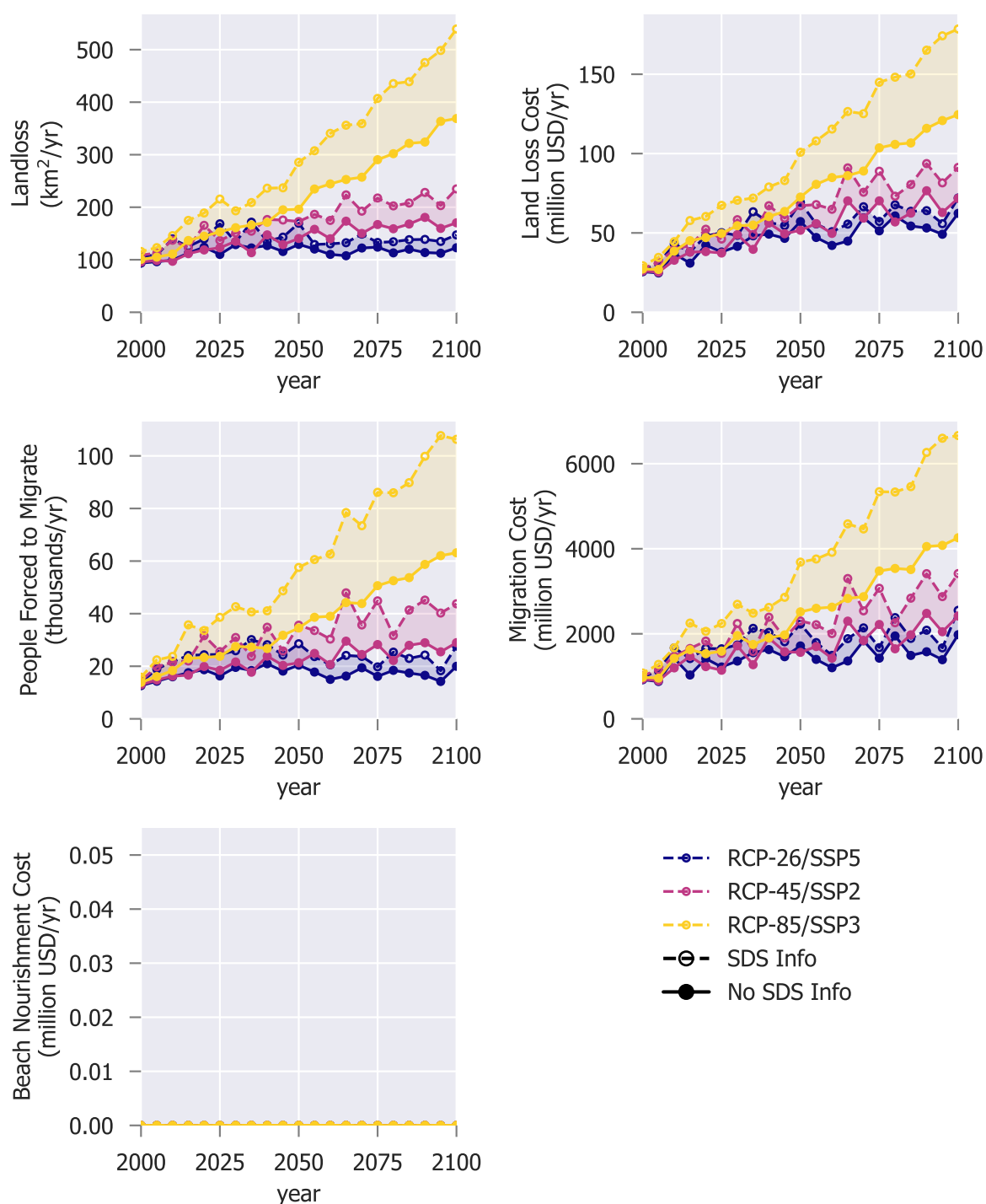
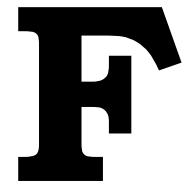


Figure E.7: The implication of the both GSCD and NCM on the DIVA Model without adaptation. Includes projections for loss of land (TL), economic value of lost land (TL), forced migration (ML), economic value of forced migration (MR), and nourishment expenditure (BL).



Nourishment Sensitivity

F.1. Nourishment Cost Model Sensitivity Analysis

This appendix applies a sensitivity analysis to the basic cost level used in the Nourishment cost model. This is an effective one-dimensional sensitivity analysis, and outlines key factors which are sensitive to the changes in cost at a global level. For a more detailed level of sensitivity analysis, the procedure outlined by [Saltelli *et al.* \(2010\)](#) could be modified to evaluate the impacts of changing the selected boundary conditions for the Nourishment Cost Model. However, variance-based methods to measure sensitivity require many more model runs than feasible at this time (approximately 6000).

