Improving the representation of the spatial distribution of population for coastal impact and vulnerability assessments

Dissertation

zur Erlangung des Doktorgrades
der Mathematisch-Naturwissenschaftlichen-Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von
Jan-Ludolf Merkens

Kiel, 2019

Erster Gutachter: Prof. Dr. Athanassios T. Vafeidis
Zweiter Gutachter: PD Dr. habil Jochen Hinkel

Tag der mündlichen Prüfung: 03.02.2020
Zum Druck genehmigt: 03.02.2020

gez. Prof. Dr. Frank Kempken

Danksagung

An dieser Stelle möchte ich mich bei allen Personen bedanken, die mich auf dem Weg zum Abschluss meiner Dissertation begleitet haben.

In erster Linie bedanke ich mich herzlich bei meinem Betreuer Prof. Dr. Athanasios Vafeidis, der mir in den letzten fünf Jahren stets mit Rat und Geduld zur Seite stand. Er hat ein sehr angenehmes und produktives Arbeitsumfeld geschaffen, welches den Austausch von Gedanken und Erfahrungen förderte. Durch die Projekte RISES-AM (EU) und SEASCApe Baltic (DFG) ermöglichte er mir zudem die aktive Teilnahme an internationalen Konferenzen und gab mir die Möglichkeit meine Ergebnisse zu präsentieren und Kontakte zu knüpfen.

Ein großer Dank geht auch an meinen Zweitbetreuer PD Dr. Jochen Hinkel (GCF Berlin). Durch seine Einblicke im IPCC hat er mir Forschungslücken aufgezeigt, die ich in Rahmen meiner Publikationen adressiert habe. Meinen Arbeitskollegen Claudia Wolff, Lena Reimann, Joschua Kiesel, Sara Santamaria-Aguilar, Leigh MacPherson, Bente Vollstedt, Maureen Tsakiris, Jana Koerth und Tobias Dolch danke ich für interessante Diskussionen, einen regen Gedankenaustausch und gegenseitige Unterstützung. Bei meinen ehemaligen Kollegen Mark Schürch und Barbara Neumann möchte ich mich insbesondere für die Unterstützung auf dem Weg zu meiner ersten Publikation bedanken.

Diese Arbeit wäre in dieser Form nicht möglich gewesen, wenn andere Forschungsteams ihre Daten nicht teilen würden. Daher danke ich insbesondere dem *Global Urban Footprint Team* am Deutschen Zentrum für Luft- und Raumfahrt, dem *Center for International Earth Science Information Network* an der Columbia University für die Bereitstellung von GRUMP und GPW und dem *International Institute for Applied System Analysis* für die SSP-Database.

In Rahmen dieser kumulativen Dissertation sei auch meinen Co-Autoren Lena Reimann, Daniel Lincke, Sally Brown, Jochen Hinkel und Athanasios Vafeidis gedankt. Durch ihre Zuarbeit haben sie zu soliden Manuskripten beigetragen, die in den anschließenden Review-Prozessen zu hilfreichen Reviewer-Kommentaren geführt haben.

Ein großer persönlicher Dank gebührt meiner Frau Thea-Lina. Du unterstützt mich sehr, indem du dich gedanklich mit der Thematik auseinandersetzt und Ideen mit mir diskutierst. Auch in schwierigen Phasen findest du immer die richtigen Worte und Taten, um mich zu motivieren. Ich danke auch meinen Töchtern Elsa-Marie und Rosa-Amalie. Ihr sorgt jeden Tag für eine wunderbare Abwechslung vom Büroleben und macht mir immer wieder bewusst, was wirklich wichtig ist.

Zusammenfassung

Menschen, die in niedrig gelegenen Küstengebieten leben, sind durch Sturmfluten und den Meeresspiegelanstieg gefährdet. Gefährdungsanalysen quantifizieren die potenziell betroffene Küstenbevölkerung und stellen die Basis bei der Identifikation und Auswahl von geeigneten Anpassungsmaßnahmen dar. Vor allem räumlich hochaufgelöste Informationen zur Bevölkerungsverteilung stellen dabei einen elementaren Eingangsparameter der Gefährdungsanalysen dar. Bei grobskaligen Betrachtungen (multinational bis global) bilden Bevölkerungsinformationen auf Zensusebene die räumlich höchstaufgelöste Informationsquelle. Die dabei angenommene Gleichverteilung der Bevölkerung innerhalb von Zensuseinheiten kann bei kleinflächigen Zensuseinheiten (wenige Hektar) akkurat sein, entspricht bei großflächigen Zensuseinheiten (mehreren Quadratkilometer) jedoch nicht der tatsächlichen Bevölkerungsverteilung. Bisherige Studien modellieren die Verteilung der Bevölkerung mit einer Vielzahl von Hilfsvariablen, was die Übertragbarkeit in Gebiete mit spärlicher Datenverfügbarkeit einschränkt.

Die vorliegende Arbeit hingegen arbeitet mit einem neuartigen Ansatz, indem Siedlungsgebiete aus dem ‚Global Urban Footprint' abgeleitet werden. Untersucht wird, ob diese abgeleiteten Siedlungsgebiete hinreichend sind, um die tatsächliche Bevölkerungsverteilung innerhalb von Zensuseinheiten nachzubilden. Für die Untersuchungsregion der deutschen Ostseeküste zeigt sich, dass die abgeleiteten Siedlungsgebiete bis zu 95,3 % der tatsächlichen Bevölkerung erfassen und somit einen geeigneten Parameter zur Bevölkerungsmodellierung darstellen. Darüber hinaus vergleicht die vorliegende Arbeit sechs Ansätze, die die Bevölkerungsdichte innerhalb der Siedlungsgebiete differenzieren. Im Vergleich zur Gleichverteilung der Bevölkerung weisen die verwendeten Ansätze bis zu sechs Mal geringere Fehlerwerte auf. In flutgefährdeten Gebieten reduzieren die verwendeten Ansätze die Überschätzung der gefährdeten Bevölkerung um bis zu 29 %. Somit zeigt sich, dass mit Hilfe der aus dem ‚Global Urban Footprint' abgeleiteten Siedlungsgebiete eine realistischere Verteilung der aktuellen Bevölkerung innerhalb von Zensuseinheiten abgebildet werden kann, die zu einer verbesserten Abschätzung der Flutgefährdung beiträgt.

Den zweiten inhaltlichen Schwerpunkt der Arbeit bildet die Regionalisierung von Bevölkerungsprojektionen im Küstenraum. Viele Gefährdungsanalysen berücksichtigen die Auswirkungen des Klimawandels auf den Meeresspiegel sowie auf die Häufigkeit und die Intensität von Sturmfluten, während sozioökonomische Veränderungen entweder nicht betrachtet oder auf subnationaler Ebene nicht differenziert werden. Diese Arbeit beschreibt fünf sozioökonomische Entwicklungspfade für den Küstenraum, die die bestehenden „Shared-Socioeconomic-Pathways" erweitern. Basierend auf beobachteten Unterschieden im Bevölkerungswachstum zwischen Küsten- und Inlandsgebieten sowie Bevölkerungs- und Urbanisierungsprojektionen werden räumlich explizite Bevölkerungsprojektionen mit globaler Abdeckung entwickelt. Für die „Low Elevation Coastal Zone" werden diese Bevölkerungsprojektionen anschließend mit Bevölkerungsprojektionen verglichen, die innerhalb eines Landes eine einheitliche Bevölkerungsänderung annehmen. Basierend auf dem regionalisierten Bevölkerungswachstum leben in diesen Gebieten im Jahr 2100 zwischen 85 Millionen und 239 Millionen Menschen mehr als bei einem national einheitlichen Wachstum. Um zu untersuchen, ob Urbanisierung oder Küstenmigration stärker zu diesen Unterschieden beitragen und ob Suburbanisierung diese Unterschiede verstärkt oder verringert, verwendet die vorliegende Arbeit das „Dynamic Interactive Vulnerability Assessment" Tool. Im Vergleich zu homogenem Wachstum auf nationaler Ebene zeigt sich, dass die geschätzte Gefährdung der Bevölkerung durch Urbanisierung um 7 % bis

20 % ansteigt, durch Küstenmigration um weitere 1 % bis 20 % ansteigt und durch Suburbanisierung um 12 % bis 22 % abfällt. Diese Ergebnisse zeigen, dass Urbanisierung, Küstenmigration und Suburbanisierung auf subnationaler Ebene zu Unterschieden im Bevölkerungswachstum führen und deren differenzierte Berücksichtigung zu einer verbesserten Abschätzung der zukünftigen Flutgefährdung von Bevölkerung im Küstenraum beiträgt.

Summary

Extreme sea levels and sea-level rise are two hazards that can harm populations situated in low elevated coastal areas. Impact and vulnerability assessments quantify the number of people living in flood prone areas and serve as a basis for planning adaptation measures. One of the prerequisites for these assessments is a realistic spatial representation of the potentially affected coastal population. Census data provide the highest spatial detail for assessments on coarse scales (multi-national to global). Within census units, population is assumed to be distributed homogeneously. This assumption might hold true for small census units (few hectares) but does not represent the actual distribution of population in large census units (several square kilometres). Previous studies use many ancillary data to allocate population within census units which restricts their transferability to data sparse regions.

This thesis in contrast uses a novel approach by deriving settlement extents from the 'Global Urban Footprint'. It examines whether these derived settlement areas are sufficient to reproduce the actual population distribution within census units. For the German Baltic Sea region, the settlement extents capture 95.3 % of the actual population, qualifying them as a suitable parameter to model the distribution of population. In addition, this thesis compares six approaches to differentiate population density within the derived settlement extents. Compared to a homogeneous distribution of population, the error in the tested approaches is up to six times smaller. In flood prone areas, the tested approaches reduce the overestimation of population exposure by up to 29 %. These results thus show that settlement extents derived from the 'Global Urban Footprint' lead to a more realistic distribution of the current population within census units, which improves the assessment accuracy of population exposure to coastal flooding.

The regionalisation of population growth projections in coastal areas is the second focus of this thesis. Previous studies that assess exposure to coastal flooding account for changing sea-levels or the changes in the frequency and intensity of floods due to climate change. However, these studies do not consider socioeconomic development at all, or do not differentiate socioeconomic development at subnational level. This thesis extends the 'Shared Socioeconomic Pathways' for the coastal zone by providing narratives of socioeconomic development under five scenarios. Furthermore, it combines observed differences in population growth between coastal and inland areas with existing projections on population and urbanisation to develop spatially explicit population projections for the entire globe. Subsequently, this work compares these projections to projections that do not differentiate population growth within countries. Depending on the scenario, it finds the population living in the 'low elevation coastal zone' in the regionalised projections in 2100 to be 85 million to 229 million people larger. Furthermore, the thesis investigates, to what extent urbanisation or coastal migration contribute to these differences and whether urban sprawl increases or decreases these differences by employing the 'Dynamic Interactive Vulnerability Assessment' Tool. Compared to homogeneous population growth within countries, urbanisation increases the assessed exposure by 7 % to 20 %, coastal migration increases the assessed exposure by 1 % to 20 % and urban sprawl decreases the assessed exposure by 12 % to 22 %. The results show that urbanisation, coastal migration and urban sprawl lead to heterogeneous population growth on a subnational level. Accounting for these differences in population growth contributes to improved estimates of the future population exposure to coastal floods.

Contents

List of figures

List of tables

Abbreviations

DEM. *Digital Elevation Model*
DIVA. *Dynamic Interactive Vulnerability Assessment, Dynamic Interactive Vulnerability Assessment*
ESL. *Extreme Sea Levels*
GADM. *Global Administrative Areas*
GD. *Growth Difference*
GDP. *Gross Domestic Product*
GD^R. *Rural Growth Difference*
GD^U. *Urban Growth Difference*
GHS-POP. *Global Human Settlement Layer*
GPW. *Gridded Population of the world*
GRUMP. *Global Rural and Urban Mapping Project*
GTSR. *Global Tide and Surge Reanalysis, Global Tide and Surge Reanalysis*
GUF. *Global Urban Footprint*
GUF0.4. *Global Urban Footprint (0.4 arc-seconds spatial resolution)*
$GUF0.4_{5\%}$. *Global Urban Footprint (0.4 arc-seconds spatial resolution; urban share larger than 5%)*
GUF2.8. *Global Urban Footprint (2.8 arc-seconds spatial resolution)*
HYDE. *History database of the global environment*
IAV. *Impact, Adaptation and Vulnerability*
IIASA. *International Institute for Applied Systems Analysis*
IPCC. *Intergovernmental Panel on Climate Change*
LAatC. *Latin America and the Caribbean*
LECZ. *Low Elevation Coastal Zone*
LiDAR. *Light Detection and Ranging*
MAE. *Mean Average Error*
MHHW. *Mean Higher High Water*
NCAR. *National Center of Atmospheric Research*
RCP. *Representative Concentration Pathways*
RMSE. *Root Mean Square Error*
RTAE. *Relative Total Absolute Error*
SDG. *Sustainable Development Goal*
SLR. *Sea-level Rise*
SPA. *Shared Policy Assumptions*
SRES. *Special Report on Emissions Scenarios*
SRTM. *Shuttle Radar Topography Mission*
SRTM-EGM. *SRTM Enhanced Global Map*
SSP. *Shared-Socioeconomic Pathway*
UN. *United Nations*

1 Introduction

Coastal areas offer resources for subsistence, which make them attractive locations for human settlement (Neumann et al. 2015). Furthermore, coastal areas are used for recreational activities and provide access points to trade and transport. This is reflected in a high population density, which is three times higher than the global average and in a high urbanisation level, which exceeds the global average by 40 % (Kummu et al. 2016). Land areas that are hydrologically connected to the ocean and not exceeding an altitude of 10 m are also known as the Low Elevation Coastal Zone (LECZ). Globally, these areas amount to 2 % of the land area but host more than 10 % of the total population (McGranahan et al. 2007). In 2010, 20 out of 31 megacities (population > 8 million) were located in the LECZ (Brown et al. 2013).

However, coastal areas face hazards, such as coastal floods. In the period from 1900 to 2015, coastal floods affected about 172.5 million people and caused almost 1 million fatalities (Bouwer and Jonkman 2017). Most fatalities occur in places with high population densities but with low protection levels and insufficient warning systems. In order to identify these places impact and vulnerability assessments are used. These assessments aim to quantify the risk of coastal flooding. According to the Intergovernmental Panel on Climate Change (IPCC) risk is defined as a function of hazard, exposure and vulnerability (Field et al. 2012). More detailed, hazard refers to natural or human-induced physical events that have a negative effect on exposed or vulnerable elements. Exposure encompasses all elements in an area where hazards may occur. Elements outside the hazard zone are not exposed to specific events and therefore not at risk. Vulnerability describes the capacity of an element to endure negative effects caused by a hazard event (Cardona et al. 2012). For example, if the population is prepared for hazard events by taking adaptation measures, it might not be vulnerable but still be exposed. However, being vulnerable to a hazard also means being exposed (Cardona et al. 2012). Consequently, exposure needs to be assessed before risk can be quantified.

Exposure assessments that quantify the number of people living in flood prone areas on a global scale are of specific interest for international organisations, such as the United Nations (UN) and the World Bank (Ward et al. 2013). If consistent methods are used on a global scale, the exposure of countries becomes comparable and regions that are most exposed can be identified. In a next step, international investments can be allocated to those regions to implement measures to reduce the risk of coastal flooding (Hammond et al. 2013).

To decide on specific measures, stakeholders require information on current and future exposure. The current exposure of coastal population is mainly induced by extreme sea levels (ESL), which lead to a temporal inundation of land areas (hours to days). However, some coastal regions already face the consequences of sea-level rise (SLR), leading to permanent inundation of land areas. For the next decades SLR will continue and the rate of SLR is projected to increase. This results in the permanent flooding of larger areas and also more intense ESL (Church et al. 2013). At the same time, population in coastal areas is projected to grow (Brown et al. 2013; Neumann et al. 2015; Jones and O'Neill 2016). These physical (SLR and ESL) and socioeconomic changes (population growth) lead to an increase of population exposure to coastal floods.

The remainder of chapter 1 is structured as follows: subsection 1.1 discusses the drivers leading to SLR and gives an overview of observed global SLR. It introduces the Representative

Concentration Pathways (RCPs) and states the projected changes in sea-level until 2100. Subsection 1.2 provides an overview of methods and data employed in previous studies to assess land areas exposed to coastal flooding. Then, subsection 1.3 introduces spatially explicit population datasets that serve as a basis for assessing current exposure. Subsection 1.4 describes approaches to consider population changes employed by previous studies and compares their findings. Furthermore, it introduces the Shared-Socioeconomic Pathways (SSPs). This is followed by the research questions of this thesis in subsection 1.5.

1.1 Climate change and coastal floods

Although climate change has many implications for coastal areas, this thesis focusses on the effects on coastal floods. Global warming is the main driver of SLR (Gregory and Lowe 2000). Higher temperatures lead to melting of land ice (glaciers and ice sheets) and to thermal expansion of ocean water. Consequently, the volume of the ocean water mass increases. The extraction of groundwater and surface water on land enhances the increase of the ocean water mass (Church et al. 2013). However, sea levels do not change at the same rate all over the globe but show regional differences. Changes in the distribution and strength of ocean currents, in salinity and in the distribution of atmospheric pressure as well as isostatic adjustment and land subsidence affect regional sea levels. The net result of the global and regional factors gives the regional sea level change (Kopp et al. 2014).

The global mean SLR amounted to 19 cm in the period from 1901 to 2010, which corresponds to a rate of 1.7 mm per year. The rate increased considerably in the last decades: the observed mean rate of global SLR was 1.5 mm per year from 1901 to 1990, 2 mm per year from 1971 to 2010 and 3.2 mm per year from 1993 to 2010 (Church et al. 2013). The rate of future SLR depends on the emission of greenhouse gasses. Higher emissions lead to higher concentrations of greenhouse gasses in the atmosphere, which lead to an increase of the radiative forcing levels compared to pre-industrial conditions. Increased radiative forcing leads to higher temperatures, which again cause thermal expansion of the ocean water and melting of land ice (Church et al. 2013). The level of future greenhouse gas emissions depends on socio-economic development and on the willingness or unwillingness to reduce greenhouse gas emissions. The IPCC uses four RCPs to represent different levels of greenhouse gas emissions leading to forcing levels of 2.6 W/m², 4.5 W/m², 6 W/m² and 8.5 W/m² in 2100 (van Vuuren et al. 2011). The stated levels indicate the increase in radiative forcing compared to pre-industrial levels. In RCP2.6 radiative forcing peaks at 3 W/m² before 2050 and declines to 2.6 W/m² by 2100. In RCP4.5 and RCP6.0 the radiative forcing stabilises after 2100 due to a reduction of emissions by 2050. RCP8.5 is the only RCP where emissions continuously increase until 2100, which also leads to rising radiative forcing levels beyond 2100 (van Vuuren et al. 2011).

The global mean sea level for the period 2081 to 2100 is projected to rise by 40 cm in RCP2.6, by 47 cm in RCP4.5, by 48 cm in RCP6.0 and by 63 cm in RCP8.5 compared to the period of 1986 to 2005. The rate of SLR in 2100 is 4.4 mm per year in RCP2.6, 6.1 mm per year in RCP4.5, 7.4 mm per year in RCP6.0 and 11.2 mm per year in RCP8.5 (Church et al. 2013). A structured expert judgement study undertaken by Bamber et al. (2019) suggests that these projections underestimate the potential contribution of ice sheet melting to global SLR in 2100 by 8 cm under RCP2.6 and by 30 cm under RCP8.5. The IPCC Special Report on Ocean and Cryosphere considers higher contribution of ice sheet melting and updated the projected global mean SLR to 0.43 m (RCP2.6), 0.55 m (RCP4.5) and 0.84 m (RCP8.5) (Oppenheimer et al. 2019).

The total water level is a combination of the mean sea level, the tide and the surge component (Santamaria-Aguilar et al. 2017). ESL occur at high astronomical tides and strong surge components. SLR affects all components of the total water level. SLR leads to more frequent and more intense flood events, as it rises the mean sea level. Furthermore, studies find that SLR has a non-linear effect on tides (Pickering et al. 2017; Mawdsley et al. 2015), which can further intensify ESL. Lastly, changes in the intensity, frequency, duration and the path of tropical and extratropical storms effect the surge component (Church et al. 2013).

The heights of SLR and ESL serve as a basis to define current and future exposure of land areas to coastal floods. Coastal impact assessments then combine these areas with population data to analyse the current exposure of population and to project the future exposure of population.

1.2 Assessing flood-prone areas

To identify areas affected by coastal floods on a global scale, studies employ digital elevation models (DEMs) (McGranahan et al. 2007; Lichter et al. 2011; Hinkel et al. 2014; Neumann et al. 2015; Muis et al. 2017). Only few DEMs have a (near) global coverage, which is required for consistent global assessments. The Shuttle Radar Topography Mission (SRTM) (Farr et al. 2007) is the most popular open-access DEM (Hawker et al. 2018). SRTM has a coverage from 56° S to 60° N and a horizontal resolution of 1 and 3 arc-seconds (approximately 30 m and 90 m at the equator). For high latitudes outside the coverage of SRTM, studies employ elevation datasets with a coarser resolution of 30 arc-seconds (approximately 1 km at the equator), such as GLOBE (Hastings and Dunbar 1998) or GTOPO30 (USGS 1996) (Neumann et al. 2015). SRTM, GLOBE and GTOPO use integers to represent elevation heights in meters. The Multi-Error-Removed Improved -Terrain DEM (MERIT-DEM) is the first nearly global DEM (coverage 60° S to 90° N) that uses floating-point numbers instead of integers (Yamazaki et al. 2017). This allows to differentiate elevation heights in higher detail than meters. However, these freely available (nearly) global DEMs are surface models, not terrain models. They cannot differentiate between the elevation of objects and the bare ground, which can lead to an overestimation of elevation in built-up areas or in areas with a high vegetation coverage. Gesch (2018) found that in the United States of America SRTM overestimates the elevation of the ground by about 4 m. For flood impact assessments, this leads to an underestimation of the extent of flood prone areas. The CoastalDEM (Kulp and Strauss 2018) aims to overcome this limitation by utilising neuronal networks to correct SRTM elevation heights. For the United States of America, Kulp and Strauss (2018) compare SRTM elevation to elevation heights derived from light detection and ranging (LiDAR) data. They employ 23 variables derived from DEMs, population densities, vegetation and the Ice, Cloud and land Elevation Satellite (ICESat) to explain these differences. The variables are then used to predict SRTM errors for the entire globe and to correct SRTM elevation data accordingly.

To define areas exposed to coastal floods on a spatially explicit level, the elevation of each cell in a DEM is compared to an elevation threshold which defines the height of a coastal flood. For the LECZ, a threshold of 10 m is used, whereas a varying threshold is employed to assess the floodplain of ESL. In case the elevation value of a cell does not exceed the elevation threshold, the cell represents a low-lying area that is potentially prone to coastal flooding. Then, the identified areas are checked for hydrological connectivity to the ocean (Poulter and Halpin 2008). Hydrological connectivity ensures that landlocked depressions with an elevation below the given threshold are not identified as areas prone to coastal flooding. However, on local scales the omission of hydrological connectivity might be desirable, if groundwater intrusion as a consequence of SLR is considered (Rotzoll and Fletcher 2013).

Whereas the described DEM-based scheme (also known as bathtub approach) is accepted for identifying areas exposed to SLR, studies question the applicability for modelling the flood extent of ESLs (Vousdoukas et al. 2016). The bathtub approach tends to overestimate the flood extent of observed events because it does not consider the available water volume (Breilh et al. 2013) or water attenuation (Vafeidis et al. 2019). On local scales, hydrodynamic models (e.g. DELFT3D) are used to simulate the actual flow movement of water during extreme events (Teng et al. 2017). After calibration to site-specific characteristics, these hydrodynamic models can simulate the flood extent of observed events. However, the models are computationally expensive and require time series of water levels and detailed data on elevation and protection measures which are not available for many coastal regions (Teng et al. 2017; Ramirez et al. 2016). Hydrodynamic models of reduced complexity appear to be a compromise between hydrodynamic models and the bathtub approach. Although the computational costs are higher compared to the bathtub approach, the overestimation of floodplains can be considerably reduced. Ramirez et al. (2016) simulate ESL without waves of three events at different sites and compare the results of the bathtub approach to a reduced complexity hydrodynamic model. They find that the overestimation of the floodplain in low lying areas can be reduced from ~200 % to ~60 % if a reduced complexity hydrodynamic model is used instead of the bathtub approach. Vousdoukas et al. (2016) use a reduced complexity hydrodynamic model to simulate ESL including waves and show that the overestimation of the floodplain can be reduced from ~230 % to ~70 % compared to the bathtub approach. On the other hand, the studies of Ramirez et al. (2016) and Vousdoukas et al. (2016) show that the reduced complexity hydrodynamic models lead to a three- to fourfold increase of areas actually flooded during an event but not predicted to be flooded. Depending on the risk-tolerance of decision makers, it might be more desirable to decide on flood protection measures based on a model that overestimates flood extents (worst-case flood extents) than based on a model that falsely claims flood prone areas as safe areas that do not need protection. Particularly for multi-national to global assessments that account for different scenarios and require more than one simulation, the low computational costs of the bathtub approach still makes it a valid approach.