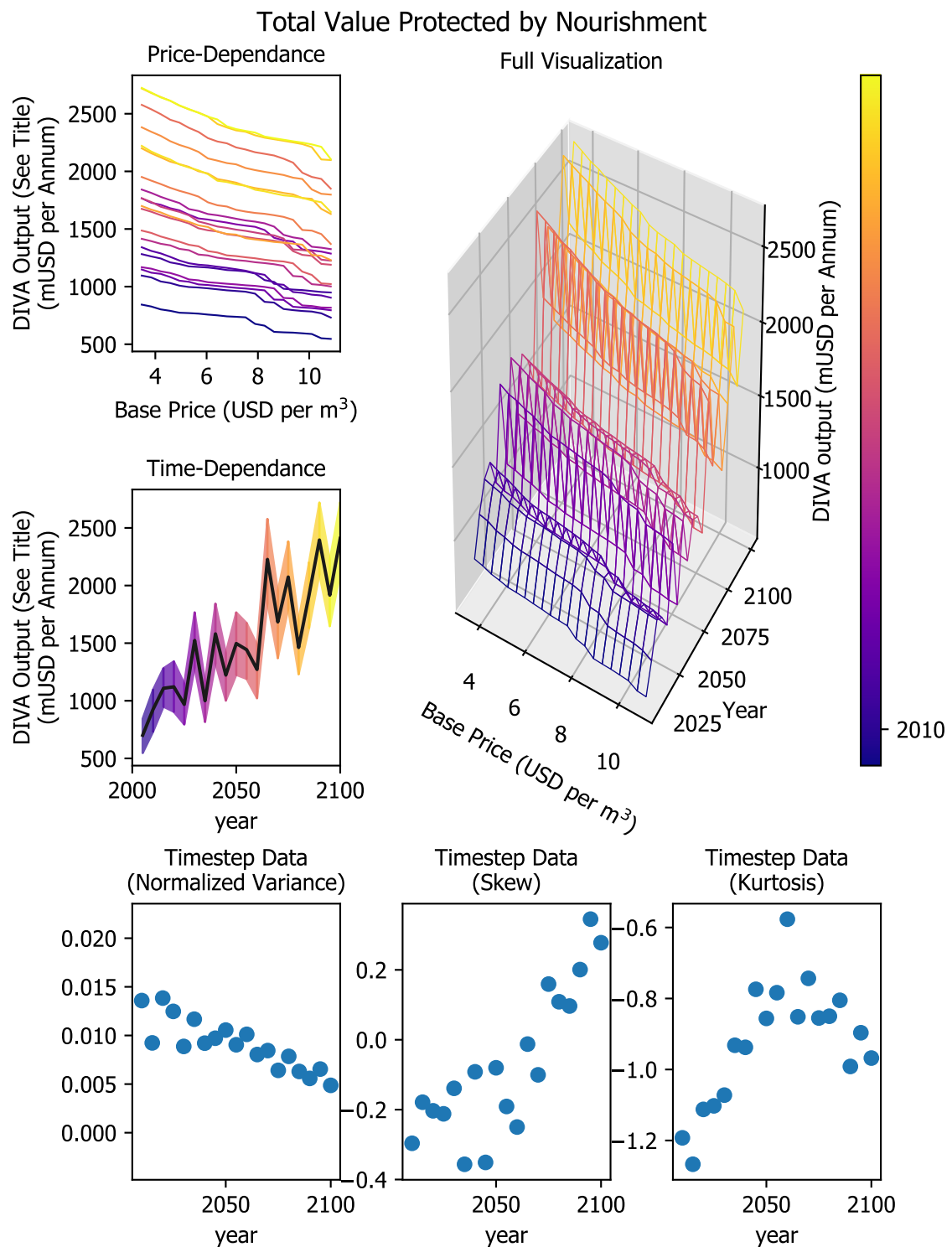


Figure F.1: This page shows the sensitivity of monetary impacts from SLR-induced Beach erosion to changes in the baseline global reference price when adaptation by beach nourishment is implemented. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

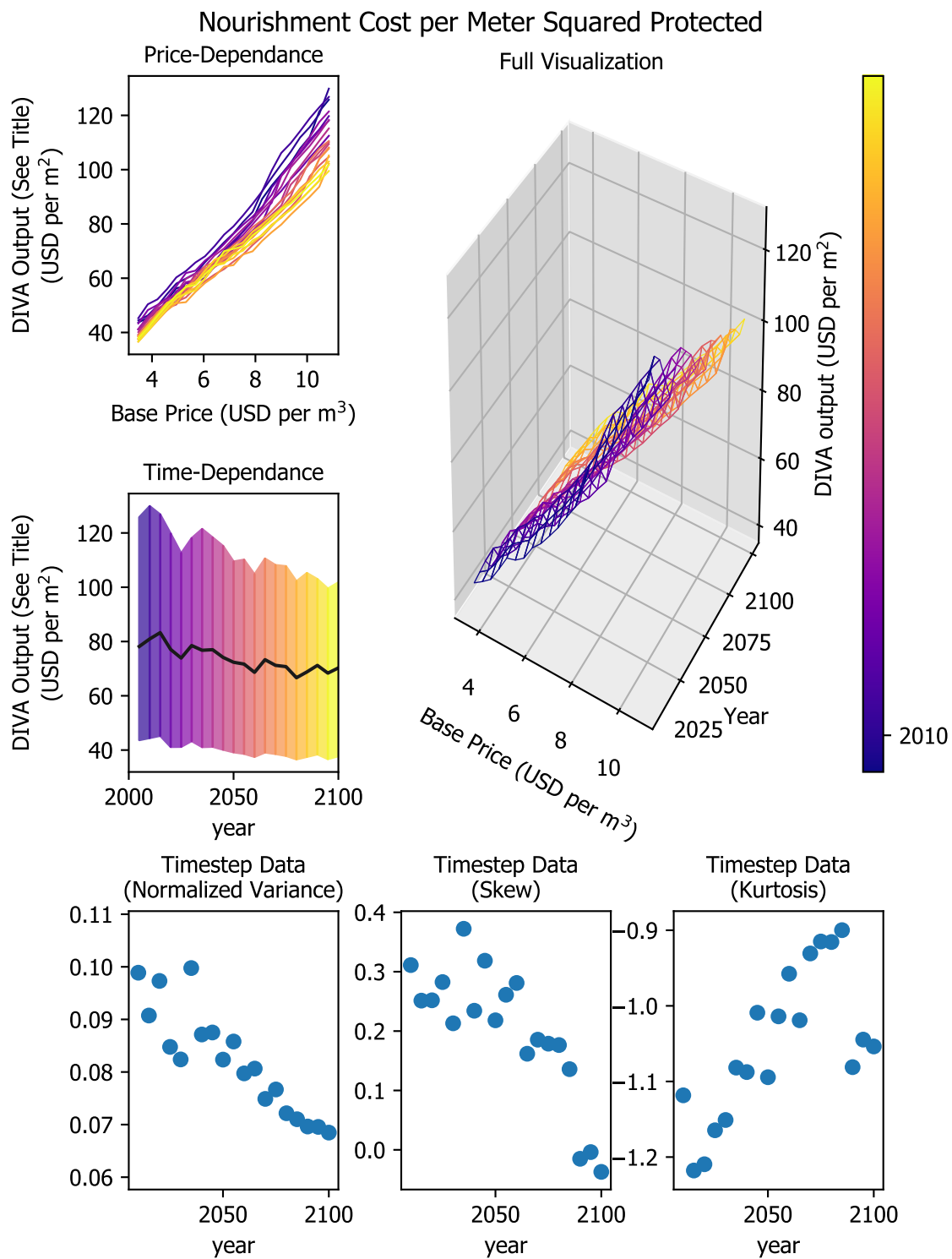


Figure F.2: This page shows the sensitivity of the nourishment cost per area of protected land to changes in the baseline global reference price when no adaption measure is employed. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/m³. (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