On a global scale, several studies employ the bathtub approach to quantify the size of the LECZ or to assess areas exposed to 1 in 100-year coastal floods (see Table 1.1). Lichter et al. (2011) determine and compare the size of the LECZ based on GTOPO, GLOBE and the SRTM Enhanced Global Map (SRTM-EGM), which combines SRTM with GTOPO elevation data for the high latitudes. They find differences of 17 % with SRTM showing the smallest exposed area. Based on McGranahan et al. (2007) and Neumann et al. (2015) the LECZ is 11 % and 9 % larger than reported by Lichter et al. (2011), although the three studies use the same DEM. In contrast to the other two studies, the study of McGranahan et al. (2007) does not explicitly mention the consideration of hydrological connectivity, which could explain the reported larger area of the LECZ in their study. Furthermore, Neumann et al. (2015) use another source of elevation data for Greenland, which restricts the comparability to the other two studies to some extent.

Table 1.1: Global exposure of land areas to coastal hazards.

Study	Hazard Area	DEM	Exposure (Mio km²)
Lichter et al. 2011	LECZ	GTOPO30	2.78
	LECZ	GLOBE	2.78
	LECZ	SRTM-EGM	2.38
McGranahan et al. 2007	LECZ	SRTM-EGM	2.64
Neumann et al. 2015	LECZ	SRTM-EGM	2.60
Hinkel et al. 2014	1 in 100-year (DIVA*)	GLOBE	1.20
	1 in 100-year (DIVA)	SRTM	0.66
Muis et al. 2017	1 in 100-year (DIVA)	SRTM	0.65
	1 in 100-year (GTSR**)	SRTM	0.45

* Dynamic Interactive Vulnerability Assessment (DIVA); ** Global Tide and Surge Reanalysis (GTSR)

The relative differences in exposed areas between different datasets become larger if the floodplain of a 1 in 100-year coastal flood is analysed instead of the LECZ. For example, Hinkel et al. (2014) show that the floodplain based on GLOBE elevation data is almost twice the size of the SRTM floodplain. This observation is in line with the study of Lichter et al. (2011) who find that the relative differences between SRTM and GLOBE increase with smaller elevation thresholds. For example, based on SRTM, the area between 0 and 2 meters elevation is 50 % smaller than that based on GLOBE or GTOPO, whereas the LECZ is 17 % smaller (Lichter et al. 2011).

The study of Muis et al. (2017) shows that the underlying ESL data affect the estimation of exposed area considerably. They compare the flood heights and the corresponding flood extent of 1 in 100-year coastal floods based on the Dynamic Interactive Vulnerability Assessment Tool (DIVA) (Vafeidis et al. 2008) and the Global Tide and Surge Reanalysis (GTSR) (Muis et al. 2016). Their study finds the flooded areas based on DIVA flood heights to be ~40 % larger than based on GTSR flood heights. Differences in ESL heights can emerge from differences in the length of water level time series, the detrending of the original data and the sampling of extreme values (Arns et al. 2013).

This type of uncertainty does not apply to studies focussing on the LECZ, which is defined by a fixed elevation level of 10 m. As exposed areas serve as basis for assessing exposure of population, the data-related uncertainties stated in this subsection also apply to subsections 1.3 and 1.4. In the future, the estimates of flood-prone areas will become more robust as the coverage and availability of LiDAR data improves (Gesch 2018).

1.3 Current exposure of population

Assessing the exposure of population adds substantial value to impact assessments as populated areas in the zone of exposure can serve as a basis for decisions on adaptation (Tamura et al. 2019). Comparable to elevation, the number of population datasets that cover the entire globe is limited. Different versions of four population datasets are commonly used for assessing the current exposure of population to coastal flooding on a global scale (Table 1.2): Gridded Population of the world (GPW), Global Rural and Urban Mapping Project (GRUMP), LandScan and History database of the global environment (HYDE). The latter focusses on historic population distributions and utilises LandScan data for current population distribution and is therefore not introduced in more detail (Klein Goldewijk et al. 2010). The Global Human Settlement Layer (GHS-POP) is another global population dataset, which has so far not been used for assessing population exposure to coastal hazards on a global scale but on a continental scale (Vousdoukas et al. 2018). All gridded population datasets assume the underlying census data to be accurate. However, census data only cover where population is registered, but does not include unregistered population (Leyk et al. 2019). Furthermore, some countries (e.g. Germany) interview only parts of the population for the census and apply statistical methods to project these samples to the national level (SBL 2015).

Table 1.2: Global population dataset used in coastal exposure analysis.

Data	Resolution	Year(s)	Reference
GPW v2	2.5’ (~5 km)	1990, 1995	-
GPW v3	2.5’ (~5 km)	1990, 1995, 2000, 2005*, 2010*, 2015*	CIESIN et al. (2005)
GPW v4	0.5’ (~1 km)	2000, 2005, 2010, 2015*, 2020*	CIESIN (2017)
GRUMP alpha	0.5’ (~1 km)	1990, 1995, 2000	-
GRUMP v1	0.5’ (~1 km)	1990, 1995, 2000	CIESIN et al. (2011a)
LandScan	0.5’ (~1 km)	1998, 2000 - 2017	Dobson et al. (2000)
HYDE	5’ (~10 km)	10.000 BC - 2005	Klein Goldewijk et al. (2010)
GHS-POP	250 m & 1 km	1975, 1990, 2000, 2015	JRC and CIESN (2015)

* extrapolations

GPW, GRUMP and LandScan are based on compilations of census data but apply different techniques to redistribute the population within census units. GPW uses areal weighting to distribute population on land area, leading to a homogeneous distribution of population on land areas within administrative units (Doxsey-Whitfield et al. 2015). GRUMP and LandScan employ dasymetric mapping to refine the aerial weighting. GRUMP utilises night-time lights satellite measurements to define urban and rural areas. In the next step of the GRUMP processing scheme, the urbanisation level and the total population per administrative unit are used to calculate the total urban and rural population, which are subsequently allocated to urban or rural areas (Balk et al. 2006). LandScan employs land cover data, slope, roads, night-time lights and settlement points as ancillary data to calculate probability coefficients for disaggregating population within administrative units. Different to GPW or GRUMP that give the number of people physically present at the time of the census (de facto population), LandScan provides an average of day and night population (ambient population) (Dobson et al. 2000).

Figure 1.1 visualises the differences between the datasets. For the New York metropolitan area, small census units lead to slight differences in the distribution of people between the datasets. For the south-western Baltic Sea region, the Nile delta and the Mekong delta, LandScan shows a heterogeneous distribution of population. The differences between GPWv4 and GRUMP are relatively small. For the Nile and Mekong deltas, GRUMP allocates the population more heterogeneously than GPWv4 does, whereas finer resolved census data lead to a more heterogeneous distribution of population for the south-western Baltic Sea region in GPWv4 as compared to GRUMP.

The processing scheme of GHS-POP is comparable to the processing scheme of GRUMP. Instead of night-time lights GHS-POP utilises a build-up mask generated based on Sentinel 1 and Landsat satellite images. Population counts per administrative unit are taken from GPW v4. Within administrative units, population is disaggregated based on the density of built-up areas (JRC and CIESN 2015). Other population datasets cover continents (e.g. WorldPop project for Africa (Linard et al. 2012), Asia (Gaughan et al. 2013) and Latin America (Sorichetta et al. 2015); GEOSTAT for Europe (Batista e Silva et al. 2013)) or individual countries. These datasets on national scales can provide very detailed information if they are products of the national census. However, the quality, frequency and availability of census products can differ considerably between countries, which limits the consistency and comparability for global or multi-national assessments (Wardrop et al. 2018; Lloyd et al. 2019).

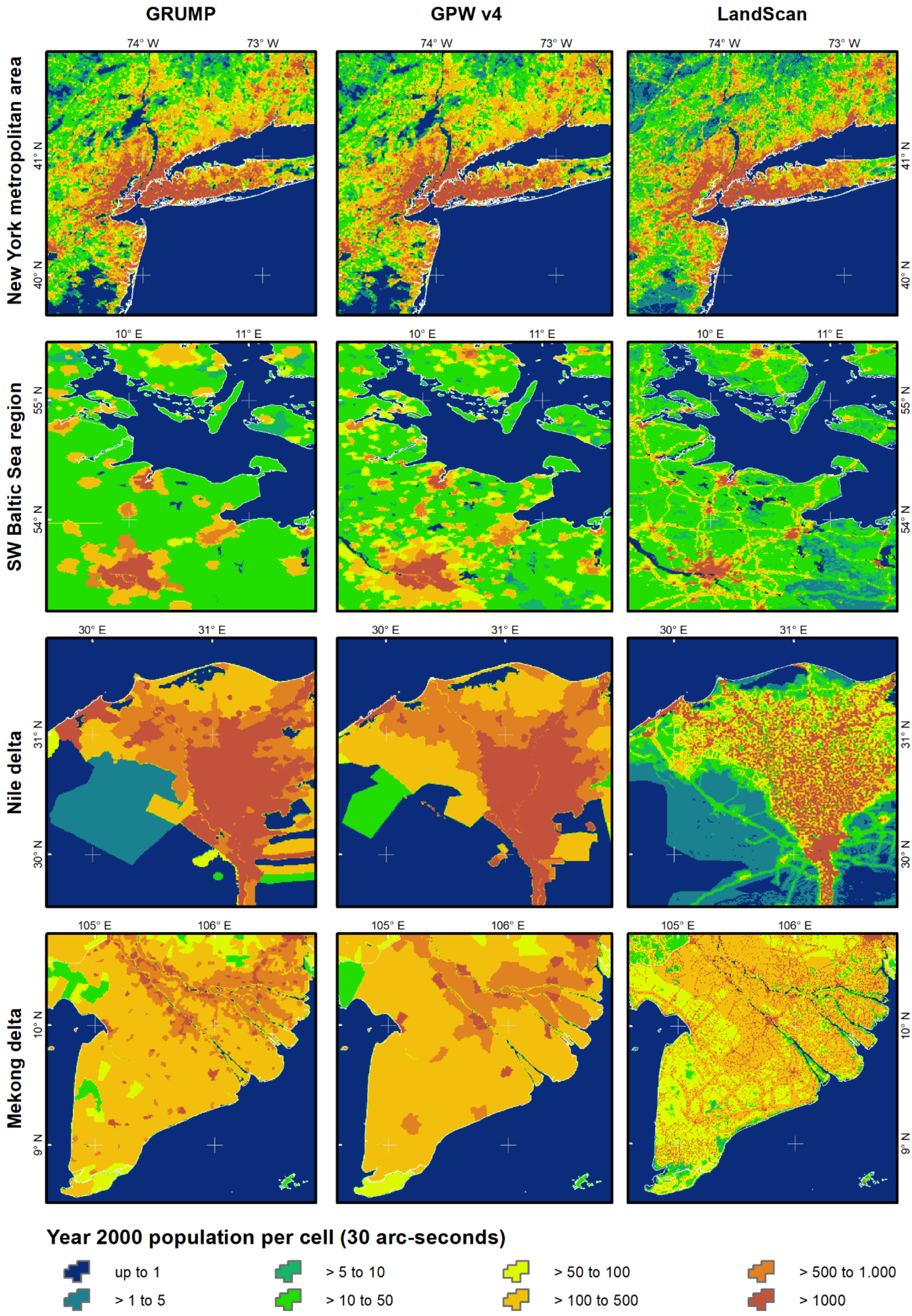

Figure 1.1: Allocation of population in GRUMP, GPWv4 and LandScan for four regions. All maps use the same scale.

For coastal exposure assessments, population located in the LECZ and in the 1 in 100-year coastal floodplain are of specific interest (Neumann et al. 2015). The population in the LECZ for the year 2000 ranges in most studies from 560 million to 630 million, depending on the population dataset and the DEM used to identify the LECZ (Table 1.3). However, Jones and O'Neill (2016) estimate 700 million people living in the LECZ based on GPW data for the year 2000. The population located in the floodplain of 1 in 100-year coastal floods in 2010 between different studies ranges from 93 million to 310 million, depending on the elevation, population and ESL data. The following paragraphs compare these numbers in more detail.

Uncertainties in the delimitation of exposed areas also affect the assessment of population exposure. The studies of Lichter et al. (2011), and Kulp and Strauss (2019) quantify these uncertainties by comparing population exposure under different DEMs. Lichter et al. (2011) find the LECZ population based on SRTM-EGM is up to ~10 % (~65 million) higher than that based on GLOBE. Kulp and Strauss (2019) focus on areas 10 m above mean higher high water (MHHW) and identify 25 % (260 million) more population exposed under the CoastalDEM than compared to SRTM v2.1. The large difference between SRTM v2.1 and the CoastalDEM are due to the different characteristics of the elevation datasets. Whereas SRTM v2.1 is an uncorrected DEM that represents the surface (including e.g. vegetation and urban development), the CoastalDEM aims to predict and remove deviations between the surface and the terrain (Kulp and Strauss 2018).

Population is not static but changes over time, which makes the reference year a relevant parameter to look at. A study by Small and Nicholls (2003) assesses 1200 million people located in 'near coastal' areas (maximum distance of 100 km to the coast and an altitude of less than 100 m) for 1990 (see Table 1.3). Kummu et al. (2016) identify 25 % more people (1500 million) living in near coastal areas for 1990 than Small and Nicholls (2003) and a total of 1900 million for the year 2010. These numbers show differences between population datasets (HYDE and GPW v2) but also indicate considerable population growth in these areas between 1990 and 2010.

The studies of Lichter et al. (2011), Mondal and Tatem (2012) and Hinkel et al. (2014) compare different population data to assess exposure to coastal floods. For the LECZ population in 2008, Mondal and Tatem (2012) find LandScan to exceed GRUMP v1 by 30.3 million people (~4 %). Comparing LandScan year 2006 and GRUMP alpha year 2000 population data, Lichter et al. (2011) find LandScan resulting in ~90 million (14 %) to ~110 million (20 %) people more in the LECZ than GRUMP alpha. For the floodplain of 1 in 100-year coastal floods, Hinkel et al. (2014) find GRUMP v1 population to be 20 million (7 %) to 67 million (~70 %) higher than LandScan population. Furthermore, the comparison of the year 2000 LECZ population based on GPW v3 (2.5 arc-minutes) and LandScan or GRUMP alpha (0.5 arc-minutes) suggest that coarse resolutions lead to higher estimates of exposure than fine resolutions (Table 1.3). These high differences in population exposure based on existing population datasets highlights the need for a consistent global population dataset of high spatial resolution that transparently distributes population within census units.

Table 1.3: Global population located in areas exposed to coastal hazards.

Study	Hazard Area	Population Data	Year	DEM	Exposure (Million)
Small and Nicholls 2003	Near coastal [a)]	GPW v2	1990	GTOPO30	1200
Kummu et al. 2016	Near coastal [a)]	HYDE	1990	GTOPO30	1500
			2010		1900
Lichter et al. 2011	LECZ	Grump alpha	2000	GTOPO30	578.7
				GLOBE	557.1
				SRTM-EGM	620.6
		LandScan	2006	GTOPO30	690.3
				GLOBE	668.0
				SRTM-EGM	709.1
Mondal and Tatem 2012	LECZ	GRUMP v1	2008 [c)]	SRTM-EGM	695.7
		LandScan	2008		726.0
Kulp and Strauss 2019	MHHW [b)] + 10 m	LandScan	2010	SRTM v2.1	780
				CoastalDEM	1040
Jones and O'Neill 2016	LECZ	GPW v3	2000	SRTM-EGM	702.2
McGranahan et al. 2007	LECZ	GRUMP alpha	2000	SRTM-EGM	634
Neumann et al. 2015	LECZ	GRUMP alpha	2000	SRTM-EGM	625.2
	1 in 100-year (DIVA)				189.2
Muis et al. 2017	1 in 100-year (DIVA)	GRUMP v1	2015 [d)]	SRTM v4.1 + GTOPO30	157 [h)]
	1 in 100-year (GTSR)				99 [h)]
Jongman et al. 2012	1 in 100-year (DIVA)	HYDE	2010 [e)]	SRTM v4.1 + GTOPO30	271
Hinkel et al. 2014	1 in 100-year (DIVA)	GRUMP v1	2010 [f)]	SRTM + GLOBE	160
				GLOBE	310
		LandScan	2010 [g)]	SRTM + GLOBE	93
				GLOBE	290

[a)] Maximal distance to the coast of 100 km and maximal elevation of 100 m; [b)] Mean Higher High Water; [c)] year 2000 data projected to 2008; [d)] year 2000 projected to 2015; [e)] year 2005 projected to 2010; [f)] year 2000 projected to 2010; [g)] year 2006 projected to 2010; [h)] vertical datum referenced to mean seal-level.

1.4 Future exposure of population

A number of coastal exposure studies account for changes in physical components (i.e. SLR) but keep socioeconomic conditions constant (e.g. Nicholls and Mimura 1998). Other studies consider socioeconomic changes but do not account for changes in the frequency or intensity of hazards (e.g. Jongman et al. 2012). The value of both types of studies is therefore limited, as both physical and socioeconomic conditions change over time. For long term projections (e.g. year 2100) changes in population and SLR cannot be predicted, as many drivers remain uncertain. The use of scenarios helps to overcome this problem (Moss et al. 2010). The Special Report on Emissions Scenarios (SRES) have been widely used to represent future changes in SLR and population (e.g. Nicholls 2004; Arnell et al. 2004). After the fourth assessment report of the IPCC, the climate change research community initialised the development of a new scenario framework (Moss et al. 2010; O'Neill et al. 2017). In contrast to the SRES scenarios that aim to represent a wide range of emissions, the new scenario framework aims to be useful for adaptation and mitigation analysis by increasing the comparability and interdisciplinarity of studies and by explicitly capturing uncertainties in climate change outcomes (O'Neill et al. 2014).

The core of the new scenario framework is a matrix architecture with the RCPs representing the increase of the forcing level on one axis and the SSPs representing different socioeconomic developments on the other axis (van Vuuren et al. 2014). Each SSP consists of a qualitative narrative describing the respective scenario (O'Neill et al. 2017) and a quantification of key elements, such as population (KC and Lutz 2017), economics (Leimbach et al. 2017) and urbanisation (Jiang and O'Neill 2017). The SSPs can be extended and refined for the use on local scales or for the work on specific sectors or variables (O'Neill et al. 2017; Riahi et al. 2017). In general, the SSPs describe the ability of society to prepare for and respond to climate change impacts, which is represented by the 'challenge space' for mitigation and adaptation ranging from low to high (Kriegler et al. 2012). RCPs and SSPs represent development pathways and only their combination leads to integrated scenarios (van Vuuren et al. 2014). These scenarios can be refined by the Shared Policy Assumptions (SPAs), which allow, for example, to account for different levels of international cooperation or pricing concepts of carbon emissions (Kriegler et al. 2014).

A number of studies assesses future exposure of population to coastal hazards (Table 1.4). However, the comparability between these studies is limited, as they employ scenarios of different scenario families with different assumptions on global population. For example, Neumann et al. (2015) use four population scenarios developed by the UK Government's Foresight project on Migration and Global Environmental Change (Foresight 2011). Global population in these scenarios ranges from 7.9 to 11.3 billion in 2060. Jongman et al. (2012) utilises the medium fertility scenario of the 2006 Revision of the United Nations' World Population Prospects, which projects global population at 9.2 billion people by 2050 (UN 2007). Nicholls (2004) employs the SRES scenarios in which global population for 2100 ranges from 7 to 15 billion (Nakicenovic et al. 2000). Jones and O'Neill (2016) use the population projections of the five SSPs, which project global population between 6.9 and 12.6 billion people in 2100 (KC and Lutz 2017).

Table 1.4: Future population located in areas exposed to coastal hazards.

Study	Hazard Area	Year	Population Scenario	Exposure (Million)	Relative Exposure*
Nicholls (2004)	1 in 1000-year	2080s	SRES A1FI	314 – 482 **	5.9 % - 9.1 %
			SRES A2	564 - 907 **	4 % - 6.3 %
			SRES B1	304 - 466 **	3.8 % - 5.9 %
			SRES B2	399 - 591 **	3.9 % - 5.8 %
Jongman et al. (2012)	1 in 100-year	2050	UN (2006) med	345	3.8 %
Neumann et al. (2015)	1 in 100-year (DIVA)	2060	Foresight A	393	3.5 %
			Foresight B	316	4 %
			Foresight C	411	3.6 %
			Foresight D	340	3.5 %
	LECZ	2060	Foresight A	1318	11.9 %
			Foresight B	1053	13.3 %
			Foresight C	1388	12.3 %
			Foresight D	1128	11.8 %
Jones and O’Neill (2016)	LECZ	2100	SSP1	742	10.8 %
			SSP2	905	10.1 %
			SSP3	1146	9.1 %
			SSP4	793	8.6 %
			SSP5	798	10.8 %

* share of global population, ** Nicholls (2004) uses a ‘low growth’ and a ‘high growth’ population scenario. Coastal population in the ‘low growth’ scenario changes at the same rates than on national average, whereas in the ‘high growth’ it increases double the rate on national average and decreases half the rate of national average (in case national population decreases)

Beside the use of different scenario families, studies employ different approaches to account for future population change in coastal areas. Jongman et al. (2012) and Hinkel et al. (2014) assume population in coastal areas to change at the same rate as the national average. This approach is easy to apply, as it does not require additional data or computational effort to redistribute population. However, this approach does not consider processes on subnational levels such as coastal migration or urbanisation, which lead to higher population growth in coastal areas (McGranahan et al. 2007; Seto et al. 2012). Nicholls (2004) and Neumann et al. (2015) apply correction factors to model higher population growth rates in coastal areas as compared to inland areas. Correction factors implicitly account for processes on subnational level and require little additional computational effort to determine population growth rates for coastal areas.

In contrast, spatially explicit population projections allow for implementing heterogeneous growth characteristics on subnational levels. Grübler et al. (2007) develop gridded projections for three out of the four SRES and Jones and O’Neill (2016) develop spatially explicit population projections for the SSPs. Both studies consider urbanisation and urban sprawl. However, the spatial resolution of the gridded population projections (7.5 arc-minutes; circa 15 km at the equator) is too coarse for assessing exposure to coastal flooding as only few locations in the floodplain of 1 in 100-year coastal floods extend more than 15 km inland. Furthermore, the studies of Grübler et al. (2007) and Jones and O’Neill (2016) do not explicitly account for coastal migration, which can underestimate population exposure to coastal hazards.

1.5 Research objectives and structure of the thesis

The aim of this thesis is to improve the spatial population distribution for coastal flood impact assessments on a global scale. Following subsections 1.3 and 1.4, this thesis differentiates between current and future population. For current population it aims to improve the allocation of population within census units, and for future population to regionalise population growth characteristics.

The first research question of this thesis is as follows:

> **Can satellite derived global settlement extents be used to improve the representation of population living in flood prone areas?**

Available global datasets on the current distribution of population either assume homogeneous distribution of population on land areas within census districts or follow complex modelling schemes. As stated in subsection 1.3, these complex modelling schemes are either non reproducible 'black boxes' or utilise a high number of ancillary variables, which are not available consistently for the entire globe (Lloyd et al. 2019). These restrictions rule out the identification of relevant processes in population development because a signal identified in the data might result from inconsistencies in the input data or from dependences of the variables used for modelling. This thesis tests if the use of one ancillary variable (i.e. satellite derived settlement extents) is sufficient to improve the allocation of population within census units.

Although the focus of this thesis is on improving the representation of coastal population on a global scale, the first research question is addressed on a subnational level for the German Baltic Sea region. This is due to the availability of gridded census data at high spatial resolution (i.e. 100 m) for validation. As the employed settlement extents have a global coverage, the transferability to other regions as well as the entire globe is ensured.

The second research question of this thesis is:

> **How does accounting for coastal migration, urbanisation and urban sprawl affect the estimates of future population exposure to coastal flooding?**

Jones and O'Neill (2016) provide spatially explicit population projections that account for urbanisation and urban sprawl based on the SSPs. As coastal migration affects the population growth characteristics in coastal locations (McGranahan et al. 2007; Seto et al. 2012; Neumann et al. 2015), it needs to be considered explicitly when downscaling population projections for coastal impact assessments. This thesis extends the SSPs for the coastal zone and develops spatially explicit population projections for the LECZ at a temporal resolution of 5 years and a spatial resolution of 30 arc-seconds (~1 km at the equator), which is 15 times finer than existing gridded population projections. This meets the request of Melchiorri et al. (2018), demanding for projections at high temporal and spatial resolution. Furthermore, the projections are consistent with the RCP-SSP-scenario framework to ensure comparability to other studies (Moss et al. 2010). The developed spatially explicit projections consider coastal migration and urbanisation. Subsequently, the thesis uses DIVA to assess the exposure of population to 1 in 100-year coastal floods until 2100 based on the developed population projections, national average population growth and the population projections of Jones and O'Neill (2016) that account for urbanisation and urban sprawl.

The remainder of the thesis is structured as follows: Chapter 2 evaluates the performance of six approaches to allocate population within census units. A gridded census dataset for the German Baltic Sea area is used to evaluate the approaches. While a reference approach assumes homogeneous population distribution within each census unit, the other five approaches redistribute population based on settlement extents derived from built-up areas of the Global Urban

Footprint (Esch et al. 2017; Esch et al. 2011). Furthermore, the approaches differ in resolution of input data and in the complexity of algorithms used to disaggregate population. The Chapter is published as *Merkens J-L, Vafeidis A (2018) Using Information on Settlement Patterns to Improve the Spatial Distribution of Population in Coastal Impact Assessments. Sustainability 10(9):3170, doi: 10.3390/su10093170.*

Chapter 3 proposes the coastal SSPs, which employ the concept of extending the 'basic SSPs' for specific applications (O'Neill et al. 2017). The coastal SSPs provide spatially explicit population projections with a horizontal resolution of 30 arc-seconds for the five SSPs until 2100. Based on a literature review, narratives for the coastal zone are developed. Historical population growth differences (GDs) between coastal and inland areas are analysed for more than 190 countries and GDs are projected for the future using scenario specific modification factors. The chapter is published as *Merkens J-L, Reimann L, Hinkel J, Vafeidis AT (2016): Gridded population projections for the coastal zone under the Shared Socioeconomic Pathways. Global and Planetary Change 145:57–66. doi: 10.1016/j.gloplacha.2016.08.009.*

Chapter 4 compares four approaches to regionalise population growth projections. In a reference approach population changes uniformly within a country. The second approach additionally accounts for urbanisation and allows to quantify implications for exposure analysis. The third and fourth approach also consider urban sprawl and coastal migration, respectively. The population totals in the four approaches match the population projections developed as part of the SSPs (KC and Lutz 2017) on national levels but differ in the population projections for coastal zones. The chapter is published as *Merkens J-L, Lincke D, Hinkel J, Brown S, Vafeidis AT (2018) Regionalisation of population growth projections in coastal exposure analysis. Climatic Change 14(1):3. doi: 10.1007/s10584-018-2334-8.*

Finally, Chapter 5 synthesises the key findings of chapters 2 to 4 and discusses them in relation to the research questions of this thesis. Furthermore, the chapter proposes activities of future research in this field.

2 Using Information on Settlement Patterns to Improve the Spatial Distribution of Population in Coastal Impact Assessments

Jan-Ludolf Merkens and Athanasios T. Vafeidis

Sustainability (2018), doi: 10.3390/su10093170

Received: July 15, 2018; accepted: September 3, 2018

Changes made to the published version:

To harmonise the style of the thesis, British English is used instead of American English.

Abstract

Broad-scale impact and vulnerability assessments are essential for informing decisions on long-term adaptation planning at the national, regional, or global level. These assessments rely on population data for quantifying exposure to different types of hazards. Existing population datasets covering the entire globe at resolutions of 2.5 arc-minutes to 30 arc-seconds are based on information available at administrative-unit level and implicitly assume uniform population densities within these units. This assumption can lead to errors in impact assessments and particularly in coastal areas that are densely populated. This study proposes and compares simple approaches to regionalize population within administrative units in the German Baltic Sea region using solely information on urban extent from the Global Urban Footprint (GUF). Our results show that approaches using GUF can reduce the error in predicting population totals of municipalities by factor 2 to 3. When assessing exposed population, we find that the assumption of uniform population densities leads to an overestimation of 120 % to 140 %. Using GUF to regionalise population within administrative units reduce these errors by up to 50 %. Our results suggest that the proposed simple modelling approaches can result in significantly improved distribution of population within administrative units and substantially improve the results of exposure analyses.

Keywords

spatial population; Global Urban Footprint; Dasymetric Mapping; coastal exposure; impact assessment; Baltic Sea

2.1 Introduction

Coastal areas are highly exposed to natural hazards (Kron 2013) and this exposure will increase as a result of climate-change-induced sea-level rise (SLR) and associated impacts such as flooding, erosion, permanent inundation, and saltwater intrusion (Nicholls and Cazenave 2010). Coastal flooding, in particular, will increase in frequency and intensity (Wong et al. 2014) and is expected to be the most costly impact of SLR (Hinkel et al. 2014). At the same time, rapid socioeconomic development (Neumann et al. 2015; Merkens et al. 2016; Jones and O’Neill 2016), leading to high concentration of people assets in coastal regions and particularly in large urban centres, is expected to further exacerbate flood risk.

Adaptation measures, in the form of protection, accommodation or retreat, can reduce the impact of coastal flooding by several orders of magnitude (Hinkel et al. 2014). In this context, establishing long-term adaptation policies constitutes a key element for the sustainability of coastal regions (Brown et al. 2013) and will be necessary for achieving the United Nations Sustainable Development Goals (SDG) outlined in the '2030 Agenda' (Neumann et al. 2017). In particular, coastal adaptation explicitly relates to SDGs 11 (Sustainable Cities and Communities), 13 (Climate Action), and 14 (Life below Water) and is indirectly linked to other SDGs.

To inform decisions on coastal adaptation, assessment of the impact of coastal flooding has been carried out at different scales (Vousdoukas et al. 2016; Crowell et al. 2010; Hallegatte et al. 2013; Hinkel et al. 2014), from global to local. An essential input, but also one of the main sources of uncertainty for these assessments, is the spatial distribution of population. This parameter is important for defining exposure to hazards, particularly in global and regional studies. However, available global datasets are limited in the way they represent how people are distributed in space. Two of the most commonly employed datasets are the Gridded Population of the World (GPW) (CIESIN 2017) and the Global Rural Urban Mapping Project (GRUMP) (CIESIN et al. 2011a). They cover the entire globe at a spatial resolution of 30 arc-seconds (approximately 1 km at the equator) and have been widely used in coastal-exposure analysis (e.g., Paprotny et al. (2018), Reimann et al. (2018), and Jones and O'Neill (2016) for GPW; McGranahan et al. (2007), Merkens et al. (2016) and Neumann et al. (2015) for GRUMP). GPW is based on population census tables of administrative units and distributes population uniformly on land areas within administrative units (Doxsey-Whitfield et al. 2015). GRUMP additionally differentiates between rural and urban areas, which are derived from nightlight satellite images. This method performs better in developed regions than in developing or undeveloped regions due to lack of electricity and less light pollution (Balk et al. 2006). The assumption of a uniformly distributed population is, however, rather crude and does not necessarily represent the true distribution of population. Dasymetric-mapping approaches aim to overcome this limitation by using ancillary data to spatially differentiate population within administrative units (Deville et al. 2014). The algorithms used in dasymetric mapping can become very complex and data-demanding. WorldPop, for example, which provides freely available gridded population data for Latin America (Sorichetta et al. 2015), Asia (Gaughan et al. 2013) and Africa (Linard et al. 2012), uses about 40 variables to model population densities (Stevens et al. 2015). The spatial resolution of these datasets is 30 arc-seconds for data on the continental level and 3 arc-seconds (approximately 100 m at the equator) for country-level data. For global or continental studies, finer spatial resolution would be desirable, as the use of data of higher spatial resolution can result in more detailed impact assessments (Vousdoukas et al. 2018). However, collecting data for such large numbers of variables is time- and resource-intensive, and very difficult to implement on a global scale.

In this study, we used simple modelling approaches that were based on low data requirements, for producing improved estimates of population distribution at high spatial resolution. We applied and compared these approaches in the German Baltic Sea coast by assessing exposure of population to coastal flooding. To ensure transferability to other areas of interest, we used solely the Global Urban Footprint (GUF) (Esch et al. 2011; Esch et al. 2017) as ancillary data for regionalizing population within census units. The GUF is a binary settlement mask that covers the entire globe. It is available at spatial resolutions of 2.8 arc-seconds (~84 m at the equator) and 0.4 arc-seconds (~12 m at the equator).

We further investigated which of the two GUF produce result in more realistic spatial population patterns, thus providing improved estimates of population exposure to coastal flooding. For evaluating the proposed approaches, we compared the estimates of exposed population produced with the use of modelled population distributions to the actual exposed population based on gridded census population data. Although the focus of this study is on coastal impact assessment, reliable estimates of the spatial distribution of population have a wide range of applications, such as impact assessments of other natural hazards or quantification of exposure of population to diseases.

2.2 Study Area

We analysed 17 districts (NUTS-3 level) in the federal states of Schleswig-Holstein and Mecklenburg-Vorpommern in northern Germany that extend to the Baltic Sea. Ten of the districts are rural (see Figure 2.1) and consist of 816 municipalities (LAU-2 level). The seven urban districts consist of one municipality each, which leads to 823 municipalities in total.

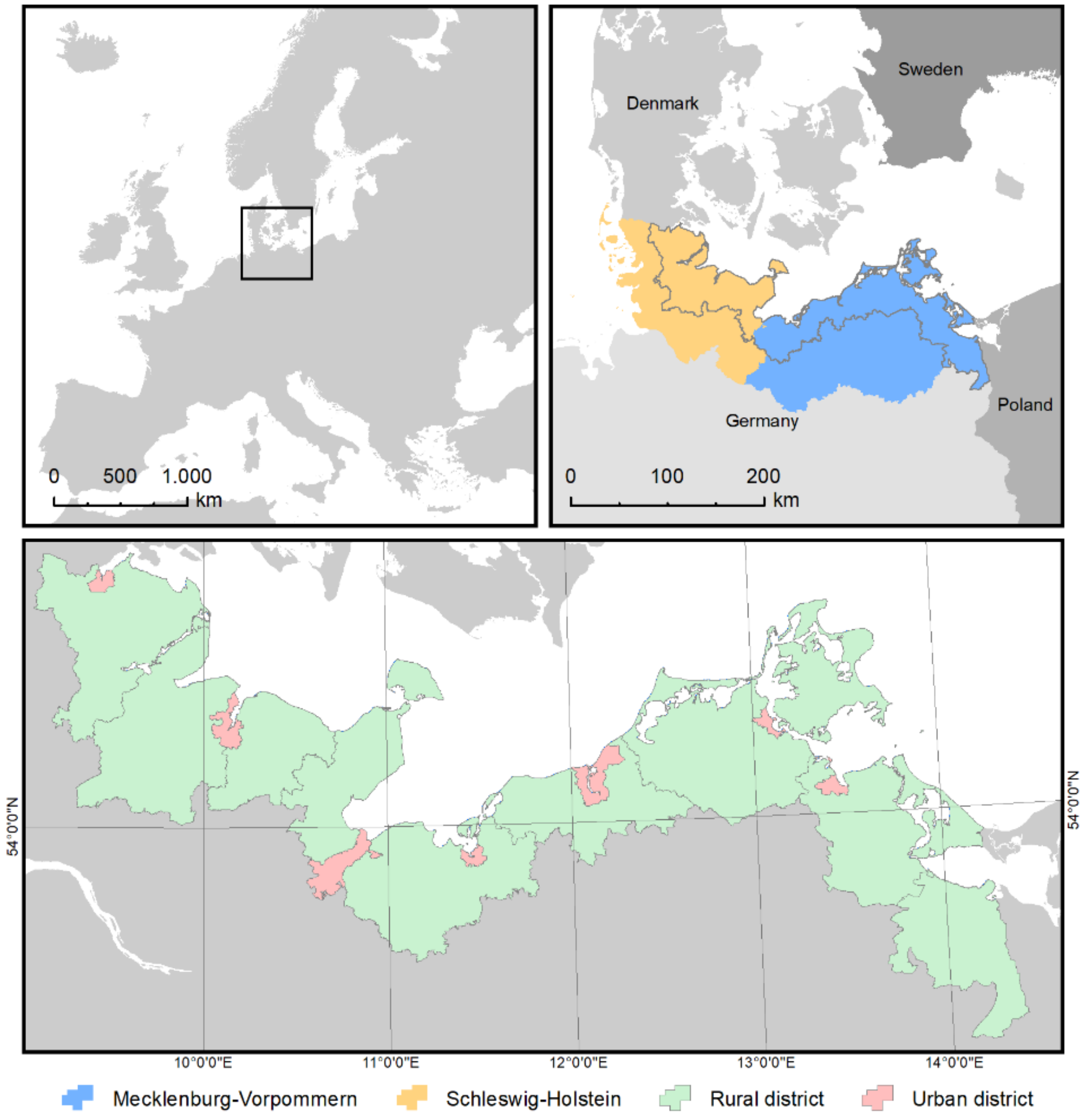

Figure 2.1: Location, administrative boundaries, and distribution of urban/rural districts for the study area.

Circa 2.25 million people live in the study area, which encompasses approximately 17,000 km². With a mean population density of about 130 people per km², the study area is predominantly rural. The three cities with the highest population are Kiel (235,000), Lübeck (210,000), and Rostock (200,000) (Destatis 2015). Including islands, the coastline has a length of approximately 2600 km (MLUV-MV 2009). About a quarter of the coast is protected by dikes, which mostly protect densely populated areas (Sterr 2008). Storm surges constitute the primary coastal hazard in the region, with the highest storm surge recorded occurring in 1872 with a measuring a peak height of 3.30 m in Travemünde (Schleswig-Holstein) (MELUND-SH 2013) and 2.83 m in Wismar (Mecklenburg-Vorpommern) (MLUV-MV 2009).

2.3 Data and Methods.

2.3.1 Data

2.3.1.1 Population

We used two products of the 2011 Census. First, we used the regular population grid with a horizontal resolution of 100 m (Destatis 2015). The population density (population per hectare) and population count (population per cell) did not differ due to the Lambert Azimuthal Equal Area Projection (LAEA-EPSG:3035) used in this study. For the 100 m population grid, all cells with population below 3 people per hectare were adjusted for data-protection reasons; namely, the values of cells with a population of 2 have been adjusted to 3, and cells with a population of 1 have been adjusted to 0 (Destatis 2018b, 2013). To assess the effects of this data manipulation on the total population numbers in the study area, we aggregated the population in the grid of the entire study area. We compared the totals to the population count reported on the municipality level (Destatis 2018a), which is the finest level of census data and the second product of the 2011 Census used in this study. The sum of the gridded population exceeded the sum of population reported per administrative unit by 6404 for the entire study area. As this was a share of circa 0.3 % on the total population, we considered the 100 m population grid as reliable reference data for evaluating different population regionalization approaches.

2.3.1.2 Urban extent

For the identification of urban areas, we employed the GUF, which is a binary settlement mask that has been derived from TanDEM-X and TerraSAR-X radar images collected in 2011 and 2012 (Esch et al. 2017). It is a global dataset, which is available in two resolutions, namely 2.8 arc-seconds (hereinafter referred to as GUF2.8), and 0.4 arc-seconds (hereinafter referred to as GUF0.4). At the equator, this corresponds to a resolution of approximately 84 m and 12 m, respectively.

We projected both GUF2.8 and GUF0.4 to LAEA (see Figure 2.2). For GUF2.8 we used the cell positions of the census population raster and assigned the value of the nearest neighbour. For GUF0.4, we also used the cell positions of the census population raster and calculated the share of urban GUF0.4 cells assigned to each cell with a spatial resolution of 100 m. For the original GUF0.4, we used all cells with an urban share larger than 0 % and classified them as urban. Additionally, we created an urban mask (hereinafter referred to as $GUF0.4_{5\,\%}$) that employed a threshold of 5 % to classify cells as urban (see subsection 2.4 for discussion on the threshold).

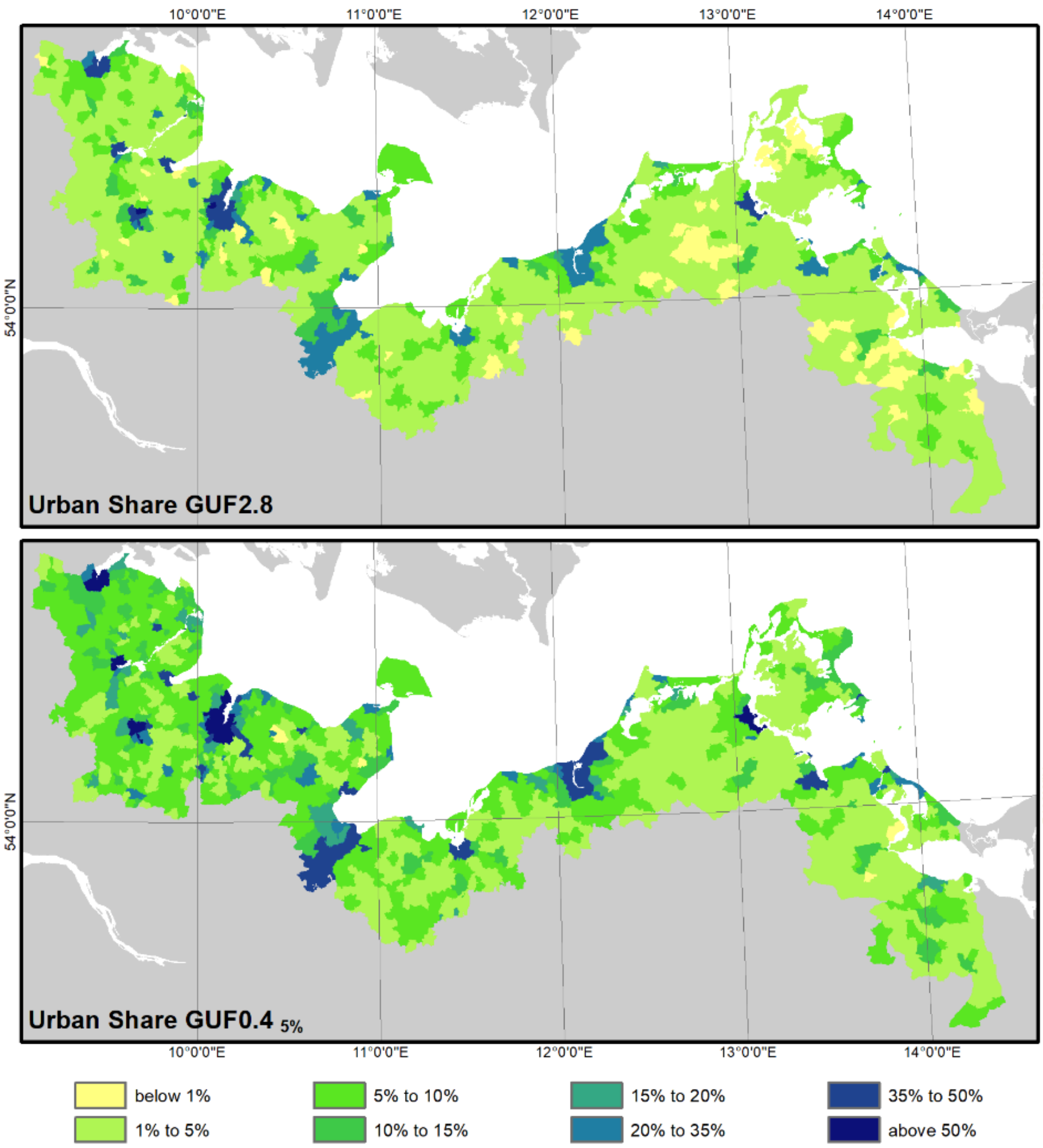

Figure 2.2: Urban share per municipality for GUF2.8 and GUF0.4 $_{5\,\%}$. We defined urban share as the percentage of land area classified as urban.

2.3.1.3 Exposed Area

We used a Digital Elevation Model (DEM) representing surface heights with a vertical accuracy of approximately 15 cm and a horizontal resolution of 1 m (AdV 2017) to assess the exposed area (see Figure 2.3). In a first step, we projected the data to the LAEA projection and aggregated the data to a spatial resolution of 10 m to reduce processing time. Next, we estimated the coastal floodplain considering 8-sided hydrological connectivity to the sea (Poulter and Halpin 2008). We used a threshold of 3 m, which corresponds approximately to the height of the 1872 storm surge. As all non-river-induced floodplains were within a distance of 24 km to the coastline, we additionally implemented a maximum flow distance of 24 km from the Baltic Sea to prevent overestimation of the floodplain due to rivers and channels. In a last step, we further aggregated the data to 100 m to match the spatial resolution of the population data. In the aggregation process, we calculated the share of cells representing exposure per hectare and assessed exposed population by multiplying the calculated share with the population count.

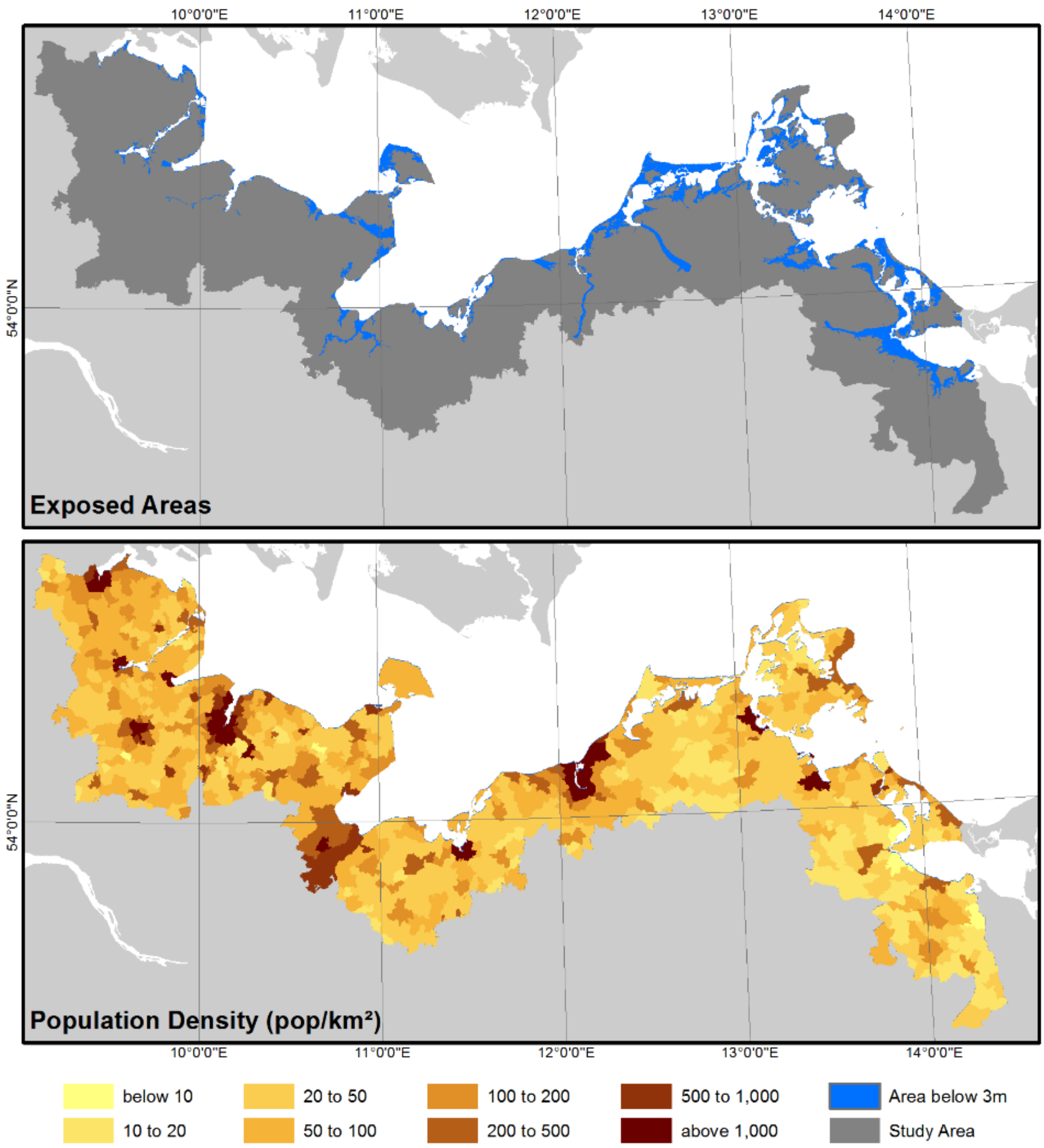

Figure 2.3: Exposed areas and population density per municipality.