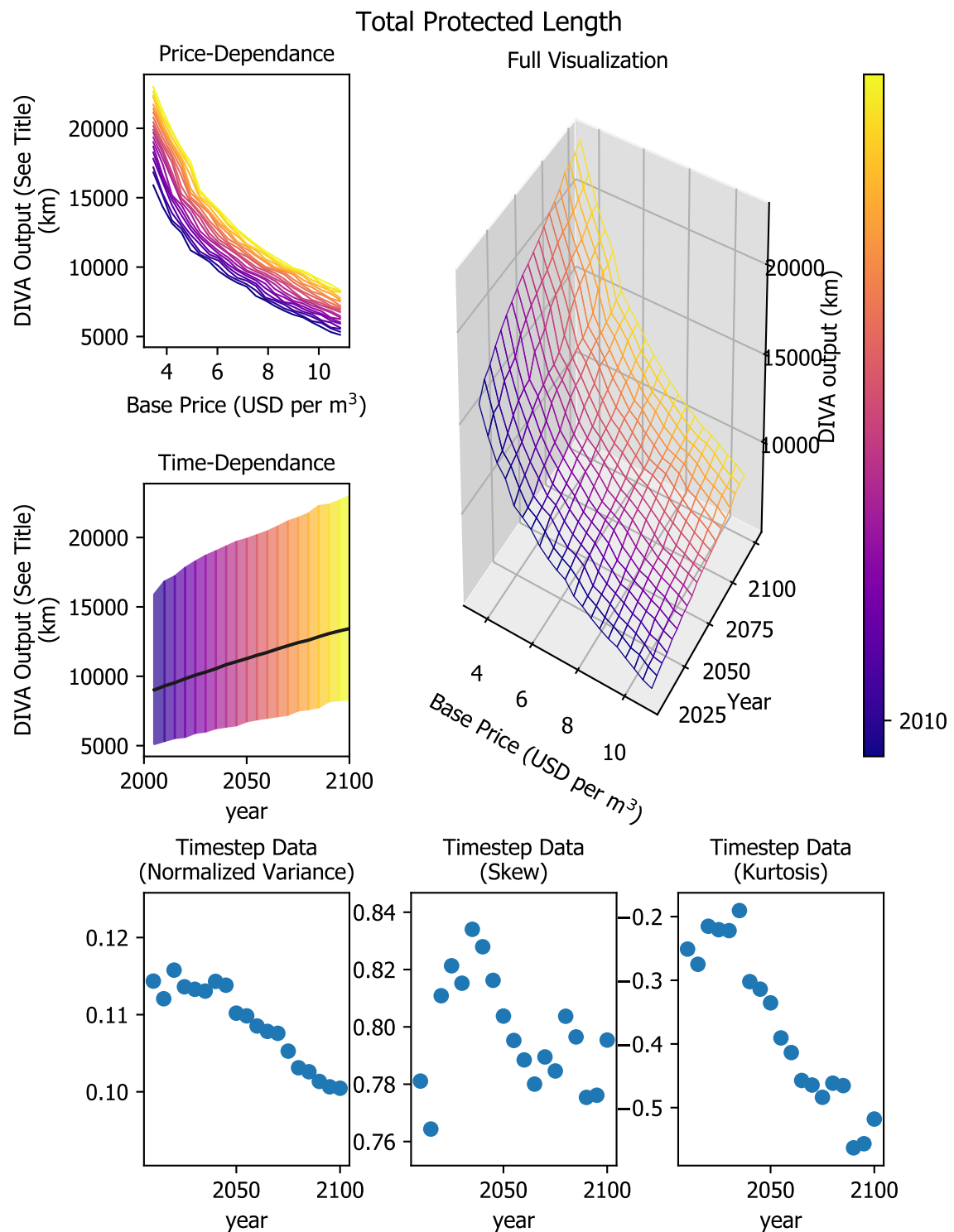


Figure F.3: This page shows the sensitivity of protected land area through nourishment to changes in the baseline global reference price when no adaption measure is employed. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

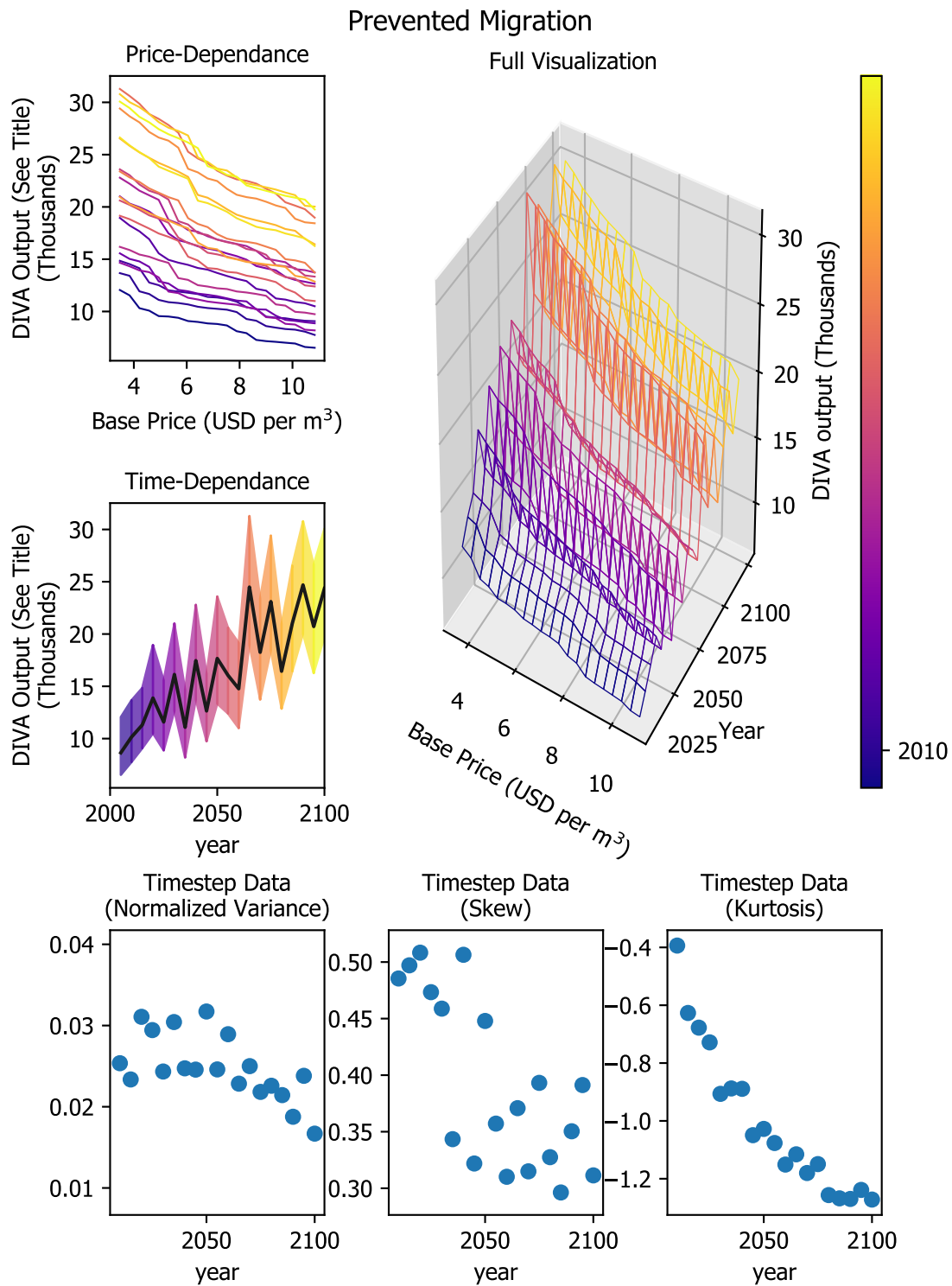


Figure F.4: This page shows the sensitivity of people protected from forced migration through nourishment to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