2.3.2 Resampling of Population

We compared 6 approaches to regionalise population within administrative units (Table 2.1). Approach I served as the baseline approach presenting population distribution in global datasets. Approaches II to VI employed the GUF. In this context, we used 'urban' as areas identified as urban in the GUF, which included cities as well as rural settlements. All approaches were applied on both the district and municipality level.

Table 2.1: Main concept the 6 approaches tested.

Approach	Description
I	+ no ancillary data used + uniform population density within administrative units
II and III	+ population is only assigned to urban areas + uniform population density within urban areas of an administrative unit
IV	+ population is only assigned to urban areas + population is assigned proportionally to the share of urban extent per cell + uniform population density in cells with the same urban share within one administrative unit + population density across and within settlements of the same administrative unit differ if urban share differs
V and VI	+ population is only assigned to urban areas + settlements can extend over more than one administrative unit + population density increases with extent of settlements + population density between settlements of an administrative unit differs + uniform population density within a settlement

In Approach I, we assumed that population is uniformly distributed within each administrative unit, which means that all cells within an administrative unit had the same population count (and density as we used an equal area projection). Between administrative units, population density differed. This approach is similar to the one used in GPW (Doxsey-Whitfield et al. 2015) but does not account for water bodies. In Approach II, we identified the urban extent per administrative unit based on GUF2.8. We assumed that population is solely located in these areas and distributed the population uniformly in the urban areas of each administrative unit. All settlements within an administrative unit had the same population density. In Approach III, we used GUF0.4 $_{5\,\%}$ instead of GUF2.8 to identify urban extent per administrative unit and assumed uniform population densities within these areas. Approaches II and III are comparable to dasymetric approaches that distribute population based on land cover or land use (e.g., Gallego (2010) and Linard et al. (2011)) but less complex, as they assign population solely to urban areas. In Approach IV, we weighted the population count per administrative unit based on the share of urban extent per 100 m cell calculated from GUF0.4 $_{5\,\%}$. Within an administrative unit, the population count in a cell with an urban share of 80 % was twice as high as in a cell with an urban share of 40 %. Between administrative units, the population count of cells with the same urban share differed. In Approach V, we assumed that population density increases with the size of urban clusters. To define urban clusters, we first buffered clusters in GUF2.8 by 150 m (one cell in all directions) to avoid clusters being divided by rivers and parks. Second, we performed an 8-sided connectivity analysis of the buffered GUF2.8 to group cells to clusters. Finally, we reduced the extent of the defined clusters to the original extent of GUF2.8. Next, we calculated the extent and population count for each cluster. We grouped these clusters into small (<10 ha), medium (10 ha to 150 ha), and large (>150 ha) clusters based on the extent. We assumed a linear correlation between the log cluster extent (in ha) and mean population density per cluster. We used the stats package of R Version 3.3.1 (R Core Team 2016) to fit linear models for both medium and large clusters. We set the upper threshold to 150 ha to minimize the offset between the linear fit for medium and large clusters and the lower threshold to 10 ha to exclude outliers. For medium clusters, we achieved the best fit with an intercept of –0.771 and a slope of 3.607. For large clusters, an intercept of –14.16 and a slope of 6.29 led to the best fit. For all small clusters, we applied the modelled population density for an extent of 10 ha. Next, we multiplied the modelled mean population density with the cluster extent to calculate the modelled population count per cluster. Within a cluster, we assumed uniform population densities. On the administrative level, we adjusted in a final step the modelled population totals to the population totals reported in the census. In Approach VI, we followed the scheme described in Approach V but used GUF0.4 $_{5\,\%}$ instead of GUF2.8. Subsequently, we buffered all urban pixels by 150 m. We used the same threshold of 10 ha to differentiate between small and medium clusters but a threshold of 235 ha to differentiate between medium and large clusters. For medium clusters, an intercept of –2.85 and a slope of 2.78 led to the model with the best fit. For large clusters, we achieved the best fit with an intercept of –20.8 and a slope of 6.0. Approaches V and VI are described in more detail in subsection 2.6.

2.4 Results and Discussion

To assess if the GUF can be used as an estimator for population, we compared the urban extents classified in GUF2.8, in GUF0.4 without any threshold, and in GUF0.4 $_{5\,\%}$. The latter employs an urban coverage threshold of 5 % to the areas that actually are populated in the census population raster. Results are presented in Table 2.2. We found that 83 % of the population live in areas that are defined as urban in GUF2.8. 44 % of all populated areas are not classified as urban (omission error) and 31 % of areas that are classified as urban are not populated at all (commission error). GUF0.4 appears to be a better estimator than GUF 2.8, as 95.3 % of the population live in areas classified as urban in GUF0.4. The commission error of 46 % is higher as in GUF2.8, but the omission error of 18 % is considerably lower. Using a 5 % urban coverage threshold reduces the population living in areas classified as urban to 94 % and increases the omission error to 22 %, but reduces the commission error to 40 %. Since the sum of the omission and commission error is lower in GUF0.4 $_{5\,\%}$, we did not use the original GUF0.4 for our analyses.

Table 2.2: Confusion matrix for population and urban settlements.

Urban Extent	**GUF2.8**	**GUF0.4**	**GUF0.4 $_{5\,\%}$**
Area (ha) with Population not Classified as Urban	49,960	20,482	25,074
Area (ha) without Population Classified as Urban	28,357	79,221	59,183
Area (ha) with Population Classified as Urban	63,708	93,186	88,594
Omission Error [1]	44.0 %	18.0 %	22.1 %
Commission Error [2]	30.8 %	45.9 %	40.0 %
Population captured [3]	83.1 %	95.3 %	94.1 %

[1] Omission error is defined as the share of cells with population >0 that are not classified as urban in the GUF on the total amount of cells with a population greater than zero. [2] Commission error is defined as the share of cells that are classified as urban in GUF but with a population of zero on the total amount of cells that are classified as urban in GUF. [3] Population captured is the share of the sum of population in cells that are classified as urban in the GUF on the total sum of population in the study area.

As cells with a population of one have a value of zero in the census population raster, the ‘true’ error of commission is lower than the one reported in Table 2.2. The percent of population that overlays with urban cells in GUF is also affected by the fact that the values of cells with low population (< 3) have been altered in the original census raster (Destatis 2013). Replacing population counts of 1 by 0 (2 by 3) reduces (increases) the proportion of population in urban areas. As 97.1 % of the population is located in cells with a population larger three, we expect this effect to be negligible.

2.4.1 Performance on Municipality Level

We tested the performance of the six approaches on the district level by comparing the predicted population on municipality level to the census population on the municipality level (Stevens et al. 2015). The performance metrics of the approaches presented in Table 2.3 are only representative for the rural districts, as urban districts consist of only one municipality each. In the case that urban districts would consist of more than one municipality, we would expect the differences in performance metrics between the tested approaches to be smaller, as the proportion of built-up area on the total area in urban districts is larger than in rural districts (see Figure 2.1 and Figure 2.2). For Approach I, this would lead to an improvement of the performance metrics, as the share of nonurban areas and thus the potential of wrongly allocated population would reduce. The performance metrics of the other approaches would depend on the actual characteristics of urban areas. We expect all approaches to perform best, if population within cities is homogeneously distributed. In case of heterogeneously distributed population, e.g., due to multi-storey housing, which the GUF and consequently our approaches do not consider, we expect the performance of the proposed approaches to decline, as population densities are underestimated. However, if population data are available for city districts, the approaches can resolve differences in population density within cities.

Table 2.3: Performance metrics for the six approaches[1].

Approach	I	II	III	IV	V	VI
GUF	-	GUF2.8	GUF0.4 $_{5\,\%}$	GUF0.4 $_{5\,\%}$	GUF2.8	GUF0.4 $_{5\,\%}$
Homogenisation	admin level	urban area	urban area	-	settlement	settlement
Q_{25}[2]	0	−73	0	−81	−280	−223
Q_{50}[2]	431	59	173	46	−121	−57
Q_{75}[2]	867	257	377	218	22	89
MAE[3]	1278	402	570	376	433	395
RTAE[4]	0.467	0.147	0.208	0.137	0.158	0.144
RMSE[5]	2572	892	1270	835	940	796
%RMSE[6]	94 %	33 %	46 %	31 %	34 %	29 %

[1] Calculations are based on the difference (error) in total population per municipality between predicted population by the six approaches adjusted to district level minus the census population. [2] Q25, Q50 and Q75 are the 25th, 50th, and 75th quantile of the error. [3] MAE is the Mean Absolute Error. [4] RTAE is the Relative Total Absolute Error, which is defined as the sum of the deviations between modelled and true population on the municipality level divided by the total population (Batista e Silva et al. 2013). [5] RMSE is the Root Mean Square Error. [6] %RMSE is defined as the RMSE divided by the mean population of administrative units (Stevens et al. 2015).

Approach I shows overall the highest differences to the census data. The Mean Average Error (MAE) and the Root Mean Square Error (RMSE) are approximately double of the respective ones in Approach III, which has the second-highest differences to the census data. Both Approaches I and III overestimate population in three out of four municipalities. Approaches II, IV, and VI show similar MAEs, with Approach IV leading to the smallest MAE. Approach VI has the best performance based on RMSE.

Comparing our results, in terms of absolute values, to other studies is not straightforward, as characteristics of settlements in different study areas can considerably differ. In addition, many studies use the RMSE or the MAE to compare model performance within a study area. If different study areas are compared, the information value that these indicators provide is limited, as study areas with high population counts will lead to higher RMSE than study areas with small population counts. To overcome this issue and to provide a first-order comparison, we used the relative indices %RMSE and Relative Total Absolute Error (RTAE); %RMSE is defined as the RMSE divided by the mean population count of the administrative units (Stevens et al. 2015) and RTAE is defined as the sum of the deviations between modelled and true population over all administrative units divided by the total true population (Batista e Silva et al. 2013). Stevens et al. (2015) calculated %RMSE for GPW for Cambodia (82 %), Vietnam (100 %), and Kenya (146 %). Approach I, which is comparable to the approach used in GPW, shows an %RMSE of 94 %, which agrees with the findings of Stevens et al. (2015). The different approaches proposed in this study reduce the %RMSE by a factor of 2 to 3, which is comparable to the factor 1.6 to 2 reported by Stevens et al. (2015), who use about 40 variables to model population density on the national level. Briggs et al. (2007) tested satellite data on light emissions and Corine Land Cover data to spatially distribute population for fourteen European countries. They validated their results against four sets of population data on the European level, and for Great Britain separately. For Great Britain, the RMSE ranged from 238 to 346 with reported mean populations of 228 and 370. Based on these reported numbers, we calculated the %RMSE to be 105 % and 94 %, respectively. The performance is in the same order of magnitude as Approach I in our study, but the error is 2 to 3 times higher than in Approaches II to VI that actually employed the GUF. On the European level, the RMSE in the study of Briggs et al. (2007) ranged from 240 to 412 with reported mean populations of 228 and 370. This corresponds to a %RMSE of 105 % and 114 %, respectively. However, Briggs et al. (2007) validated their results on cell level (1 km resolution), whereas we validated the tested approaches on municipality level. Batista e Silva et al. (2013) used a refined version of Corine Land Cover to spatially distribute population data on community level for Europe to a spatial resolution of 100 m. They reported RTAE on national level between 0.106 and 0.892. For Germany, their approaches led to RTAE between 0.247 and 0.281 (Batista e Silva et al. 2013). The approaches tested in the present study led to an RTAE of 0.467 for Approach I, and a range from 0.137 to 0.208 for the approaches employing GUF data (see Figure 2.3). Based on these numbers, the performance metrics suggest that GUF can lead to slightly better results than land-cover-based approaches. However, our study analysed a subregion of Germany, whereas the model performance presented by Batista e Silva et al. (2013) is evaluated nationwide.

The performance of the proposed approaches on the municipality level varies over the study area (Figure 2.4). Approach I overestimates population in municipalities with mean population densities below the average of the respective district. The overestimation is higher the more concentrated the population is in urban centres. Approaches II and III show in general lower prediction errors than Approach I. However, Approach III considerably overestimates population in some municipalities, which also leads to higher RMSE and %RMSE than in Approach II (Table 2.3). Approach IV seems to perform well all over the study area and shows the lowest overall MAE. Approach VI and particularly Approach V underestimate population in most municipalities. Furthermore, Approach VI shows overall the lowest RMSE and %RMSE but considerably overestimates population in some municipalities.

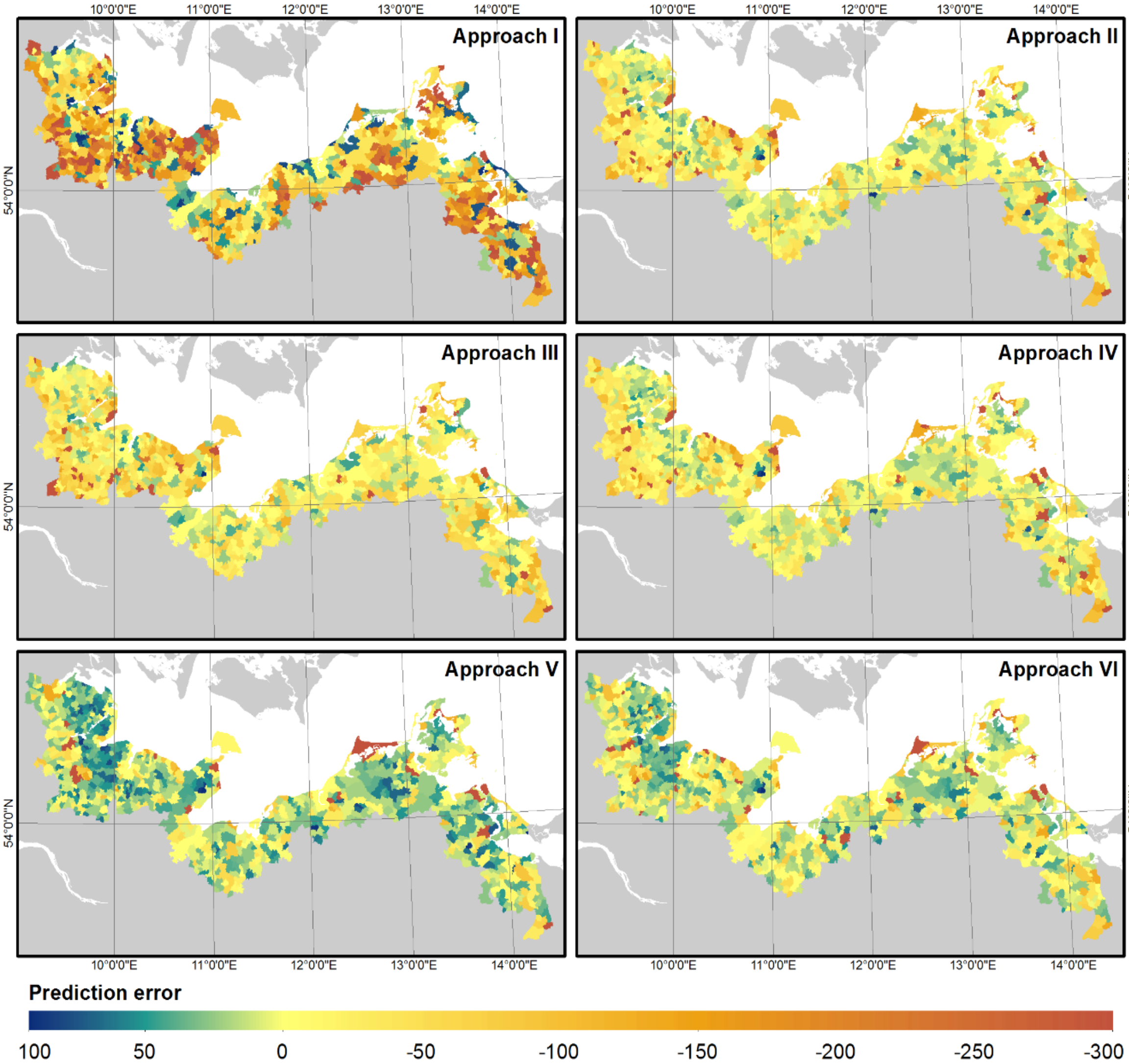

Figure 2.4: Prediction errors (observed minus predicted) as percentage of the observed population per municipality. Prediction errors bigger than –300 were set to –300 for visualisation.

Approach VI leads in 27.6 % of all municipalities to the smallest absolute error (Figure 2.5), followed by Approach IV (20.5 %), Approach V (15.8 %), Approach II (14.6 %), Approach III (14.2 %), and Approach I (5.7 %). For 1.6 % of the municipalities, at least two approaches led to the smallest error. Approach I leads for 69.3 % of all municipalities to the highest absolute error, followed by Approach V (12.6 %), Approach VI (7.2 %), Approach III (4.9 %), Approach II (3.0 %), and Approach IV (2.0 %). For another 1.0 % at least two approaches lead to the highest error. This is in agreement with the results shown in Table 3, which indicate the smallest errors for Approaches VI and IV.

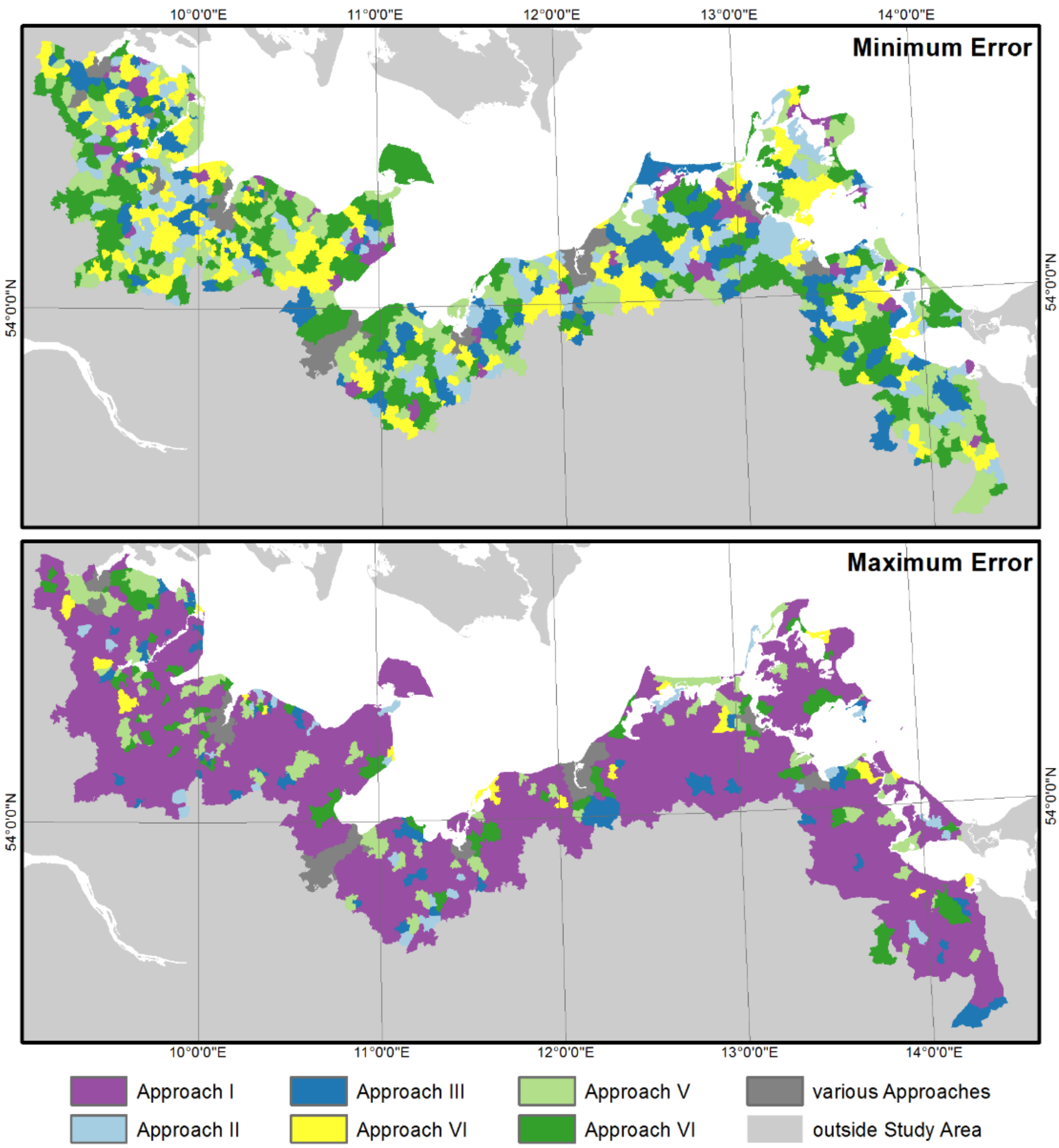

Figure 2.5: Approaches with the lowest and highest absolute error in predicting population on municipality level.

2.4.2 Exposed Population

We evaluated the six Approaches by assessing the exposure of population to coastal flooding and comparing it to the 'true' exposure. We assessed the 'true' exposure by analysing the population living below 3 m based on the 100 m census grid (Destatis 2015). We found that all tested approaches led to a considerable overestimation of exposure in our study area. The results are shown in Table 2.4. Approach V, in which the population density increases with city size, shows the lowest error (overestimation of 72 %) if population is adjusted on municipality level. Approach I, which distributes population uniformly on municipality level, shows the highest error (overestimation of 143 %).

Table 2.4: Exposed population for the six approaches adjusted on the district and municipality level.

Approach	GUF	Homogenisation Level	Adjustment Level	Exposed Population	Error	Error%
I	-	admin level	district	218,478	119,043	120
I	-	admin level	municipality	241,293	141,858	143
II	GUF2.8	urban area	district	185,517	86,082	87
II	GUF2.8	urban area	municipality	174,280	74,856	75
III	GUF0.4 $_{5\,\%}$	urban area	district	188,853	89,418	90
III	GUF0.4 $_{5\,\%}$	urban area	municipality	183,793	84,358	85
IV	GUF0.4 $_{5\,\%}$	-	district	187,490	88,055	89
IV	GUF0.4 $_{5\,\%}$	-	municipality	174,465	75,030	75
V	GUF2.8	settlement	district	184,052	84,617	85
V	GUF2.8	settlement	municipality	170,623	71,189	72
VI	GUF0.4 $_{5\,\%}$	settlement	district	191,590	92,155	93
VI	GUF0.4 $_{5\,\%}$	settlement	municipality	182,035	82,600	83
	'True' Exposure			99,435		

For all approaches that employ the GUF, we found that population adjustments on finer levels lead to improved estimates in exposure analysis. As population is not distributed uniformly within an administrative unit, errors are reduced by adjusting data on finer administrative units. Nevertheless, in Approach I, which is comparable to widely used approaches on global and regional scales, the adjustment of the data on finer scale led to considerably higher errors in exposed population. This suggests that, in the German Baltic Sea region, people tend to live near the coast but not in exposed areas. For example, the population density in coastal rural municipalities is 34 % higher than in non-coastal rural municipalities. If the seven municipalities of urban districts (which are all coastal) are also considered, population density in coastal municipalities is 175 % higher than in non-coastal municipalities.

We also found that previous studies were likely to have overestimated exposed population, although different reference dates for population and the modelled flood heights make a direct comparison difficult. For example, Sterr (2008) used population numbers on the municipality and district level to estimate the 1995 population living on an elevation of 5 m or lower above mean sea level for Mecklenburg-Vorpommern at 319,400. This value is more than three times higher than the 2011 exposure of population living on elevations of 3 m or lower above mean sea level reported for the entire study area. Considering a decline of population in Mecklenburg-Vorpommern of 12 % between 1995 and 2011 (StatA MV 2017), the exposed population is in the same magnitude as in Approach I or even higher.

Our results demonstrate that the use of the GUF reduces the overestimation of exposed population by 22 % to 27 % on district level and by 40 % to 50 % on municipality level (Table 2.4). This shows that by not assigning any population to areas with no urban settlements errors in impact assessment can be reduced considerably. We also found that approaches with GUF2.8 led to better results than approaches with GUF0.4 $_{5\,\%}$ (see Approach II vs. Approach III, and Approach V vs. Approach VI). This may seem surprising, as GUF2.8 covers 83 % and GUF0.4 $_{5\,\%}$ 94 % of the population in the study area. However, according to our findings the commission error in GUF0.4 $_{5\,\%}$ is higher than in GUF2.8 (see Table 2.2), which means that more uninhabited areas are classified as urban. One reason for this is that urban uninhabited structures, such as industrial areas, secondary housing, or small buildings, are resolved at finer spatial resolutions. Approach IV shows that GUF0.4 $_{5\,\%}$ can lead to improved results, if it is used to differentiate population density within settlements.

We must note that our study is based on census data. This means that the population counts represent where the population is registered but not necessarily, where the population resides.

This is of particular relevance for exposure analysis. Deville et al. (2014) show for France and Portugal, that during the summer holiday period (July and August), coastal areas face a population increase of > 60 % compared to the population officially registered in the coastal areas. We assume that their findings also hold true for the German Baltic coast. As surges in the study area are observed during winter, when few tourists are in the study area, we did not explicitly account for tourism. However, as GUF does not differentiate between touristic accommodation (e.g., secondary houses and hotels) and houses permanently inhabited, we accounted implicitly for tourism. This also led to an overestimation of exposed population in all Approaches II to VI, if touristic infrastructure is located in exposed areas and residential population are assigned erroneously to these areas. The same effect can be seen in industrial areas. These are also resolved in GUF but have very low population density or are uninhabited. In the study area, this led to an overestimation of exposure, as harbours and shipyards are typically located on low elevated zones close to the coastline. A further limitation is that large agglomerations of people, e.g. multi-storey residential buildings, cannot be represented by all tested approaches. This can lead to considerable underestimation of population in a small number of cells. This limitation does not only apply to this this study but, in general, to dasymetric-mapping approaches (Briggs et al. 2007).

We expect that our findings are transferable to other study regions. Globally, 39 % of the population lives within a distance of 100 km from the coast (Kummu et al. 2016). This population is also not distributed uniformly within administrative units but gathered in urban clusters (Kummu et al. 2016). As the GUF seems to provide realistic settlement patterns in study areas all over the globe (Esch et al. 2017), we expect that the proposed approaches II to IV can be applied on regional and global scales to regionalize population within administrative units, which could considerably improve the data basis for exposure analysis. Approaches V and VI perform well (Approach V lowest overall error for exposure; Approach VI lowest overall %RMSE) but rely on highly resolved census data to adjust the thresholds used in the modelling process. These are not available all over the globe (Wardrop et al. 2018; Tatem et al. 2011). Approach II performs better than Approach III as GUF0.4 $_{5\,\%}$ has a higher error of commission than GUF2.8. However, GUF2.8 does not capture 17 % of the total population within the study area. Weighting the population depending on the urban coverage in each cell (Approach IV) leads to the smallest errors on municipality level and reduces the error in exposure analysis considerable.

2.5 Conclusion

Our study shows that using uniform population densities on a municipality level (finer scale) can lead to higher errors in exposure analysis compared to using uniform population densities on a district level (coarser scale). As new population data tend to be available on ever finer scales (Doxsey-Whitfield et al. 2015), the assumption of a uniform spatial distribution of population when assessing exposure to coastal flooding may lead to substantial errors in assessing exposure to coastal flooding. By using simple methods that solely employ the GUF as ancillary data to regionalise population within administrative units the error in exposed population can be reduced by 40 % to 50 %. However, exposure analysis shows that the modelled population distributions overestimate the number of people living in the floodplain compared to gridded census data. We anticipate that accounting for the height of buildings in order to determine the number of floors can lead to improved estimates. Before any of the analysed approaches can be applied on global scale, the observations of this study would need to be further evaluated in study areas with different settlement characteristics.

Acknowledgments
This research was funded by the German Research Foundation (DFG) Priority Program (SPP) 1889 Regional Sea Level Change and Society (SeaLevel). The authors would like to thank the Mecklenburg-Vorpommern office of internal administration and the Schleswig-Holstein land surveying and geoinformation office for providing elevation data. We would also like to express our thanks to the editor and the reviewers for their valuable comments.

2.6 Appendix: Model Description

We used nine (four urban and five rural) districts to calibrate the model used in Approaches V and VI. For validation, we used eight (three urban and five rural) districts. The districts were selected randomly, but followed the conditions that two urban and two or three rural districts of each state had to be used for calibration. These conditions ensured that cities could be found in both calibration and validation data. Furthermore, the conditions allowed accounting for possible differences in settlement patterns that developed under different political systems in the study area between 1945 and 1989 (Berentsen 1982) and might persist.

2.6.1 Approach V

In Approach V, we used 3043 settlements (urban clusters) that were located in the districts selected for calibration. Of these, we classified 2352 settlement as small clusters (extent <10 ha), 653 as medium clusters (extent ≥10 ha and <150 ha), and 38 as large clusters (extent ≥150 ha). For medium and large clusters, we used a linear model to represent the correlation between the logarithm of settlement extent and the mean population density per settlement calculated by the stats package in R version 3.3.1 (R Core Team 2016). For small clusters, we used the modelled density for a settlement extent of 10 ha, independent from the actual settlement extent. For medium clusters, we achieved the best fit with an intercept of –0.771 and a slope of 3.607. For large clusters, an intercept of –14.16 and a slope of 6.29 lead to the best fit. For validation, we used 1911 settlements located in the districts selected for validation of which we classified 1336 as small clusters, 533 as medium clusters and 42 as large clusters.

We evaluated the performance of the model by calculating the RMSE and the MAE for mean population density within a settlement and the sum of population in a settlement (Table 2.5).

Table 2.5: Model performance in Approach V (using GUF2.8).

Parameter	Calibration Mean Density	Validation Mean Density	Population Sum Calibration	Population Sum Validation
RMSE	5.6	5.7	1007	854
MAE	4.7	4.7	84	96

Figure 2.6 illustrates the model used in Approach V and the settlement characteristics (extent and mean population density) used for calibration and validation.

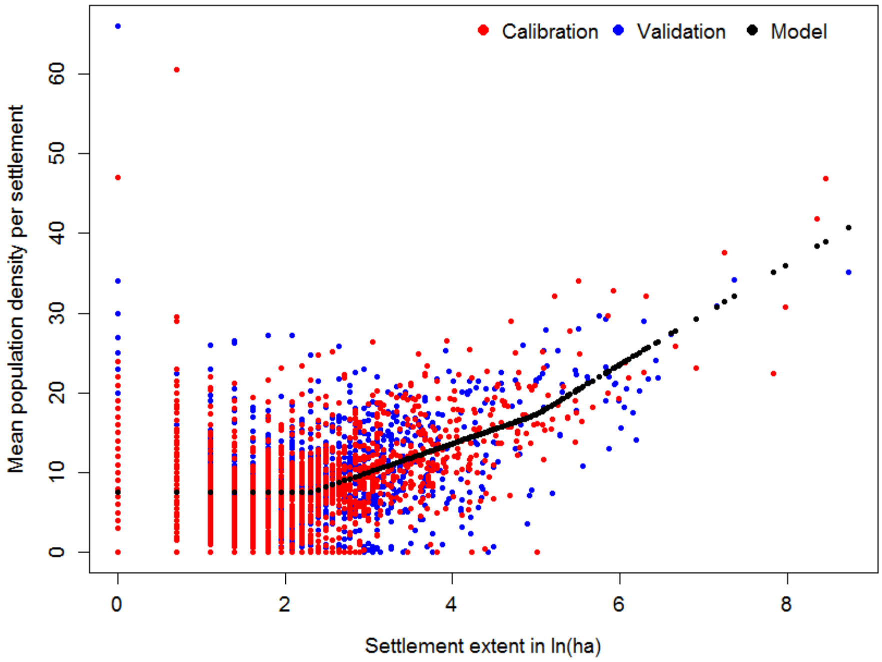

Figure 2.6: Observed and modelled mean population density and settlement extent for calibration and validation in Approach V.

GUF2.8 captures 83.1 % of the population in the study area. As the model solely used GUF2.8 as ancillary data, this led to an underestimation of the total population in the study area. Thus, we adjusted the predicted population counts to the census population on the district and municipality level (Destatis 2018a). This led to an increase of RMSE and MAE for mean population density within a settlement (Table 2.6), because people actually not living in areas defined as settlements by GUF2.8 were located to areas defined as settlements. Despite this, the RMSE of the population sum per settlement adjusted to municipality level was reduced considerably.

Table 2.6: Model performance of adjusted model in Approach V.

Parameter	Calibration Mean Density	Validation Mean Density	Population Sum Calibration	Population Sum Validation
RMSE (d [1])	6.6	6.4	1025	682
MAE (d [1])	5.7	5.3	95	101
RMSE (m [2])	11.1	10.7	537	419
MAE (m [2])	9.1	7.9	85	90

[1] adjusted to total population on district level. [2] adjusted to total population on municipality level.

Figure 2.7 shows the residuals for the unadjusted model, the model adjusted to match total district population and the model adjusted to match total municipality population. The adjusted models overestimate (positive residuals) the mean population density for large clusters. Furthermore, the model adjusted to the municipality level shows high residuals for very small clusters, which indicates a small number of urban cells in the corresponding municipality.

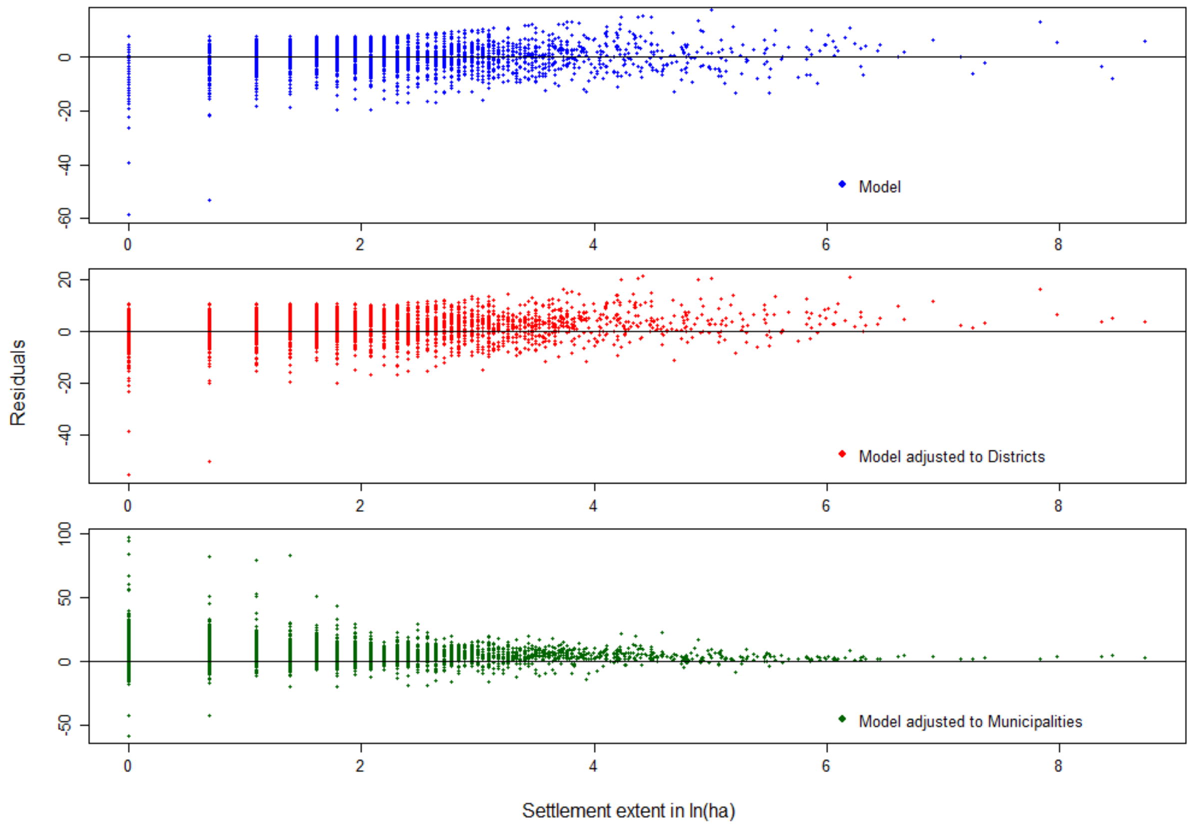

Figure 2.7: Residuals (modelled mean population density minus observed mean population density) and settlement extent in Approach V.

2.6.2 Approach VI

In Approach VI, we used the same districts for calibration and validation as we did for Approach V. Due to different urban extents the number of settlements (urban clusters) differed between the approaches. We grouped 3232 settlements in the calibration area to 2057 small clusters (below 10 ha settlement extent), 1136 medium clusters (extent ≥10 ha and <235 ha), and 39 large clusters (extent ≥235 ha). For medium clusters, a model with an intercept of –2.85 and a slope of 2.78 showed the best fit. For large clusters, an intercept of –20.8 and a slope of 6.0 led to the model with the best fit. We used the calculated mean population density for clusters with an extent of 10 ha for small clusters independently from the actual cluster extent. For validation, we grouped 2047 settlements to 1177 small clusters, 829 medium clusters, and 41 large clusters. We calculated RMSE and MAE to test the ability of the model to predict mean population density per settlement based on the settlement extent (Table 2.7).

Table 2.7: Model performance for Approach VI (using GUF0.4 $_{5\,\%}$).

Parameter	Calibration Mean Density	Validation Mean Density	Population Sum Calibration	Population Sum Validation
RMSE	3.2	3.6	918	1077
MAE	2.4	2.6	87	107

Figure 2.8 illustrates the model used in Approach VI and the settlement characteristics (extent and mean population density) used for calibration and validation.

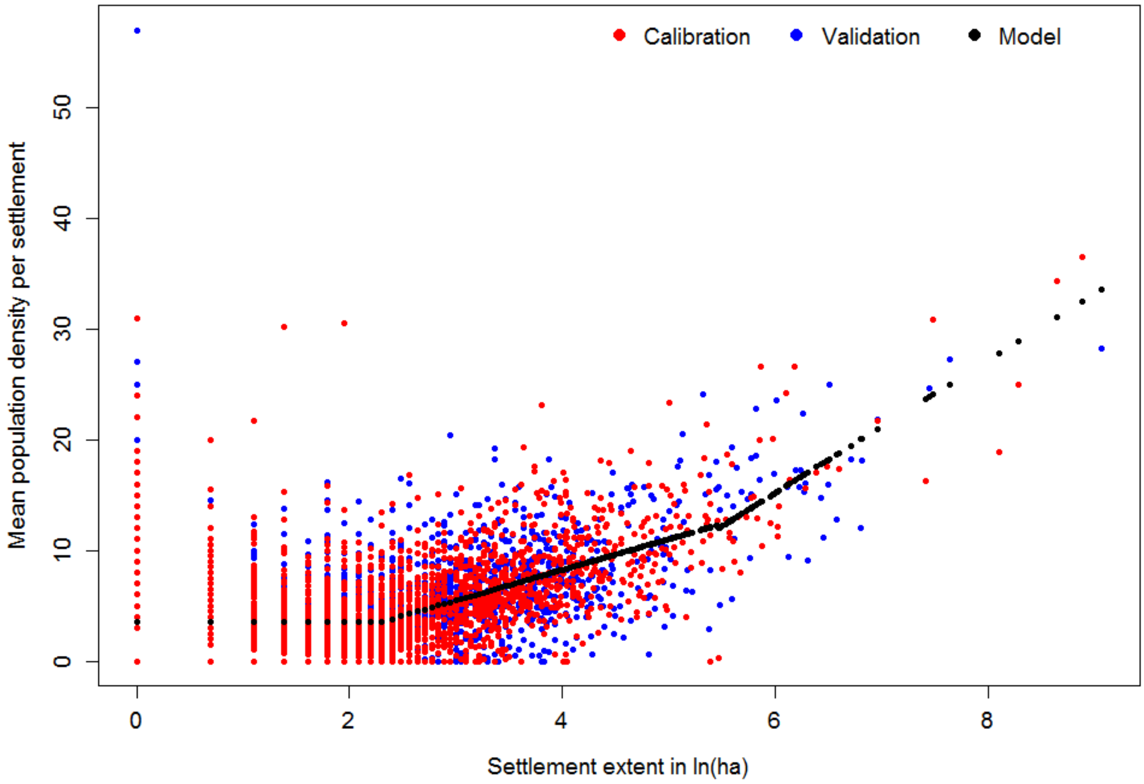

Figure 2.8: Observed and modelled mean population density and settlement extent for calibration and validation in Approach VI.

GUF0.4 $_{5\,\%}$ captured 94.1 % of the population in the study area, which is clearly more than GUF2.8 (see Table 2.2). This required smaller adjustments on district and municipality level compared to Approach V, which led to smaller errors in the model performance of the adjusted model (Table 2.8). The error indicators for population sum in calibration and validation areas were reduced considerably compared to Table 2.7.

Table 2.8: Model performance of adjusted model in Approach VI.

Parameter	Calibration Mean Density	Validation Mean Density	Population Sum Calibration	Population Sum Validation
RMSE (d [1])	3.2	3.6	611	447
MAE (d [1])	2.5	2.7	71	86
RMSE (m [2])	3.5	4.2	171	198
MAE (m [2])	2.7	2.9	43	55

[1] adjusted to total population on district level. [2] adjusted to total population on municipality level.

Comparable to Approach V (Figure 2.7), the adjusted models overestimated (positive residuals) the actual mean population density in large clusters (Figure 2.9). However, in particular the adjustment to population totals on the municipality level led to a reduction of residuals for large clusters and lowered the RMSE by factor 5 (171 (calibration) and 198 (validation) compared to 918 (calibration) and 1077 (validation) in the unadjusted model).

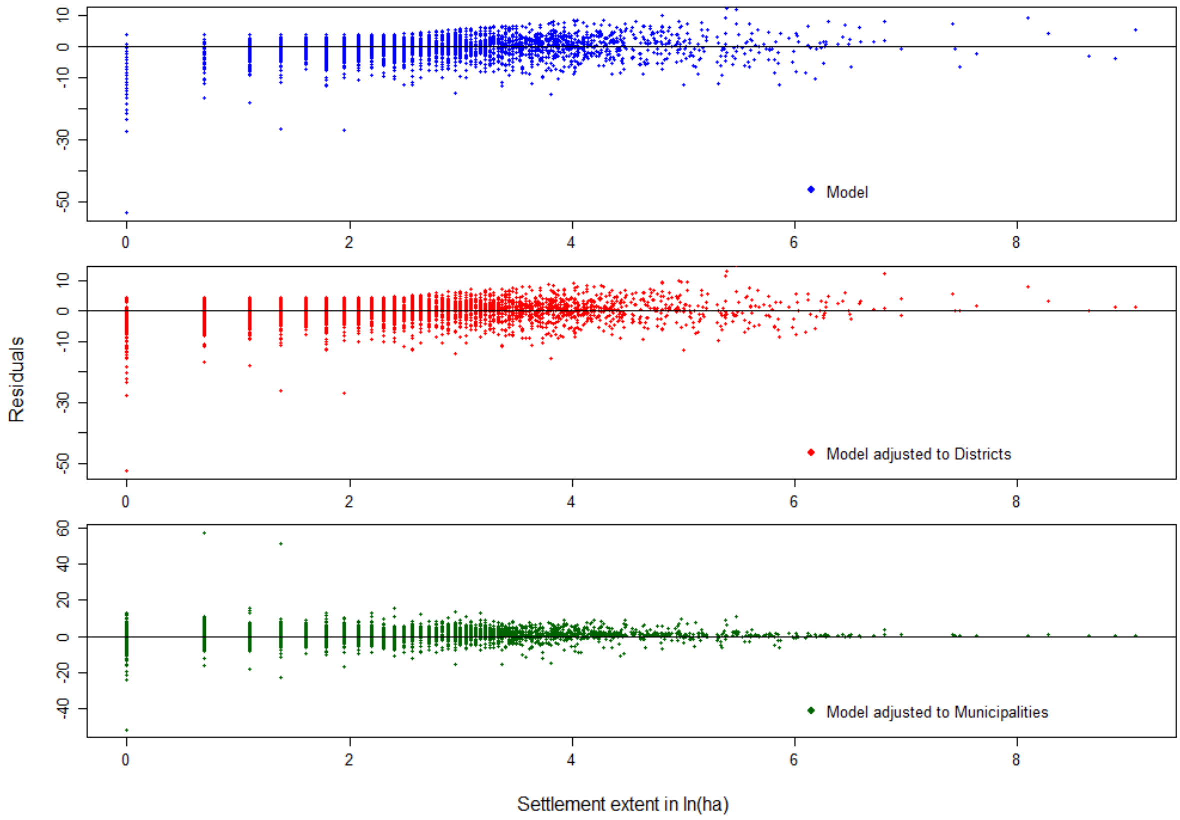

Figure 2.9: Residuals (modelled mean population density minus observed mean population density) and settlement extent in Approach VI.

3 Gridded population projections for the coastal zone under the Shared Socioeconomic Pathways

Jan-Ludolf Merkens, Lena Reimann, Jochen Hinkel and Athanasios T. Vafeidis

Global and Planetary Change (2016), doi: 10.1016/j.gloplacha.2016.08.009

Received: 27 April 2016, Accepted: 23 August 2016

Changes made to the published version:

In the formulas (7) and (9) a subtraction is used instead of an addition. This corrects a typographic error in the manuscript that did not affect the calculations.

Abstract

Existing quantifications of the Shared Socioeconomic Pathways (SSP) used for climate impact assessment do not account for subnational population dynamics such as coastward- migration that can be critical for coastal impact assessment. This paper extends the SSPs by developing spatial projections of global coastal population distribution for the five basic SSPs. Based on a series of coastal migration drivers we develop coastal narratives for each SSP. These narratives account for differences in coastal and inland population developments in urban and rural areas. To spatially distribute population, we use the International Institute for Applied Systems Analysis (IIASA) national population and urbanisation projections and employ country-specific growth rates, which differ for coastal and inland as well as for urban and rural regions, to project coastal population for each SSP. These rates are derived from spatial analysis of historical population data and adjusted for each SSP based on the coastal narratives. Our results show that, compared to the year 2000 (638 million), the population living in the Low Elevated Coastal Zone (LECZ) increases by 58 % to 71 % until 2050 and exceeds one billion in all SSPs. By the end of the 21st century, global coastal population declines to 830-907 million in all SSPs except for SSP3, where coastal population growth continues and reaches 1.184 billion. Overall, the population living in the LECZ is higher by 85 to 239 million as compared to the original IIASA projections. Asia expects the highest absolute growth (238-303 million), Africa the highest relative growth (153 % to 218 %). Our results highlight regions where high coastal population growth is expected and will therefore face an increased exposure to coastal flooding.

Keywords

coastal; Shared Socioeconomic Pathways; scenarios; spatial population projections

3.1 Introduction

In coastal areas, flood impact assessments are of high relevance because flooding from extreme water levels is considered to be the major climate change related hazard in terms of damage (Wong et al. 2014). In addition, the frequency and intensity of flooding are expected to increase due to climate-change induced sea-level rise (Hunter 2010), thus leading to higher damages (Hinkel et al. 2014). In order to assess future impacts, it is essential to understand the spatial distribution of future population exposure for a range of plausible future conditions.

Therefore, socioeconomic scenarios for the coastal zone, which consider that population in coastal and inland areas develops in different patterns (McGranahan et al. 2007), are needed. The SSPs provide a suitable framework for this exercise. As central components of the latest scenario framework developed by the climate change research community, Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) are flexible tools to create scenarios that account for a wide range of possible climatic and socio-economic futures (Moss et al. 2010; van Vuuren et al. 2011; O'Neill et al. 2014; Ebi et al. 2014). Scenarios are used in impact assessment to account for uncertainties in assessing exposure of population and assets to natural hazards (Fang et al. 2014). They have been designed to replace the SRES scenarios as a standard in climate change IAV research and will increase the comparability of studies (Ebi et al. 2014; O'Neill et al. 2014).

Five basic SSPs have been established by the research community, providing possible pathways for society and society-influenced systems to develop in the course of the 21st century (O'Neill et al. 2014). They have been developed on global to regional scales based on socio-economic challenges for mitigation and adaptation. SSP1 describes a sustainable world with low challenges for mitigation and adaptation, SSP2 is a 'Middle of the Road' pathway with intermediate challenges, whereas SSP3 assumes regional rivalry, resulting in high challenges for both, mitigation and adaptation. In SSP4, which is characterised by inequality, challenges are high for adaptation and low for mitigation. SSP5, the pathway of fossil-fuelled development, has low challenges for adaptation and high challenges for mitigation (O'Neill et al. 2017). Furthermore, the research community has devised and agreed upon four RCPs which assume different levels of radiative forcing owing to the emission of greenhouse gases: RCP2.6, RCP4.5, RCP6 and RCP8.5 (van Vuuren et al. 2011). Within the new scenario framework, individual SSPs can be combined with different RCPs in order to construct climate change scenarios for the 21st century (van Vuuren et al. 2014).