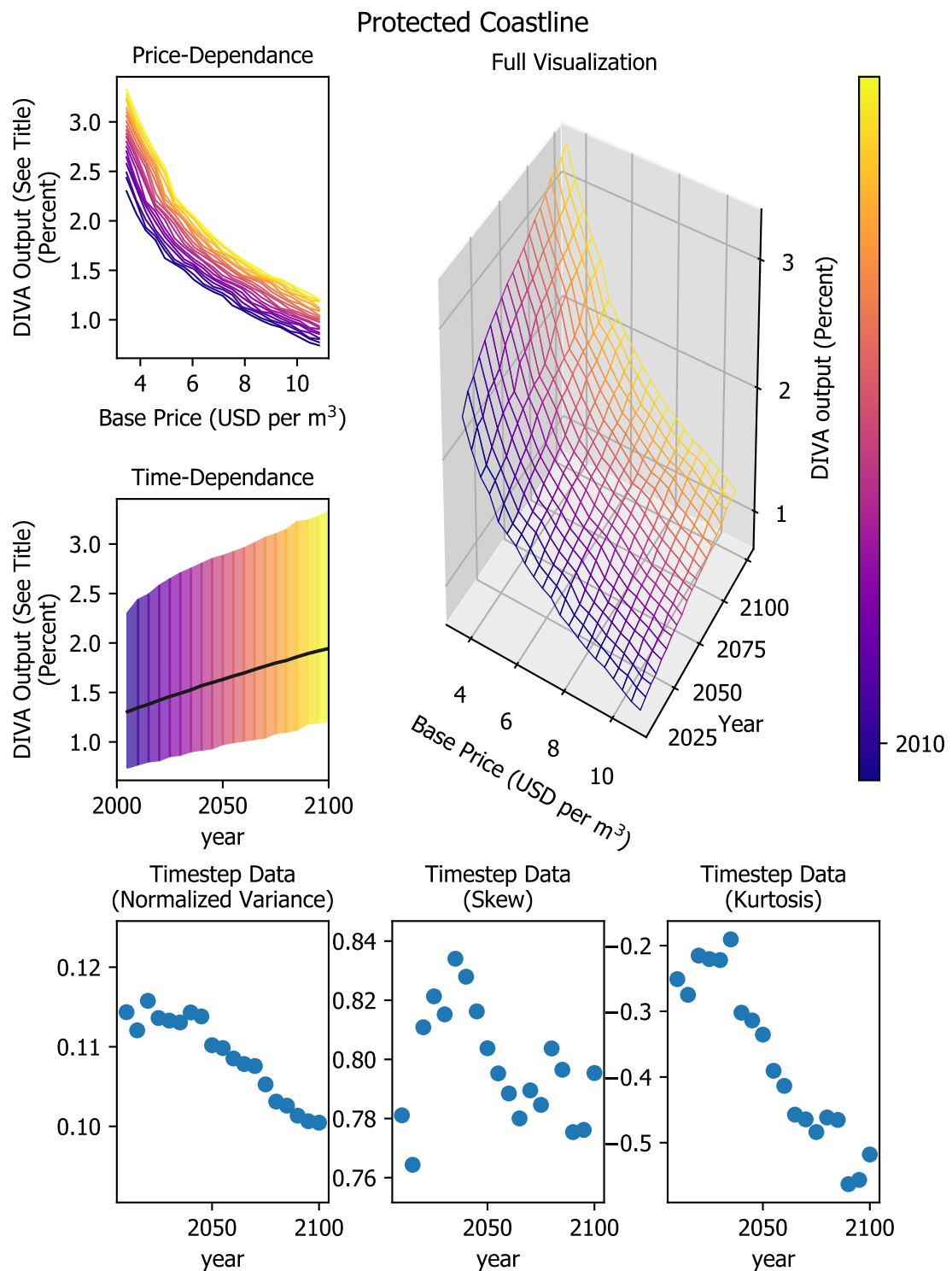


Figure F.5: This page shows the sensitivity of percentage of coastline protected to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

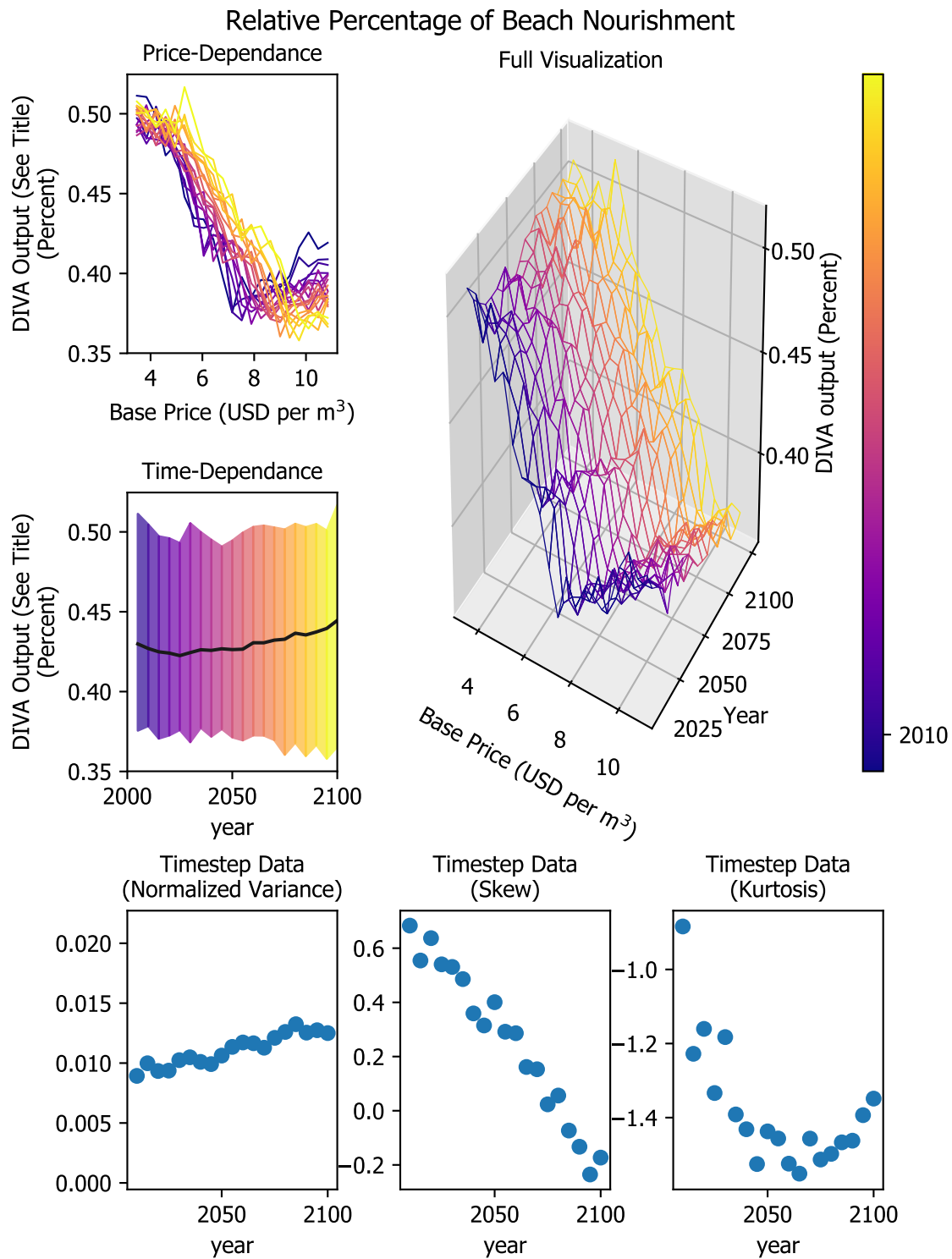


Figure F.6: This page shows the sensitivity of the proportion of beach-line nourishment (ie. beach nourishment divided by total nourishment) to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

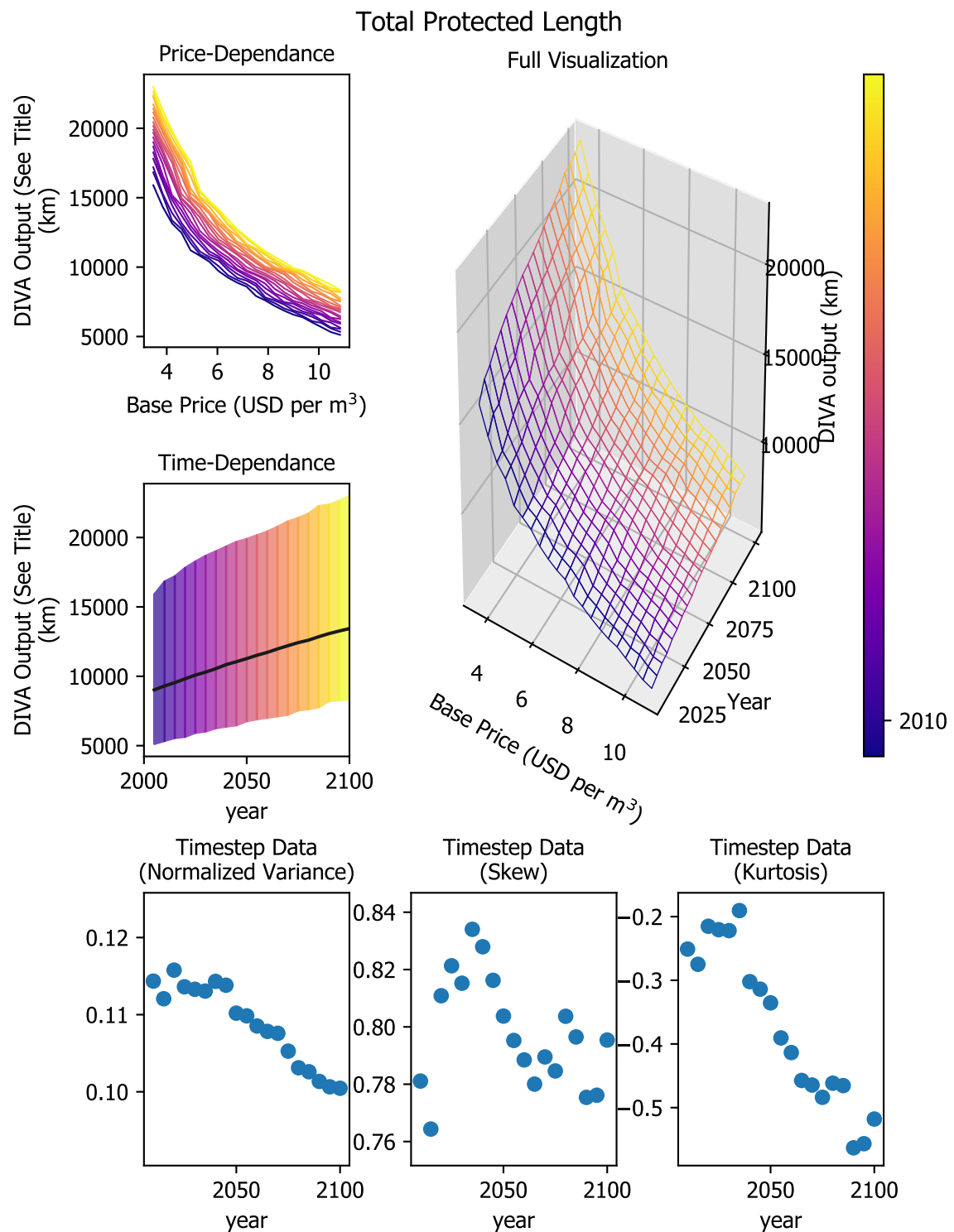


Figure F.7: This page shows the sensitivity of total length of beach nourishment to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