Each SSP consists of a qualitative narrative and quantifications for e.g. population and income projections. The narratives describe socio-economic developments in a broad enough fashion as to guarantee their utilisation in a wide range of studies (O'Neill et al. 2017). Several quantitative projections of population, urbanisation and gross domestic product (GDP) have been developed and published (see KC and Lutz 2017 for population; Jiang and O'Neill 2017 for urbanisation; and Crespo Cuaresma 2017; Leimbach et al. 2017; Dellink et al. 2017 for GDP and income). The data are available in the public database of the International Institute for Applied Systems Analysis (IIASA 2015).

So far, the basic SSPs have been developed on global to national scales without accounting for different subnational population dynamics (e.g., different growth rates of coastal and inland populations). Due to the lack of this spatial explicitness, their usefulness for regional scale analyses of population and asset exposure is limited and previous research has called for regional and sectoral extensions of the basic SSPs, at high spatial resolution (Ebi et al. 2014; van Ruijven et al. 2014; O'Neill et al. 2014; O'Neill et al. 2017). For coastal Impact, Adaptation and Vulnerability (IAV) research on global to regional scales, gridded population projections are of high interest to assess exposure to natural hazards (Moss et al. 2010; Jones et al. 2015).

This paper addresses this gap by extending the SSP narratives to the coastal zone and by downscaling national population projections to subnational gridded population projections. In these projections, we employ historical observations of differences between coastal and inland population development for each country. So far, studies have combined observations of specific areas (e.g. China and Bangladesh) with expert judgement and generally assumed future population in coastal areas to grow faster than in inland areas (Nicholls et al. 2008; Foresight 2011; Neumann et al. 2015). However, our approach also accounts for cases with faster growth of inland areas as compared to coastal areas and additionally differentiates between urban and rural areas. Based on our coastal narratives, we adjust the observed historical patterns to account for different pathways of coastal development across the SSPs.

The remainder of the paper is structured as follows. In subsection 3.2 we describe the data and methods employed for developing the coastal SSP narratives and the population projections. In the results section we provide the coastal SSP narratives along with an explanation of how we quantify them for each SSP and show the spatial projections of coastal population on global and continental scale for the 21st century. In order to test the sensitivity of the results, we compare the world's future coastal population projections of our approach to alternative approaches and discuss the differences.

3.2 Material and Methods

3.2.1 Coastal SSP narratives

The first step in our approach is the development of coastal SSP narratives. Therefore, we determine factors of coastal migration based on a literature review (Table 3.1). These factors promote settlement at the coast as compared to inland areas. We additionally differentiate between coastal migration factors for urban versus rural areas. We do not include urbanisation as a separate coastal migration factor and adopt the basic urbanisation assumptions from O'Neill et al. (2017), since urbanisation processes are already accounted for by differentiating between urban and rural migration factors.

Table 3.1: Factors of coastal migration.

Coastal migration factors		**Reference**
Urban	**Rural**	
Shipping		Balk et al. 2009; Hugo 2011
Large-scale fisheries	Small-scale fisheries	FAO 2014
Coastal Tourism		Scott et al. 2012
Lifestyle		Benson and O'Reilly 2009
Coastal management		Balk et al. 2009; Nicholls et al. 2008; UN 2015; Seto 2011

We then select a number of basic SSP key elements from O'Neill et al. (2017) which we use in two ways. First, we select the basic SSP key elements urbanisation, economic growth and technology as a general frame for our coastal SSP narratives and adopt the assumptions for these key elements from the narratives of the five SSPs. Second, we choose elements which are explanatory variables for the coastal migration factors (Figure 3.1). Based on these elements, we interpret the characteristics of the coastal migration factors for each coastal SSP. In this step, we transform the coastal migration factors into our coastal SSP elements. Specifically, we assume that high international trade and globalisation lead to high importance of shipping (Balk et al. 2009; Hugo 2011). We further expect that inequality leads to an increase in small-scale fisheries, because small-scale fisheries currently secure the livelihoods of millions of people, in particular in developing countries (FAO 2014). High meat consumption, including seafood, also implies growing importance of fisheries (FAO 2014). High agricultural productivity, however, leads to a decrease in small-scale fisheries. Tourism is another driver of coastward migration, both to rural and urban locations. Since coastal tourism is globally the largest tourism segment (Scott et al. 2012), we conclude that tourism in the coastal zone is high if the sector's contribution to the GDP is high. Further, we assume that lifestyle migration to the coast due to its natural attractiveness is high if economic growth is high and inequality is low (Benson and O'Reilly 2009). Additionally, we expect coastal zone management to be effective if international cooperation and institutions are effective (Balk et al. 2009; UN 2015). Coastal management also depends on the policy orientation. If policies are oriented towards sustainability, ecosystems are protected and land use change is restricted (Nicholls et al. 2008). If policies focus on economic growth, economic activities at the coast expand since the importance of shipping increases (Seto 2011).

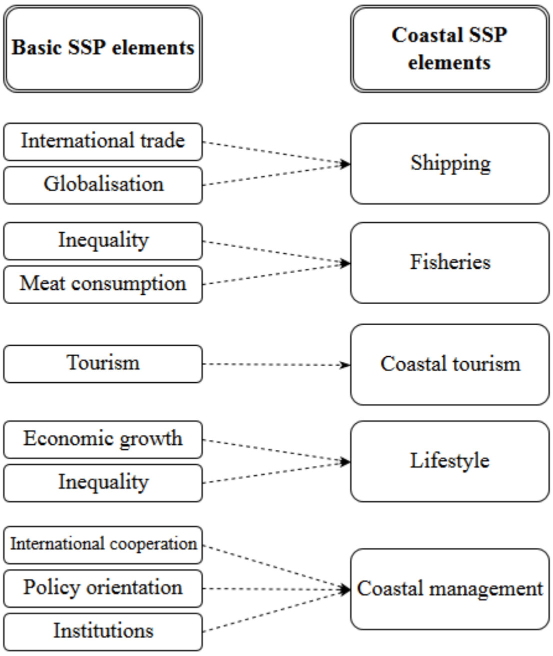

Figure 3.1: Basic SSP elements selected from O'Neill et al. 2017 as explanatory variables for the coastal SSP elements.

3.2.2 Coastal population projections

The population projections are produced in three subsequent steps. First, we utilise GRUMP (Global Urban Rural Mapping Project) population count grids (CIESIN et al. 2011a; Balk et al. 2006) to analyse the current state of the spatial population distribution. GRUMP uses night-time light satellite data to identify urban areas and reallocates census count data within administrative boundaries. The datasets have a spatial resolution of 30 arc-seconds (approximately 1 km at the equator) and represent the population adjusted to UN-national totals for the years 1990, 1995 and 2000. Furthermore, we use Urban Extents Grid (CIESIN et al. 2011b; Balk et al. 2006) to distinguish between urban and rural areas.

Second, we identify the Low Elevation Coastal Zone (LECZ), which includes all land areas up to 10 m elevation connected to the ocean (McGranahan et al. 2007), using the CGIAR-CSI SRTM v4.1 elevation data (Jarvis et al. 2008) with a spatial resolution of 3 arc-seconds (approximately 90 m at the equator) and GTOPO30 elevation data (USGS 1996) for high latitudes, not covered by SRTM. We apply an elevation threshold of 10 m to reclassify the elevation data and perform a connectivity analysis with eight neighbouring cells to ensure hydrological connectivity to the ocean (Poulter and Halpin 2008; Lichter et al. 2011; Neumann et al. 2015). Pixels below or equal to the threshold with a hydrological connection to the ocean are classified as coastal areas. Pixels above the threshold or below the threshold with no connection to the ocean are classified as inland areas. Finally, we resample the data to a resolution of 30 arc-seconds to match the spatial resolution of the population datasets.

Third, we calculate urban and rural population until 2100 by employing the population numbers and projections from the SSP database provided by the IIASA (IIASA 2015). The SSP database contains population projections for 193 countries in 5-year increments from 2015 to 2100 for each SSP (KC and Lutz 2017). Additionally, we incorporate the urbanisation rates of the National Center of Atmospheric Research (NCAR). This dataset, which is also available from the SSP database, contains projections for 151 countries with a population of more than 1 million in 2010 and an area of at least 1000 km² in 10-year time steps, from 2020 to 2100 (Jiang and O'Neill 2015). For small countries with no population or urbanisation projections, we assumed the year 2000 data to be constant over time. For the spatial delineation of countries and regions we use the Global Administrative Areas (GADM) dataset version 2.0 (http://www.gadm.org/).

We adopt the 'United Nations Method', which is defined as the difference between urban and rural growth rates (UN 2015; Jiang and O'Neill 2017), to differentiate the growth rates of coastal urban and inland urban regions (GD^U) and coastal rural and inland rural regions (GD^R). A value > 0 corresponds to a higher growth rate of the coastal region whereas a value < 0 with a higher growth rate of the inland region. Our analysis of 177 countries and regions with urban areas both inside and outside the LECZ shows that 91 regions (51 %) have a $GD^U < 0$ and 86 (44 %) out of 197 countries and region that had rural areas inside and outside the LECZ have and $GD^R < 0$. These values indicate that neither the coast nor the inland grows faster across all countries if urbanisation patterns are treated separately (Figure 3.2). We then implement the observed GDs on country level to develop spatially explicit population projections.

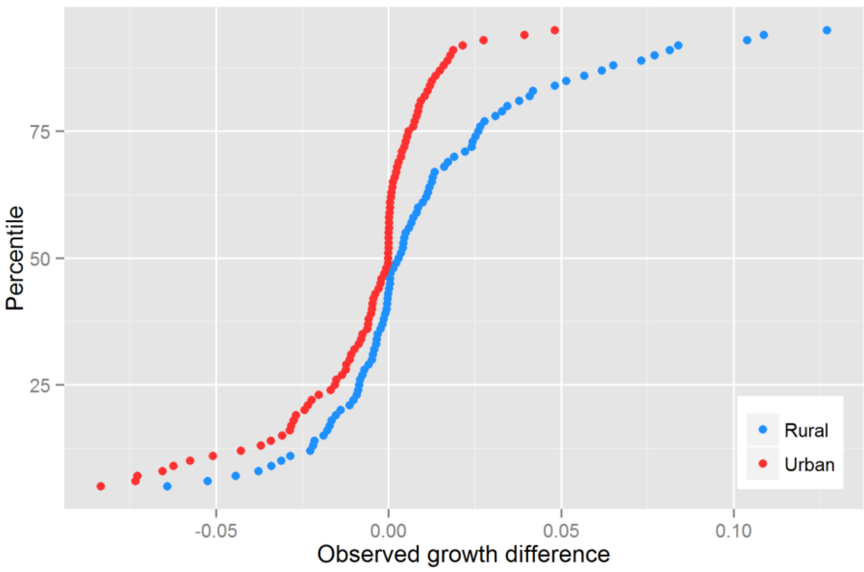

Figure 3.2: 5th to 95th percentiles of observed urban and rural growth difference.

In order to downscale future population to a subnational level, we split each country into four zones: coastal-urban (*CU*), coastal-rural (*CR*), inland-urban (*IU*) and inland-rural (*IR*) (Figure 3.3). Landlocked countries have a maximum of two zones (*IU* and *IR*).

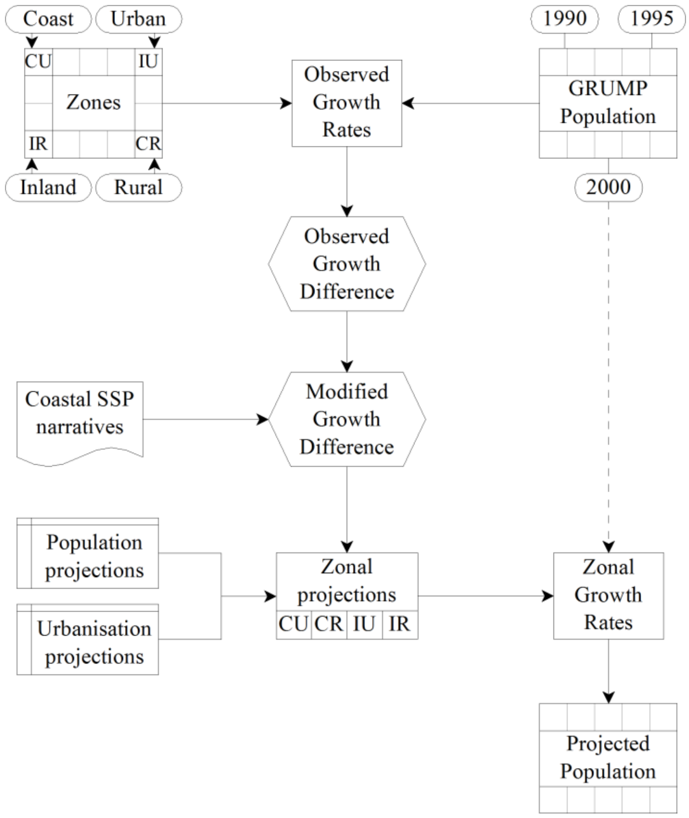

Figure 3.3: Flow chart describing the approach used to produce gridded population projections.

Based on GRUMP population count data, we calculate the population in each of the four zones on a country level for the 1990, 1995 and 2000 observations. The population living in these zones sums up to the total population of a country (P^T).

$$P^T = P^{CU} + P^{CR} + P^{IU} + P^{IR} \tag{1}$$

Subsequently, we calculate the growth rate (*gr*) between the years 1990 to 1995 and 1995 to 2000 in each zone:

$$gr_t^z = \frac{P_{t+1}^z - P_t^z}{P_t^z} \tag{2}$$

with *P* representing the population count in zone *z* and *t* the time. In a next step, we use the mean of the calculated observed growth difference (GD_{obs}) between coastal and inland zones for the 1990 to 1995 and 1995 to 2000 periods. We focus on the growth difference between the coastal urban and the inland urban zone (GD_{obs}^U) as well as the coastal rural and the inland rural zone (GD_{obs}^R).

$$GD_{obs}^U = 0.5 * (gr_{1990}^{CU} - gr_{1990}^{IU} + gr_{1995}^{CU} - gr_{1995}^{IU}) \tag{3}$$

$$GD_{obs}^R = 0.5 * (gr_{1990}^{CR} - gr_{1990}^{IR} + gr_{1995}^{CR} - gr_{1995}^{IR}) \tag{4}$$

A value of 0 indicates that the population in both zones grows at the same rate. If the GD is positive (negative), the population at the coast grows faster (slower) than in the inland. For the projections, we assume the GD to be constant over time but to differ across the SSPs. However, the growth rates differ over time. In order to make our results consistent with previous work in the SSP framework, we use the projected population totals (P_t) produced by KC and

Lutz (2017) and the projected urbanisation levels (u_t) created by Jiang et al. (2017) to calculate future urban (P_t^U) and rural population (P_t^R) for each SSP.

$$P_t^U = P_t * u_t \tag{5}$$

$$P_t^R = P_t * (1 - u_t) \tag{6}$$

Based on the coastal SSP narratives, we modify the observed growth difference for each SSP (Table 3.2). The modification is based on percentiles of the observed growth difference. In order to obtain plausible results, we select percentiles with a small interpercentile range to the previous percentile and a high interpercentile range to the following.

Using the modified growth differences for each SSP (GD_{SSP}^U and GD_{SSP}^R), we subdivide these urban and rural totals into coastal and inland components:

$$P_t^{CU} = \frac{P_{t-1}^{CU}(P_t^U + P_{t-1}^{IU} * GD_{SSP}^U)}{P_{t-1}^U} \tag{7}$$

$$P_t^{IU} = P_t^U - P_t^{CU} \tag{8}$$

$$P_t^{CR} = \frac{P_{t-1}^{CR}(P_t^R + P_{t-1}^{IR} * GD_{SSP}^R)}{P_{t-1}^R} \tag{9}$$

$$P_t^{IR} = P_t^R - P_t^{CR} \tag{10}$$

Based on these regionalised population totals we calculate the growth rate for each zone and time step (r_t^z) by using the population numbers of 2000 as a base year.

$$r_t^z = \frac{P_t^z - P_{2000}^z}{P_{2000}^z} \tag{11}$$

Assuming that the growth rates are homogeneous within a zone, we multiply them by the GRUMP grid population counts representing the year 2000 population.

3.3 Results

3.3.1 Coastal SSP narratives

Table 2 gives an overview of the main elements of the five coastal SSP narratives developed. The following subsections then present each narrative in more detail. The first paragraph of each narrative thereby provides a short overview of the basic key elements of the socioeconomic pathway and its implications for the coastal SSP elements. The second paragraph then illustrates the differences of coastal population growth as compared to inland growth, as well as those between urban and rural areas.

Table 3.2: Coastal SSP elements, quantifications for each SSP and modifications of observed urban (GD_{SSP}^{U}) and rural (GD_{SSP}^{R}) growth differences.

Coastal SSP element	**SSP1 Green Coast**	**SSP2 No Wind of Change**	**SSP3 Troubled Waters**	**SSP4 Fragmented Coast**	**SSP5 Coast Rush**
Shipping	Moderate	Moderate	Low	Moderate-high	High
Fisheries[1]	Low	Moderate	High	Very high	Low
Coastal tourism	Sustainable; low-impact, no mass tourism	Moderate; uneven	Very low; no international tourism	High for elites; low for majority of population	Very high; mass tourism
Lifestyle migration	Low	moderate	Low	High for elites; low for majority of population	Very high
Coastal management	High; towards sustainability	Moderate	Weak	Towards elite's benefit; little interest in sustainability	High; towards economic growth
Urban growth difference ($\mathrm{GD}_{\mathrm{SSP}}^{\mathrm{U}}$)	= 0	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{U}}$	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{U}}$ * 0.5	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{U}}$ + (Q.66-Q.50)	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{U}}$ + (Q.83-Q.50)
Rural growth difference ($\mathrm{GD}_{\mathrm{SSP}}^{\mathrm{R}}$)	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{R}}$ – (Q.50-Q.25)	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{R}}$	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{R}}$ * 0.5	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{R}}$ + (Q.66-Q.50)	= $\mathrm{GD}_{\mathrm{obs}}^{\mathrm{R}}$ + (Q.75-Q.50)

[1] In our coastal SSP narratives the term fisheries refers to small-scale fisheries since we do not explicitly account for large-scale fisheries as a coastal migration factor.

SSP1 – Green Coast

The world's shift towards a more sustainable pathway results in well-managed coastal zones. Global institutions and environmental policies function effectively. Therefore, socioeconomic development is highly managed and focuses on the development of compact and sustainable coastal cities without urban sprawl. Economic growth is medium to high and markets are globally connected, fostering rapid technological development and transfer. Due to more sustainable, regionalised production, international trade is on a moderate level. Therefore, shipping is moderately important. Tourism is practiced in a sustainable way. Lifestyle migration to the coast is limited. Reduced inequality, low-meat diets and improvements in farming productivity lead to decreasing importance of fisheries. The value of ecosystems and their protective function in the coastal zone are globally accepted and respected. Policies are oriented towards conservation and expansion of coastal ecosystems prevents settlement in the coastal zone.

The focus on sustainability leads to high urbanization rates and compact cities. As coastal cities are regulated by environmental policies and since their economic importance does not differ from inland cities, population growth in coastal urban locations does not differ from inland urban ones. Coastal ecosystem protection and lower importance of fisheries lead to reduction of population growth in coastal rural areas compared to inland rural areas. Consequently, we use a growth difference of 0 for urban areas and reduce the observed growth difference for rural areas by the difference of the 50^{th} and 25^{th}-percentiles of the observed rural growth difference (see Table 3.2). In total, the coastal zone is less attractive for human settlement than the inland.

SSP2 – No Wind of Change

Under SSP2, socioeconomic development in the coastal zone does not deviate significantly from historical patterns. The management of socioeconomic development in the coastal zone is limited due to relatively weak international cooperation, uneven and moderately effective institutions, and rather slow implementation of environmental policies. Hence, the urbanisation rate is moderate with considerable spatial expansion of cities. Economic growth is, on average, medium and continues to be uneven across countries. Technological development is moderate and transfer slow. The semi-open global economy is characterised by moderate international trade, keeping the importance of shipping at a similar level. Tourism also continues at historical rates. Migration to the coast for lifestyle reasons is moderate. Fisheries remain important, owing to uneven reductions in inequality, material-intensive, medium meat consumption and slow improvements in productivity. Ecosystem protection is weak and leads to environmental degradation.

This pathway shows a fragmented picture. Coastal zones remain as attractive for socioeconomic development as in the past, with rapid population growth in some coastal regions and slow growth or even declining population numbers in others. Urbanisation and urban sprawl continue in coastal as well as inland locations. Similarly, rural coastal and inland populations experience the same growth patterns as observed in the past. In total, historical patterns of coastal and inland population growth will continue at the same rates. Therefore, we use the observed urban and rural growth differences and do not modify them.

SSP3 – Troubled Waters

In this pathway, the focus on national and regional issues leads to converging population growth rates of coast and inland. International cooperation and global institutions are weak and uneven. National policies focus on security issues, resulting in poorly managed socioeconomic development. Therefore, urban areas are unattractive and urbanisation is slow. Due to a de-globalizing economy oriented towards security, international trade is strongly constrained and economic growth is slow. Therefore, technology development and transfer is limited. As a consequence, shipping experiences a marked decline. Likewise, international tourism hardly exists. Also, coastal lifestyle migration is low. Fisheries become more important because inequality is high, consumption is material-intensive and productivity is low. Further, food security needs to be guaranteed on a national level. This development in combination with the absence of environmental policies leads to serious environmental degradation.

Under SSP3 the coastal zone loses its importance as a focal point of international trade due to the orientation towards national and regional security. Since poorly managed inland urban areas also lose attractiveness, neither coastal nor inland urban areas are more attractive for human settlement. The same patterns apply to rural areas. Therefore, the population in both urban and rural locations changes at converging rates. We consider this convergence by reducing the observed growth differences for both urban and rural areas by half.

SSP4 – Fragmented Coast

SSP4 is characterised by high inequalities within and across countries. This applies to the coastal zone as well. International cooperation takes place among elites with effective institutions and policies in place for them. This leads to well-managed economic growth for the elites and leaves behind the rest of the population. Therefore, this pathway is characterised by highly fragmented socioeconomic development. Technology development is rapid but transfer among population groups is low. Economic growth is uneven and international trade is moderate since only elites are connected globally. This makes urban areas, especially port cities, very attractive because they are regarded as economic engines with abundant job opportunities. Consequently, urbanisation is fast with considerable urban sprawl, including high unemployment rates and the formation of unplanned peri-urban slums. Tourism plays an important role for elites only. Similarly, lifestyle migration to the coast is high for elites. Consumption is high for elites and low for the rest of the population, increasing the importance of fisheries for poor population groups to secure their livelihoods. Extensive agricultural use and low productivity in rural areas leads to environmental degradation, since policies focus on the local environment surrounding the elites.

In this pathway, coastal areas experience fragmented population development, both socially and economically. Coastal urban areas are subject to higher population growth than inland urban areas because they are regarded as economic engines. Rural coastal areas are more attractive than rural inland areas due to the importance of fisheries. Also, the tourism industry fosters coastal development. Overall, the coastal zone experiences higher population growth than inland areas. Therefore, we increase the observed coastal to inland growth difference for urban and rural areas by the difference of the 66th and the 50th percentile.

SSP5 – Coast Rush

In this highly globalised world, the coastal zone is of particular importance. International cooperation as well as institutions are effective. Policies focus on competitive, free markets and human well-being. This promotes socioeconomic development substantially. Global markets are highly interconnected with regional specialisation. This leads to high international trade and rapid economic growth, which promotes technological development and transfer. As a consequence, the importance of shipping increases markedly. That is why urbanisation is high and results in large cities with urban sprawl, which is managed more effectively over time.

Also, international tourism plays an important role, resulting in extensive development in coastal areas. Similarly, lifestyle migration to the coast is very high. Consumption is characterised by materialism and meat-rich diets, leading to increased importance of fisheries. Inequality is strongly reduced and agricultural productivity is high. As a consequence, small-scale fisheries are replaced by large-scale fisheries. Environmental policies focus on the local environment which is extensively engineered to ensure people's well-being. Little attention is paid to global problems.

In this pathway, robust economic growth leads to high population growth in the coastal zone. This is due to the fact that in a globalised world, port cities are centres of growth and urbanisation rates are high. Rural coastal areas also experience higher population growth than rural inland ones because coastal tourism is a major driver of rural economic growth. However, the difference between rural coastal and rural inland population growth is not as high as between urban coastal and urban inland population growth. We account for these aspects by increasing the observed urban growth difference by the difference of the 83rd and the 50th percentile and by increasing the observed rural growth difference by the difference of the 75th and 50th percentile.

3.3.2 Coastal population projections

We first present global patterns across the different SSPs and then focus to regional patterns using the UN regions definition (UN 2013).