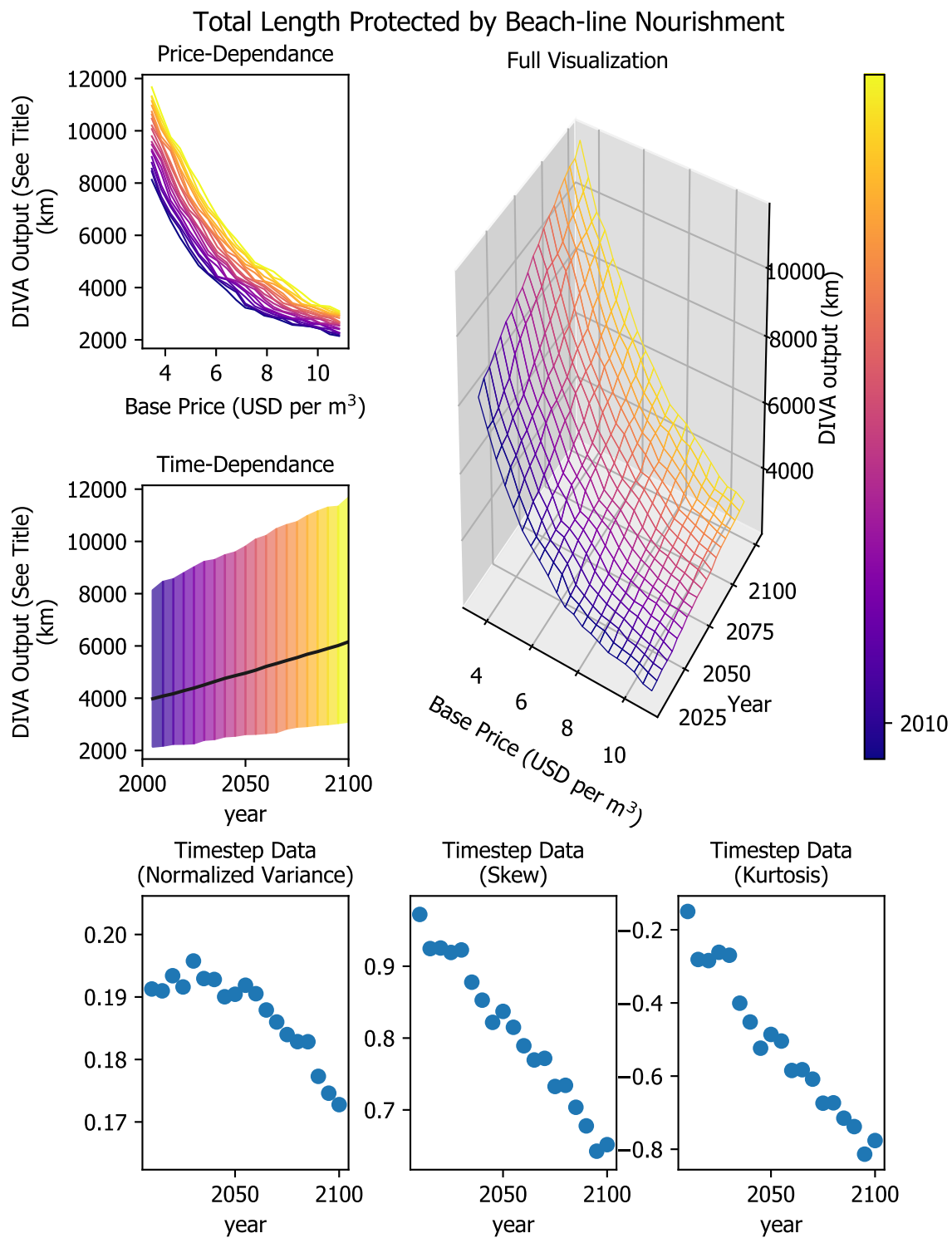


Figure F.8: This page shows the sensitivity of the length of beach nourishment protected by beach-line nourishment to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

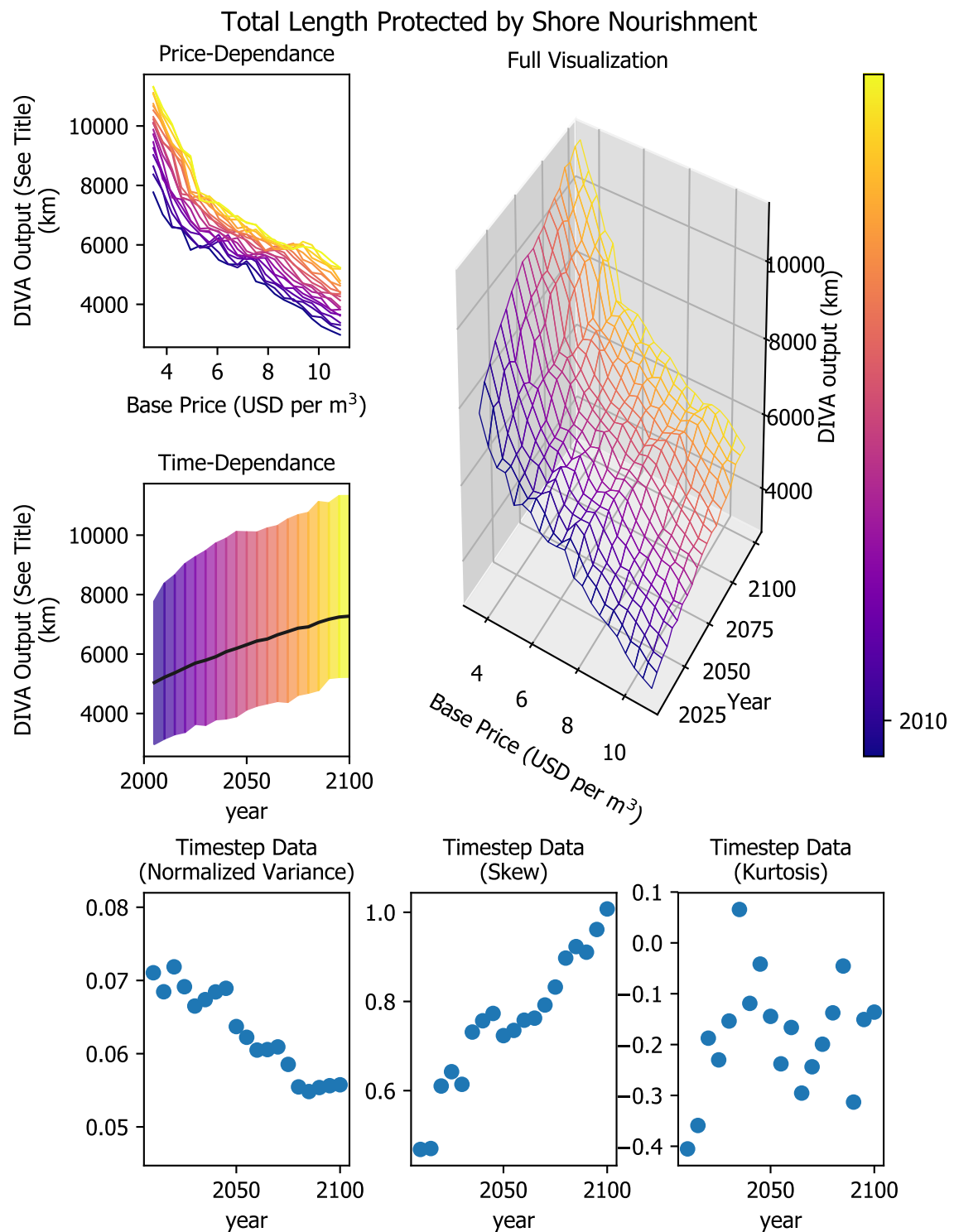


Figure F.9: This page shows sensitivity of the length of beach protected by shore nourishment to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

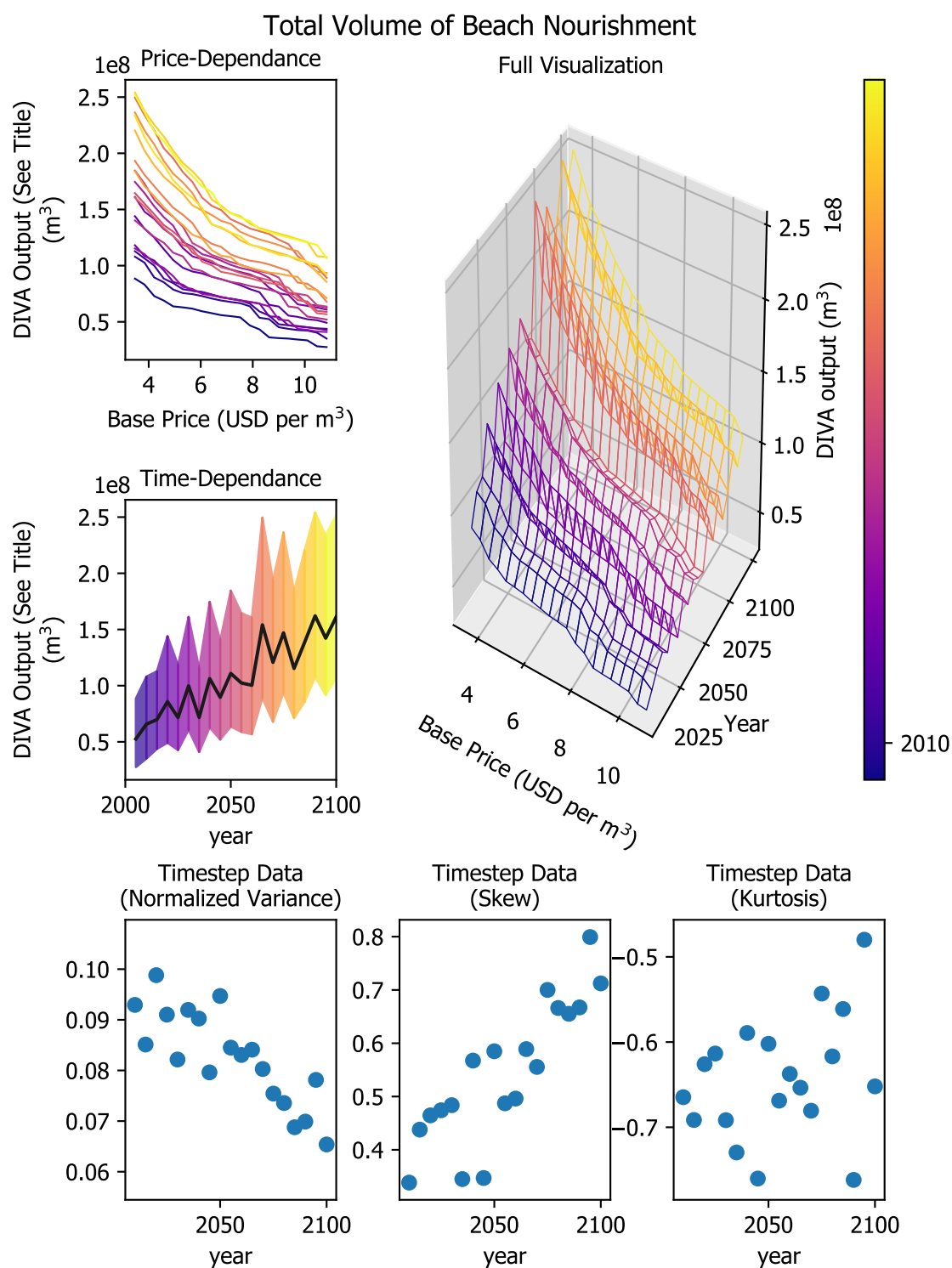


Figure F.10: This page shows sensitivity of the total nourishment volume to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