3.3.2.1 Global

Our results show that the absolute coastal population grows until 2050 across all SSPs. SSP5 shows the highest LECZ population (1.091 billion), SSP2 the lowest LECZ population (1.005 billion). The share of coastal population is highest in SSP5 (12.8 %) but lowest in SSP3 (10.5 %). Compared to the year 2000, the population living in the LECZ increases between 58 % (SSP2) and 71 % (SSP5). Across all SSPs, the proportion of coastal population increases in the first half of the 21st century.

By the end of the 21st century, the population living in the LECZ ranges from 0.830 billion (SSP4) to 1.184 billion in SSP3. The relative share of coastal population ranges from 9.0 % in SSP4 to 12.3 % in SSP1 and SSP5. Compared to the year 2000, the population grows by 30 % (SSP4) to 86 % (SSP3), whereas the other SSPs show a growth between 33 % and 42 %. Coastal growth exceeds inland growth in SSP1 and SSP5. Compared to 2050, coastal population rises solely in SSP3 (+13 %). In the other SSPs, the coastal population declines by up to 0.2 billion (SSP1 and SSP4) in the second half of the 21st century. In line with the population projections of KC and Lutz 2017), the range of coastal population across the SSPs by end of the 21st century is wider (0.354 billion) than by mid of the century (0.086 billion).

Table 3.3: Absolute and relative population living in the LECZ by UN-region and worldwide for the years 2000, 2050 and 2100.

		GRUMP	**SSP1**		**SSP2**		**SSP3**		**SSP4**		**SSP5**	
			Green Coast		**No Wind of Change**		**Troubled Waters**		**Fragmented Coast**		**Coast Rush**	
		2000	2050	2100	2050	2100	2050	2100	2050	2100	2050	2100
Africa	Count	54	140	149	144	162	172	265	159	220	137	130
	Share	6.7 %	7.9 %	8.0 %	7.1 %	6.2 %	7.4 %	6.7 %	7.1 %	6.1 %	7.9 %	7.2 %
	growth		159 %	175 %	165 %	200 %	218 %	390 %	194 %	307 %	153 %	141 %
Asia	Count	472	754	555	710	555	732	784	730	487	776	545
	Share	12.8 %	15.9 %	16.9 %	13.8 %	12.6 %	13.0 %	11.7 %	14.7 %	12.0 %	16.4 %	16.5 %
	growth		60 %	18 %	51 %	18 %	55 %	66 %	55 %	3 %	64 %	16 %
Europe	Count	49	60	56	57	57	49	35	55	45	72	96
	Share	6.8 %	7.7 %	8.6 %	7.5 %	8.1 %	7.2 %	6.5 %	7.7 %	8.4 %	8.5 %	10.5 %
	growth		21 %	15 %	16 %	15 %	0 %	-28 %	12 %	-9 %	46 %	96 %
Latin America and the Caribbean	Count	34	48	34	50	44	57	69	48	35	50	38
	Share	6.5 %	7.1 %	7.0 %	6.7 %	6.6 %	6.7 %	6.4 %	6.8 %	6.1 %	7.6 %	8.4 %
	growth		42 %	1 %	49 %	31 %	69 %	105 %	42 %	3 %	48 %	12 %
Northern America	Count	25	38	44	37	43	31	25	36	36	49	82
	Share	8.0 %	8.2 %	8.5 %	8.2 %	8.4 %	8.3 %	8.5 %	8.4 %	8.8 %	9.1 %	10.3 %
	growth		50 %	76 %	47 %	72 %	23 %	-2 %	41 %	42 %	93 %	228 %
Oceania	Count	3.4	6.6	7.3	7.0	8.9	5.7	5.4	7.0	8.1	9.1	15.4
	Share	11.0 %	11.8 %	12.4 %	12.3 %	13.7 %	11.3 %	10.9 %	12.5 %	13.3 %	14.1 %	17.7 %
	growth		95 %	115 %	108 %	162 %	70 %	60 %	108 %	141 %	170 %	355 %
World	**Count**	**637**	**1046**	**845**	**1005**	**870**	**1047**	**1184**	**1034**	**830**	**1091**	**907**
	Share	**10.5 %**	**12.4 %**	**12.3 %**	**11.0 %**	**9.7 %**	**10.5 %**	**9.4 %**	**11.3 %**	**9.0 %**	**12.8 %**	**12.3 %**
	growth		**64 %**	**33 %**	**58 %**	**37 %**	**64 %**	**86 %**	**62 %**	**30 %**	**71 %**	**42 %**

Count represents the LECZ population in million. Share is the share of LECZ population on total population in percent. Growth gives the relative growth of LECZ-population in percent compared to the year 2000 population as baseline.

3.3.2.2 Regional

On a continent scale, we expect the highest relative changes of coastal population in Africa. Compared to the base year 2000, Africa's coastal population grows between 1.4 times in SSP5 and 3.9 times in SSP3 by the end of the century. The absolute coastal population increases from 54 million in 2000 to 137 million (SSP5) and 172 million (SSP3) in 2050. By the end of the century, Africa's coastal population further increases to 265 million (SSP3). Only in SSP5 Africa's coastal population decreases from 2050 to 2100 to 130 million. The highest share of coastal population is in SSP1 (8 %) and the lowest in SSP4 (6.1 %). In SSP2 and SSP4, the inland population is growing faster than the coastal population over the 21st century, while in SSP1, SSP3 and SSP5 the coastal population is growing faster than the inland population.

In Asia, the coastal population by the end of the century grows between 3 % in SSP4 and 66 % in SSP3 compared to the year 2000 population. The absolute coastal population rises from 472 million in 2000 to a range from 710 million (SSP2) to 776 million (SSP5) in 2050. By the end of the century the coastal population will decrease from the 2050 peak to a number ranging from 487 million (SSP4) to 550 million (SSP1, SSP2 and SSP5). In SSP3, the absolute coastal population continues growing in the second half of the century leading to 784 million people living in coastal areas in 2100. SSP1 shows the highest relative share of coastal population (16.9 %). In SSP2-4, the inland population is growing faster than the coastal population over the 21st century, while SSP1 and SSP5 indicate a higher growth rate of coastal regions.

For Europe, the scenarios show a wide range in the relative change of coastal population in the 21st century. In SSP1, SSP2 and SSP5, the population grows by up to 96 % (SSP5) and declines in SSP3 (28 %) and SSP4 (9 %). By the mid of the century the absolute coastal population rises from 49 million in 2000 to a range of 49 million to 72 million (SSP3 and SSP5 respectively). In the second half of the century, the coastal population decreases to a range from 35 million (SSP3) to 57 million (SSP2). Only in SSP5 the coastal population continues to grow to 96 million, which is the highest share across all pathways (10.5 %). With the exception of SSP3, the coastal population grows faster than the inland population.

Latin America and the Caribbean face the highest relative coastal population growth in the 21st century in SSP3 (105 %) and the lowest growth in SSP1 (1 %). The absolute coastal population rises from 34 million in 2000 to a range of 48 million (SSP1 and SSP4) to 57 million (SSP3) by 2050. Solely in SSP3 the population continues to grow to 69 million by the end of the century while all other pathways show coastal population declining to a range between 34 million (SSP1) and 44 million (SSP2). SSP5 shows the highest share of coastal population (8.4 %). In SSP1, SSP2 and SSP5, coastal population grows faster than inland population.

For North America, the relative change of coastal population in the 21st century ranges from a decrease of 2 % (SSP3) to a growth of up to 228 % (SSP5). Until 2050, the absolute coastal population grows from 25 million in 2000 to a range from 31 million (SSP3) to 49 million (SSP5). The coastal population continues to grow in the second half of the century and ranges from 36 million (SSP4) to 82 million (SSP5). Only in SSP3 the population living in the coastal zone declines to 25 million. Nevertheless, coastal population is growing faster than inland population across all SSPs, as in SSP3 the inland population is declining even more. This leads to a higher share of coastal population in all SSPs, with SSP5 showing the highest share (10.3 %).

In Oceania, coastal population grows between 60 % (SSP3) and 360 % (SSP5) in the 21st century. The absolute coastal population rises from 3.4 million in 2000 to a range between 5.7 million (SSP3) and 9.1 million (SSP5) in 2050. Until the end of the 21st century, the coastal population continues growing and ranges from 7.3 million (SSP1) to 15.4 million (SSP5). Only in SSP3 the coastal population declines from its 2050 peak to reach 5.4 million in 2100. SSP5 shows the highest share of coastal population (17.7 %). With the exception of the second half of the century in SSP3, coastal population grows faster than inland population.

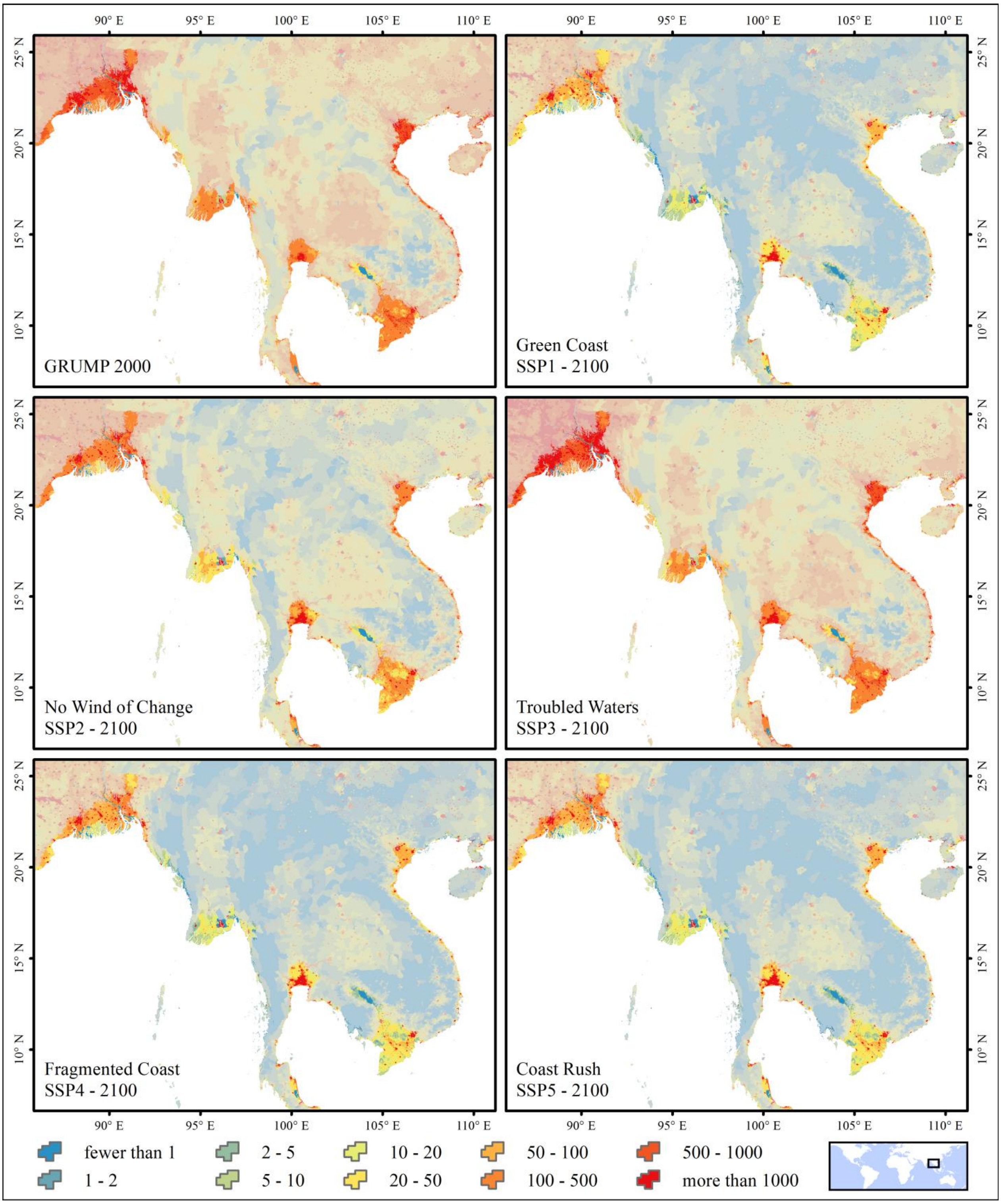

Figure 3.4: Population projections of each SSP compared to the base year 2000 for Southeast Asia. Pixel size: 30 arc-seconds (~1 km² at the equator).

3.4 Discussion

In contrast to previous studies, this study uses historical data to account for differences in population growth between coastal and inland regions at subnational level. Previous studies have either employed a uniform global constant growth rate of coastal population (e.g. Nicholls et al. 2008) or have assumed coastal population to grow faster than inland population on a national level (e.g. Neumann et al. 2015). These studies also assumed coastal regions to grow up to two times faster than inland regions. These assumptions were based on the study of McGranahan et al. (2007), who found that coastal population in China and Bangladesh grew much faster than the inland population and that the fastest growth was located in urban coastal regions. In our study, we determine the growth rate of coastal urban regions based on urbanisation and additional factors of coastal migration, for example shipping and tourism. These factors either increase or decrease the attractiveness of coastal regions compared to inland regions, thus leading to country-specific migration processes.

When comparing our results on historic growth rates with other studies, we find that contrary to McGranahan et al. (2007) and in line with the database of CIESIN (2013), our findings show no clear evidence of population to grow faster at the coast compared to inland (Table 3.4). Since a direct comparison of absolute population numbers between these studies was not possible due to the use of different input data, we compared the relative change of population in Bangladesh and China between 1990 and 2000. According to McGranahan et al. (2007), the population in the LECZ grew faster than the inland population for these two countries, with coastal urban areas showing the highest growth rates. This is neither in agreement with the findings of CIESIN (2013) nor our results, which show that in Bangladesh the inland grew faster than the coastal zone while in both Bangladesh and China inland urban areas grew faster than coastal urban areas. However, due to the high concentration of urban areas in the coastal zone of China (Neumann et al. 2015), the growth rate of population in the LECZ was higher than in inland areas, despite the growth rates of coastal urban and coastal rural areas being smaller than their inland equivalents. This illustrates that urbanisation appears to be the dominant driver of population dynamics, independent of whether areas are coastal or inland. This demonstrates that our approach of using country-specific growth rates that also account for faster population growth in the inland instead of the general assumption of faster growing population in coastal regions is valid.

Table 3.4: Relative change of population between 1990 and 2000 for Bangladesh and China [in %].

	Bangladesh			**China**		
	McGranahan[1]	CIESIN[2]	This study[3]	McGranahan[1]	CIESIN[2]	This study[3]
National	12.6	23.9	23.9	10.9	10.8	10.4
Coastal	23.6	23.1	23.2	20.8	17.8	17.8
Inland	2.7	24.6	24.5	9.7	10	9.3
Coastal Urban	32	34.1	33.9	39.6	38.2	40.5
Coastal Rural	21.1	20.3	20.5	4.1	-10.4	-0.2
Inland Urban	0.2	34.3	35	23.2	43.6	41.8
Inland Rural	3.3	22.5	22.5	4.6	-9.6	-0.1

1) Population data: GRUMPalpha, LECZ: 10 m 2) Population data: GRUMPv1, LECZ: 20 m 3) Population data: GRUMPv1, LECZ: 10 m

Next, we compare the results of our approach to other possible approaches: we (1) use an equal growth rate within each country, (2) consider urbanisation projections and use different growth rates for urban and rural areas within each country and (3) apply different growth rates for urban and rural areas within each country considering different patterns of coastal and inland development and following historical patterns. These approaches may lead to over- or underestimation of coastal population (Table 3.5).

The use of (1) a single growth rate per country is the most straightforward approach and applied in a number of studies (e.g. Hinkel et al. (2014)). This approach tends to underestimate coastal population because it does not consider urbanisation.

Enhancing (2) this approach by urbanisation projections and applying different growth rates for urban and rural areas, coastal population tends to be overestimated, due to the fact that coastal areas show a higher population density than inland areas (Neumann et al. 2015). Urbanisation is not the only determining factor of coastal population development but is additionally influenced by processes that may reduce the attractiveness of coastal areas. For example, high population density in coastal regions can lead to higher land costs, thus rendering coastal areas less attractive. To account for these processes, the use of historical growth differences is appropriate.

Considering (3) urbanisation projections and historical growth differences between coastal and inland areas on national level leads to higher coastal population compared to the approach using a single growth rate and lower projections compared to the approach enhanced by urbanisation projections. The approach implementing observed growth differences can be used for a pathway where historical patterns continue in the future (as in SSP2 – No Wind of Change). Since we account for five different coastal SSPs and coastal migration factors differ across these pathways, we refine the approach by modifying the observed growth difference for each coastal SSP.

Table 3.5: Absolute and relative global LECZ-population in 2100 calculated by different spatial approaches for the five SSPs.

	Single growth rate per country		**Urbanisation projections**		**Historical patterns**		**This approach**	
	abs.	rel.	abs.	rel.	abs.	rel.	abs.	rel.
SSP1	619	9.0 %	849	12.3 %	712	10.4 %	845	12.3 %
SSP2	785	8.7 %	1027	11.4 %	870	9.7 %	870	9.7 %
SSP3	1067	8.5 %	1287	10.2 %	1118	8.9 %	1183	9.4 %
SSP4	688	7.4 %	985	10.6 %	800	8.6 %	830	9.0 %
SSP5	668	9.1 %	899	12.2 %	763	10.4 %	907	12.3 %

abs. represents the global LECZ population in million. rel. represents the relative share of LECZ population on total population in percent.

The population projections (Table 3.3) show a decrease of coastal population in some regions in the second half of the 21st century. The predominant reasons for this decrease are the general trends in the population projections that were used as input data. The projections of KC and Lutz (2017) show that the global population declines from 2050 to 2100 under SSP1, SSP2 and SSP5. On a regional scale, this trend depends on the number of countries grouped into high fertility, low fertility and rich-OECD and can therefore differ from the global trends. For example, KC and Lutz (2017) assume natural population growth (high fertility, low mortality) and high migration to rich OECD-countries in SSP5, which leads to population growth in Europe, North America and Oceania in the second half of the 21st century. In addition, regional trends can be distorted by populous countries with a high positive or negative growth difference.

Finally, our study exhibits two limitations. First, we assume a static urban extent, which is suitable for urbanisation processes in SSP1, where urban sprawl is limited, but less suitable for

SSP2 and SSP5, where urban sprawl and urbanisation levels are high. However, since urban sprawl affects both coastal and inland regions, the effect on the total number of coastal residents on regional and global scales is small. We defined the boundaries of urban areas according to the GRUMP Urban Extent data, which are based on a more generic definition of urban extent that is not limited to built-up areas but encompasses urban agglomerations and is therefore suitable for global and regional scale analyses. However, for local scale analyses, urban sprawl processes should be implemented. A second limitation of our approach is that the growth difference is based on a relatively short observational record (10 years) and is assumed to be constant over time. This is due to the absence of global gridded population data whose temporal and spatial resolution is high enough for use in coastal analysis. A longer observational record would lead to more robust estimates and enable the use of trends in growth difference on country level over the 21st century.

The population grids developed can be downloaded at (https://figshare.com/s/9a94ae958d6a45684382). They have been produced with a specific focus on the coastal zone in order to enable coast-related IAV assessments. This should be kept in mind when analysing the population projections outside the LECZ.

3.5 Conclusion

This study has developed spatially explicit population projections for the five coastal SSPs by (i) defining SSP narratives for the coastal zone and (ii) producing gridded population projections for each coastal SSP at high temporal and spatial resolution. We combined the basic SSPs, which serve as boundary conditions, with coastal migration factors to account for differences in coastal and inland population growth across the coastal SSPs. These coastal SSPs span the range of plausible population development at the coast and project the population in a spatially explicit manner until 2100 by using a range of population growth rates at subnational level. The range accounts for potential growth but also possible decline of coastal population.

The population grids can be used in coastal IAV research to assess exposure of population to climate-change impacts and natural hazards on global to regional scale. Further, they can be summarised readily to policy-relevant administrative units for planning, decision-making or resource allocation. For studies on a local scale, the produced grids are less suitable and results should be interpreted with caution. This is due to the fact that the population grids presented here are not demographic projections, but rather aim to account for uncertainties in the future distribution of the population living in the coastal zone under different scenarios.

Future work can extend the proposed coastal SSPs and regionalise them. In this context, further differentiation in coastal population development between countries could be useful for better representing regional development trends. At local to regional scales, further criteria other than fertility and income can be considered to cluster countries and differentiate between country groups. At subnational level, the gridded population projections can be further refined with dasymetric modelling approaches to account for changes in land cover and urban extents.

Acknowledgments

The research leading to these results has received funding from the European research project RISES-AM (grant agreement no. 603396).

4 Regionalisation of population growth projections in coastal exposure analysis

Jan-Ludolf Merkens, Daniel Lincke, Jochen Hinkel, Sally Brown and Athanasios T. Vafeidis

Climatic Change (2018), doi: 10.1007/s10584-018-2334-8

Received: 14 December 2017, Accepted: 07 November 2018

Changes made to the published version:

To harmonise the style of the thesis, arc-minutes and arc-seconds are not abbreviated. In the published manuscript subsection 4.3.3 and the last paragraph of subsection 4.3.1 were moved to the supplementary material due to word limitation. This also applies to Figures 3.3-3.7 and Table 4.2. Figure 3 in the published manuscript showed only two of the four approaches. It was replaced by Figure 4.3, which was part of the supplementary material in the published version.

Abstract

Large-area coastal exposure and impact analysis has focussed on using sea-level rise (SLR) scenarios and has placed little emphasis on socioeconomic scenarios, while neglecting spatial variations of population dynamics. We use the Dynamic Interactive Vulnerability Assessment (DIVA) Framework to assess the population exposed to 1 in 100-year coastal flood events under different population scenarios, that are consistent with the Shared Socioeconomic Pathways (SSPs); and different SLR scenarios, derived from the Representative Concentration Pathways (RCPs); and analyse the effect of accounting for regionalised population dynamics on population exposure until 2100. In a reference approach, we use homogeneous population growth on national level. In the regionalisation approaches, we test existing spatially explicit projections that also account for urbanisation, coastal migration and urban sprawl. Our results show that projected global exposure in 2100 ranges from 100 million to 260 million, depending on the combination of SLR and population scenarios and method used for regionalising the population projections. The assessed exposure based on the regionalised approaches is higher than that derived from the reference approach by up to 60 million people (39 %). Accounting for urbanisation and coastal migration leads to an increase in exposure, whereas considering urban sprawl leads to lower exposure. Differences between the reference and the regionalised approaches increase with higher SLR. The regionalised approaches show highest exposure under SSP5 over most of the 21st century, although total population in SSP5 is the second lowest overall. All methods project the largest absolute growth in exposure for Asia and relative growth for Africa.

Keywords

sea-level rise, Shared Socioeconomic Pathways, coastal population dynamics, coastal flooding exposure

4.1 Introduction

A large number of studies have assessed future coastal exposure to sea-level rise (SLR) and respective impacts on a global scale (e.g. Hanson et al. 2011; Hallegatte et al. 2013; Neumann et al. 2015). These studies rely on SLR and socio-economic scenarios, because future climate and socio-economic change cannot be forecasted over decades due to deep uncertainties and alternating pathways of development involved. While a lot of emphasis has been placed on developing adequate SLR scenarios that account for uncertainties in future SLR, much less emphasis has been placed on socio-economic scenarios, even though both uncertainties are roughly at equal footing in terms of their influence on future coastal exposure and impacts (Hinkel et al. 2014).

The implementation of population changes in global coastal impact assessments has generally improved since the 1990s, as at that time studies assumed socioeconomic conditions to remain constant (e.g. Nicholls and Mimura 1998) and were therefore unrealistic for future conditions. In recent years multiple scenarios of socioeconomic development on global, continental or national level have been employed in global coastal impact assessment in order to account for uncertainties in socioeconomic development and lead to plausible estimates on future exposure (see e.g. Nicholls (2004) and Arnell et al. (2004) for the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES) and e.g. Hinkel et al. (2014) for the Shared Socioeconomic Pathways (SSPs)). However, these approaches used population projections on national level and did not account for different population change rates in coastal and inland areas. As coastal zones typically face different challenges compared to inland areas, including differing rates of economic growth and a higher density of cities (McGranahan et al. 2007; Seto 2011; Kummu et al. 2016), coastal population was underestimated.

For this reason, some recent studies of global coastal exposure have used higher growth rates for coastal population than for inland population. Nicholls et al. (2008) assumed coastal population to grow up to 2 times faster than the national average. Neumann et al. (2015) refined the approach of Nicholls et al. (2008) and differentiated between coastal and inland population development for urban and non-urban areas by using correction factors. These corrections factors allowed coastal population to remain constant if inland population was projected to decrease and grew 1.7 to 2 times faster than the inland population if the inland population was projected to increase. These approaches have the limitations of assuming first, arbitrary correction factors, and second that coastal population develop faster than inland population for all countries, which is, not always the case. Merkens et al. (2016), for example, tested this assumption against historical population data for coastal countries between 1990 and 2000 and found that for 40-50 % of all countries inland urban and rural locations grow faster than their coastal counterparts.