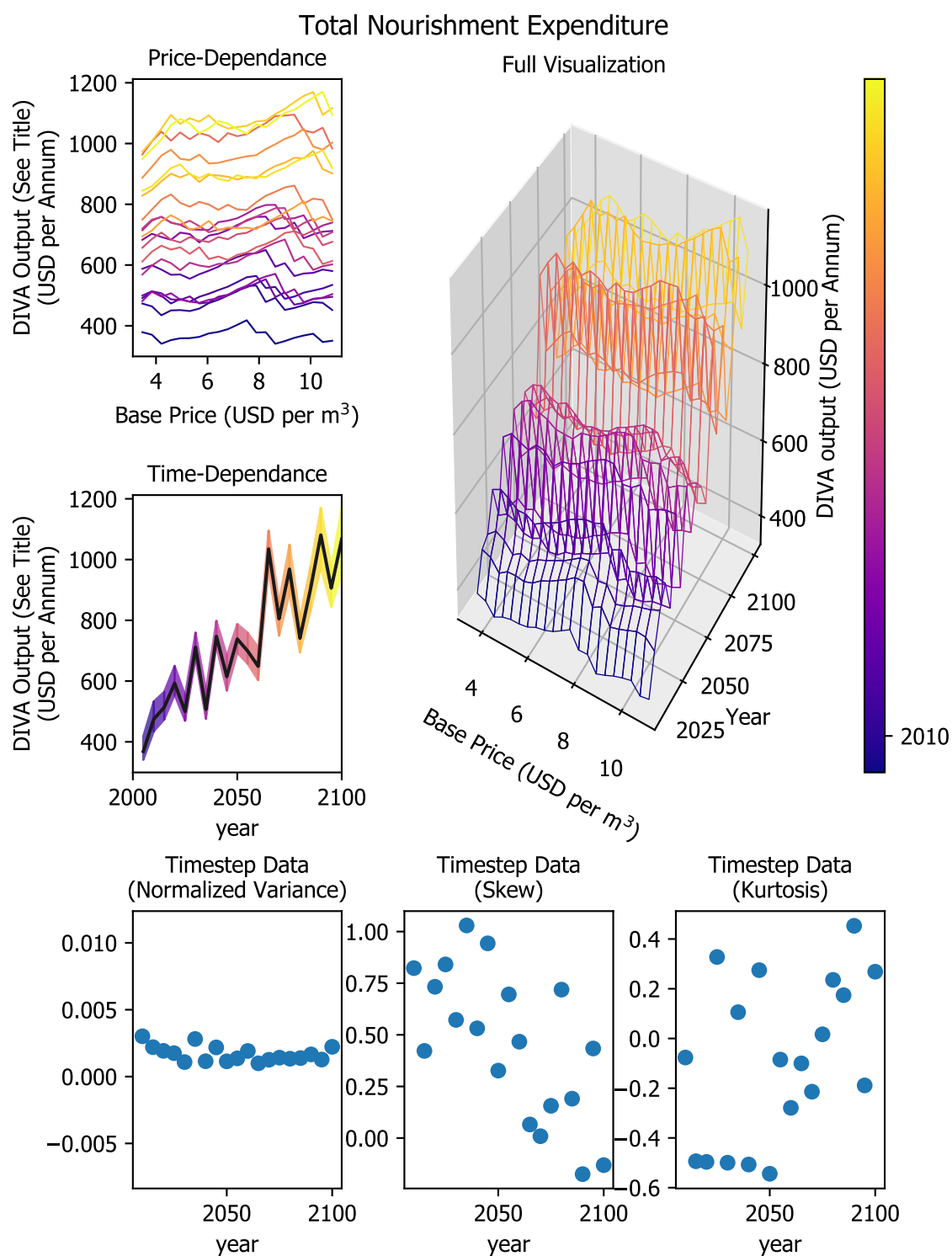


Figure F.11: This page shows the sensitivity of total nourishment cost to changes in the baseline global reference price. (TL) Indication of changes as the global reference price changes between 3.47 and 10.84 USD/ m^3 . (ML) Indication of price changes and the extent of model projections over time. (TR) 3D visualization of model results on the time-base price dimension for qualitative interpretation. (B) the variation of statistical properties across base prices as a time-varying parameter.

G

Additional Maps

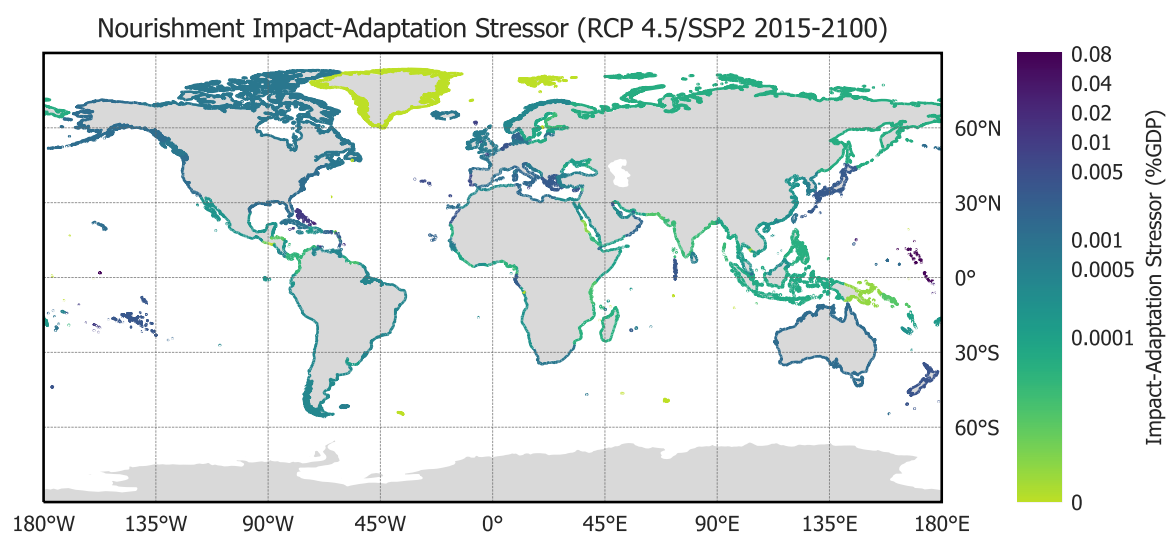


Figure G.1: This figure demonstrates coastal nourishment, forced migration, and loss of land as a portion of the available GDP mapped to physical locations. This map educates discussion on the regional variability of nourishment practices

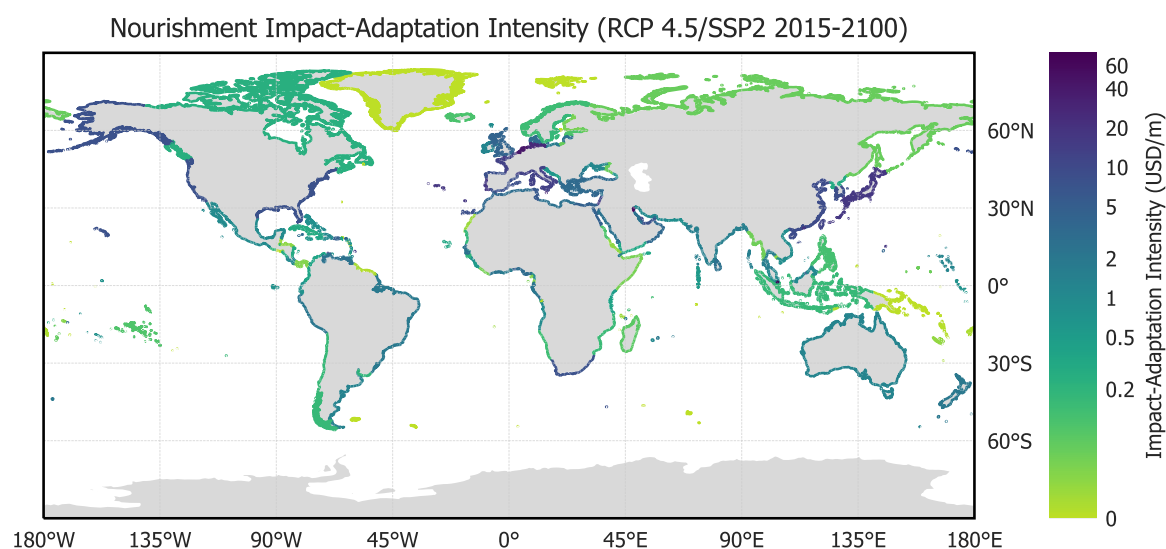


Figure G.2: This figure demonstrates the intensity of SLR adaptation stress by resolving coastal nourishment, forced migration, and loss of land per unit of coastline length. This map educates discussion on the regional variability of nourishment practices