Spatially explicit population projections provide a more realistic basis for coastal exposure analysis. Gaffin et al. (2004) developed population projections until 2100 consistent with the SRES with a horizontal resolution of 15 arc-minutes (~30 km at the equator). Grübler et al. (2007) produced gridded population projections with a horizontal resolution of 7.5 arc-minutes (~15 km at the equator) for three of four SRES scenarios. Their work was refined by Jones and O'Neill (2016), who created gridded population projection for all five SSPs at an initial horizontal resolution of 7.5 arc-minutes. Their projections were downscaled to 0.5 arc-minutes (~1 km at the equator) by Gao (2017). Jones and O'Neill (2016) analysed historical trends of population development and used a gravity-based downscaling model to simulate urban and rural population changes. For all five SSPs an index of potential attractiveness for each grid cell was used to allocate population, which indirectly leads to different growth rates on subnational level for coastal and inland areas. Merkens et al. (2016) created gridded population projections with a horizontal resolution of 0.5’ for all five SSPs that focused on coastal areas and analysed historical growth differences of coastal urban and coastal rural areas compared to the inland counterparts. Their method is described in more detail in subsection 4.2.2. In addition, they expanded the qualitative narratives of the SSPs to the coastal zone and assumed scenario-specific modifications of the observed growth differences that are based on the narratives. Both studies, Jones and O’Neill (2016) and Merkens et al. (2016), are consistent with the population projections (KC and Lutz 2017) and urbanisation projections (Jiang and O’Neill 2017) on national level that are used in the SSP framework (O’Neill et al. 2017).

In this study we assess the sensitivity of outcomes in coastal exposure analysis to inclusion of subnational heterogeneity in population projections. We compare (i) homogeneous population change on national level (hereinafter referred to as the basic approach) to (ii) the population projections of Merkens et al. (2016) that also account for urbanisation and coastal migration are have been specifically developed for coastal exposure analysis (hereinafter referred to as the coastal approach) and to (iii) the downscaled spatial projections of Jones and O’Neill (2016) by (Gao 2017) that account for urbanisation and urban sprawl (referred to as dynamic approach)). We further analyse (iv) the extent to which urbanisation can explain the differences in exposure between the basic and coastal approach (referred to as urban approach) (see Figure 4.1).

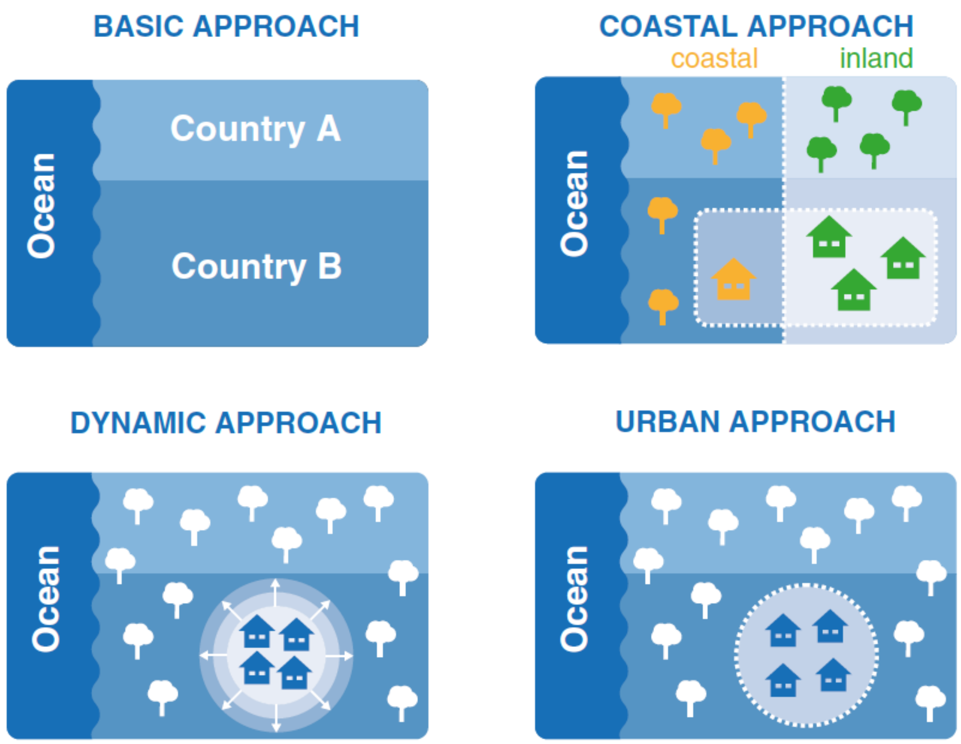

Figure 4.1: Regionalisation approaches. The basic approach assumes homogeneous population dynamics within a country. The coastal approach differentiates population dynamics between coastal urban, coastal rural, inland urban and inland rural areas. The dynamic approach uses dynamic urban extents to account for urban sprawl. The urban approach differentiates urban and rural population dynamics with static urban extents

4.2 Data and Methods

4.2.1 DIVA database

For our analysis, we employ the Dynamic Interactive Vulnerability Assessment (DIVA) modelling framework, which has been used in a wide range of applications in coastal risk assessments (see Hinkel et al. 2013 for erosion, Hinkel et al. 2010 and Hinkel et al. 2014 for adaptation, Hinkel et al. 2012 for adaptation and mitigation, Spencer et al. 2016 for wetlands). The results presented in this study are based on version 30 of the DIVA database and model version 1.7.

The DIVA database breaks the world's coasts (excluding Antarctica) into 12,148 segments. Each coastal segment provides information on administrative, bio-physical and socio-ecological attributes. In the context of this study, we focus on the population living in the 1 in 100-year floodplain, which is a well-established measure of coastal exposure analysis (e.g. Hanson et al. 2011; Vousdoukas et al. 2016; Muis et al. 2017). The 1 in 100-year coastal flood heights are taken from Muis et al. (2016). We use the DIVA flood module to calculate the number of people living in the floodplain without considering dikes. A detailed description of this approach can be found in Hinkel et al. (2014). As we account for isostatic adjustment and subsidence (see subsection 4.2.3), DIVA provides relative sea-level for all segments.

To define the floodplain, we use a global elevation dataset which is based on SRTM (Jarvis et al. 2008) and GTOPO30 (USGS 1996) data for high latitudes (>60° N and >54° S). For all elevation steps from 1 m to 16 m, we calculate the extent of the area that is hydrologically connected to the ocean and smaller or equal to the respective elevation threshold (see Poulter and Halpin 2008). Intermediate values are linearly interpolated (Hinkel et al. 2014). We utilise the GRUMPv1 grid (CIESIN et al. 2011a) to analyse the population located in each of these elevation increments for the year 2000. The coastal SSPs of Merkens et al. (2016) use the GRUMP urban extent grid, which uses census population counts, settlement points and night-time lights, to define urban areas (CIESIN et al. 2011b) and assume these to be static. GRUMP tends to underestimate the extent of settlements with none or little light at night, e.g. in parts of Africa (Balk et al. 2006), which also affects the estimates on exposed population. The estimates on exposed population also depend on the elevation model used for the analysis. Lichter et al. (2011) analysed the land area of the LECZ derived from three different elevation datasets with the same vertical and horizontal resolution of 1 m and 0.5 arc-minutes (~1 km at the equator). On a continental scale, they found differences of up to 40 %. In the same study, Lichter et al. (2011) compared two commonly used population datasets (GRUMP alpha and LandScan 2006) and analysed the population located in the LECZ. On a global scale, the LECZ population differed by ~10 %, on a continental scale by up to 28 %. They stated the combined uncertainty of elevation and population data at 20 % on a global scale and at up to 67 % on a continental scale. Mondal and Tatem (2012) compared the LECZ population for GRUMP version 1 (the same version that was used in this study) and LandScan 2008 and found differences of 4 % on a global scale and of up to 39 % on a continental scale. GRUMP's underlying assumption of homogeneous population distribution within urban and rural areas in the same administrative unit can in addition lead to an over- or underestimation of the 'true' exposure (Merkens and Vafeidis 2018). As this study uses the same population and elevation datasets throughout the analysis, we expect the relative differences between the approaches to be independent from the elevation or population data, whereas the absolute numbers are likely to be different if other population or elevation data are used.

4.2.2 Socioeconomic scenarios

We initially calculate exposure of population based on two approaches to account for future population development in coastal areas (see Figure 4.1). In the basic approach, we use national population projections taken from KC and Lutz (2017) and apply these to the baseline (i.e., year 2000) spatial population data. This approach assumes homogeneous growth rates within each country, i.e. population in coastal areas grows at the same rate than in inland areas. In the coastal approach, we use the coastal SSPs of Merkens et al. (2016). These are based on the national population projections of KC and Lutz (2017) as well, but consider urbanisation projections (Jiang and O'Neill 2017), historical growth differences and scenario-dependent modifications of growth differences. For each country, Merkens et al. (2016) analysed the population growth for coastal urban (rural) areas and inland urban (rural) areas over a 10-year period from 1990 to 2000. If coastal areas had a higher population growth rate than inland areas, the growth difference (GD) was positive and vice versa. The GD allows for negative (positive) population growth in the coast or inland even if national population growth is positive (negative). It also allows for higher population change rates in coastal areas compared to inland areas. For SSP2 Merkens et al. (2016) assumed the GD to keep constant over time for each location. For the other four SSPs they modified the GDs based on the interpretation of the coastal SSP narratives, which are introduced in the same study. They quantified the modification of the GDs based on the difference between percentiles in the distribution of the observed urban and rural GDs for all coastal countries. In SSP1 they assume no differences in growth for coastal and inland urban areas and a reduced rural GD (translates to relatively higher rural growth in inland). In SSP3 they assume that the GD to reduce by 50 % for both, urban and rural areas. In SSP4 and SSP5 they increased the GD (translates to relatively higher relative growth at the coast), whereby the increase was bigger in SSP5. Based on the scenario specific GDs and the population and urbanisation projections they calculated population counts for coastal urban, costal rural, inland urban and inland rural for each country in 5 year increments until 2100. This leads to heterogeneous growth rates within countries because urban areas develop differently to rural areas and coastal areas differently to inland areas. We then calculate the mean coastal population growth rate for each country and apply it on each coastline segment of this country. We must note that the definitions of 'urban' between GRUMP (used in Merkens et al. (2016) and Gao (2017)) and Jiang and O'Neill (2017) differ, which results in an offset in the data for the years 2005 and 2010 (see subsection 4.4 for a discussion of the implications on exposure analysis).

4.2.3 Sea-level rise scenarios

We use the projected changes in global mean sea level and the likely ranges reported in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Church et al. 2013). For each of the four RCPs, we use the ensemble median as medium SLR scenario. The 83rd percentile serves as high SLR scenario and the 17th percentile as low SLR scenario (see Table 4.1). We do not consider regional patterns of SLR due to ocean dynamics and regionally differential changes in thermal expansion and rotational and gravitational effects of the mass loss of ice sheet. Church et al. (2013) show that these regional effects are below 10 % for most of the populated coastal zone with the exception of the East Coast of the US. Hence the global effects of these regional SLR variations are expected to be much smaller than those of human-induced subsidence in densely populated river deltas, which we consider here together with isostatic adjustment. Furthermore, uncertainties in regional sea level projections are large, with different models producing different patterns and the highest deviations of regional SLR due to dynamic variability coinciding with those regions for which model uncertainties are largest (Church et al. 2013). We assume that water levels during coastal floods increase by the same amount as the projected global sea-level and do not account for non-linear interactions between the water level and SLR (Arns et al. 2017) as the focus of this paper is the comparison of population distribution approaches.

Table 4.1: Sea-level rise projections for 2100 referenced to the 1986-2005 period [in m] [1].

	low	medium	high
RCP2.6	0.28	0.44	0.61
RCP4.5	0.36	0.53	0.71
RCP6.0	0.38	0.55	0.73
RCP8.5	0.53	0.74	0.98

[1] Values are taken from Prather et al. (2013).

In this study, we use the 12 SLR scenarios from Table 4.1 (four RCPs, for each high, medium and low SLR projections). These are combined with the five SSPs. Taking into account the two regionalisation approaches (plus another two for testing our assumption) in each SSP, we end up with 240 model runs. This number could be reduced by ignoring scenario combinations that are not plausible. For example, the combination of an environmentally friendly socioeconomic scenario (SSP1) and a physical scenario with high radiative forcing (RCP8.5) would in general be inconsistent (van Vuuren et al. 2014; Engström et al. 2016). Nevertheless, we decided to analyse all scenario combinations, as this study aims to analyse and understand the effect that regionalisation approaches of socioeconomic scenarios have for impact assessment.

4.3 Results

We compare future coastal exposure to 1 in 100-year coastal floods based on the different regionalisation approaches. We define the absolute difference in exposure as the difference in the tested approach (i.e. coastal, urban or dynamic) minus the exposure in the basic approach. The relative difference is defined as the absolute difference in exposure divided by the exposure in the basic approach.

4.3.1 Global

Our first main finding is that accounting for urbanisation and coastal migration has significant implications for assessing coastal exposure. The exposure based on the coastal approach exceeds the one based on the basic approach in all scenarios over the 21st century (see Figure 4.2). This finding is consistent for all SLR scenarios (see Figure 4.3). For SSP1, 4 and 5 we find the exposure in the basic approach with high SLR in all RCPs to be lower than the respective low SLR variant in the coastal approach. In other words, in these scenarios the difference between the population distribution approaches is larger than the difference between high and low SLR. To investigate which of the two (urbanisation and coastal migration) is the dominant process leading to the difference between basic and coastal approach, we added the ‘urban approach’ to our modelling scheme (see Figure 4.1). The urban approach is based on population and urbanisation projections that are modelled in the same way as in the coastal SSPs, but uses a GD of zero, which means that the population in urban and rural zones for each SSP grows at rates consistent with projections on national level and does not differ between coastal and inland areas. We assume that the difference between the urban approach and the basic approach represents the impact of changing urbanisation levels, without considering urban sprawl. The difference between the urban approach and the coastal approach can result from differences in fertility, mortality, international migration or internal migration, of which we assume internal migration from or to the coast to have the highest impact. We find that, independently of SLR, urbanisation explains 61 % of the difference between the coastal and basic approach in SSP1, 96 % in SSP2, 54 % in SSP3, 76 % in SSP4 and 45 % in SSP5 (see Figure 4.8). This means that SSP5 is the only scenario where urbanisation appears not to be the dominant process. This can be explained by the underlying assumptions of intense coastward migration for SSP5 in the coastal approach (Merkens et al. 2016). In general, the projected increase in urbanisation levels leads to higher population growth rates in the coastal zone compared to inland areas, as coastal areas show a higher density of cities than inland areas, and population is projected to move into these cities. In the basic approach, the population in all areas within a country grows at the same rate, which leads to lower population numbers at the coast compared to the coastal approach. We therefore conclude that the higher exposure in the coastal approach compared to the basic approach is due to a combination of increasing urbanisation levels in all SSPs and migration to coastal areas, of which urbanisation is the dominant process for SSPs 1-4 and coastal migration for SSP5.

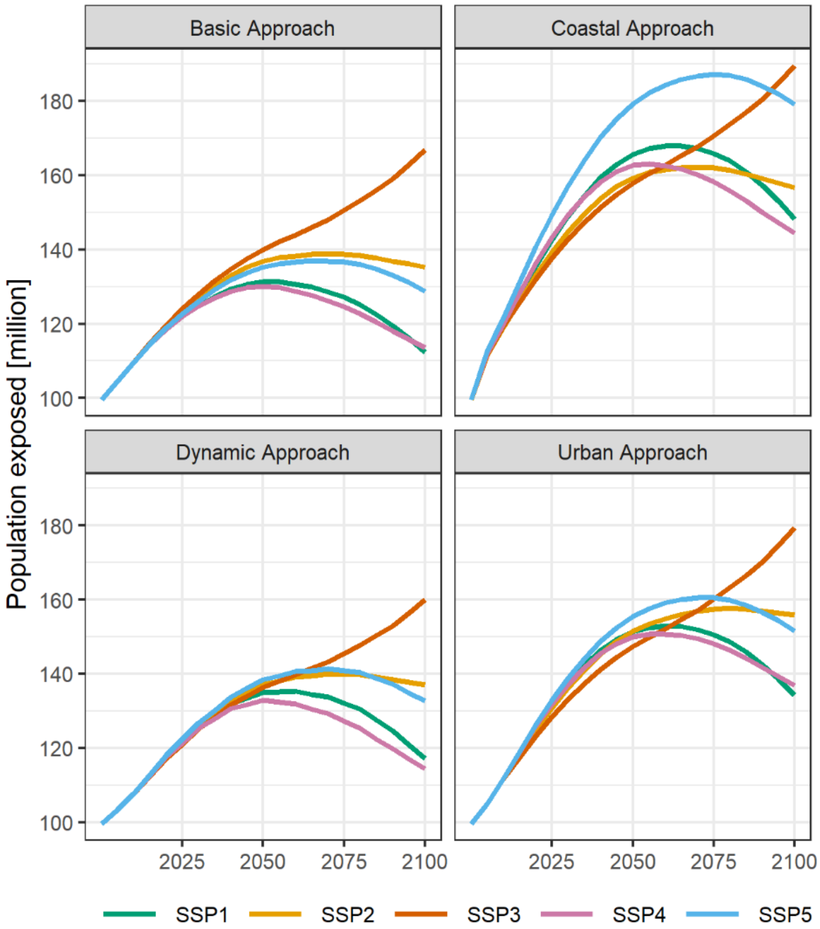

Figure 4.2: Exposure of population to 1 in 100-year coastal floods under medium SLR in RCP6.0 in the tested approaches.

Our second main finding is that the implementation of urban sprawl has a considerable impact on the estimates on exposure. We compare the urban approach to a ‘dynamic approach’, which is based on the population projections of Jones and O’Neill (2016) that were downscaled by Gao (2017). Unlike the urban (and coastal) approach, that assume urban extent to be static, the dynamic approach considers urban sprawl, which leads to wider city extents and lower population densities within cities. We assume that differences between the urban and dynamic approach are mainly due to urban sprawl, as the approaches use the same population projections of KC and Lutz (2017) and the same urbanisation projections of Jiang and O’Neill (2017).

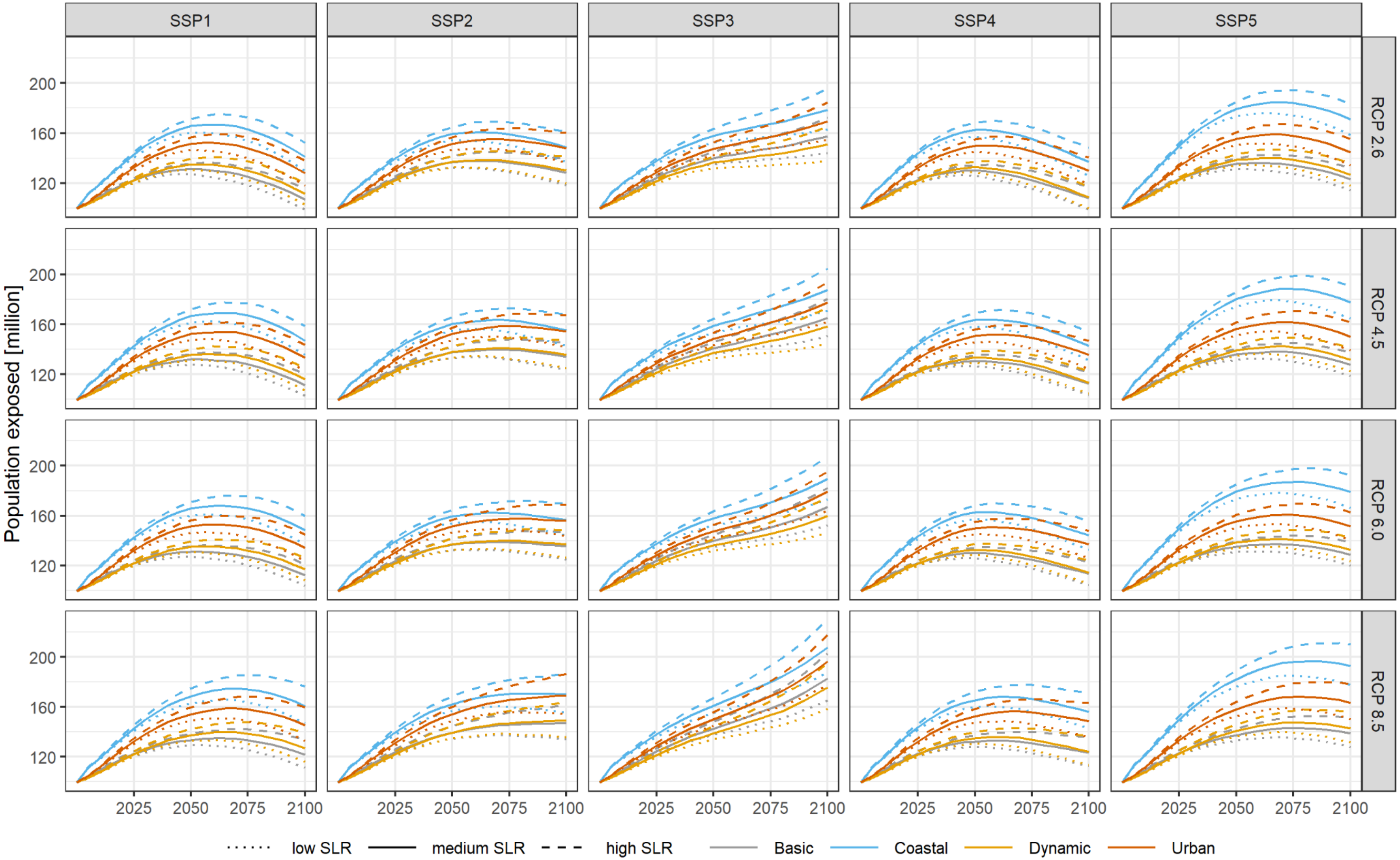

Figure 4.3: Population exposed to 1 in 100-year coastal floods under different regionalisation approaches and SLR projections.

Compared to the dynamic approach, we find exposure to 1 in 100-year coastal floods to be higher in the urban approach for all combinations of SSPs and RCPs (Figure 4.3). They differ between 15 million in SSP1 (RCP 2.6 and low SLR) and 26 million in SSP4 (RCP 8.5 and high SLR). Differences in SSP1 are lowest, as cities in the dynamic approach are assumed to be concentrated (Jones and O'Neill 2016) and urban extents to be static in the urban (and coastal) approach. However, the difference of 15 million in SSP1 is considerable and suggests that the definition of urban areas (and population) between the urban and the dynamic approach differs, as urbanisation levels and total population do not differ and cities are assumed to be concentrated (dynamic approach) or static (urban approach). For SSPs 2-5 differences between the urban approach and dynamic approach are higher, as only the dynamic approach considers urban sprawl. This suggests that urban sprawl can lead to a reduction of exposure as cities seem to expand towards less flood-prone areas. The differences between the basic and the dynamic approach are rather small (Figure 4.2). Global exposure in the dynamic approach under SSP3 for 2100 is up to 7.5 million lower than one in the basic approach. In the other SSPs, exposure based on the dynamic approach exceeds the basic approach by 1 million in SSP4, 2 million in SSP2, 5 million in SSP5 and 6 million in SSP1 (see Figure 4.9). These SSPs are also projected to have a high increase in urbanisation levels, whereas urbanisation levels in SSP3 are projected to increase little (Jiang and O'Neill 2017). This supports our first finding that neglecting urbanisation patterns would lead to an underestimation of coastal exposure. The differences between the dynamic and the coastal approach are larger than the differences between the dynamic and the urban approach (between 17 million is SSP2 under RCP 2.6 with low SLR and 54 million in SSP5 under RCP 8.5 and high SLR), as coastal migration is additionally considered in the coastal approach. Overall, we believe that the coastal approach overestimates exposure, as it does not consider urban sprawl, which appears to reduce exposure; and that the dynamic approach underestimates exposure, as it does not explicitly consider coastal migration, which appears to increase exposure to coastal flooding. We must note that this study does not aim to test the underlying quantifications on coastal migration in Merkens et al. (2016) and the quantification of urban sprawl in Jones and O'Neill (2016), but rather to investigate the implications for coastal exposure analysis when accounting or neglecting of processes actually taking place in coastal areas.

We also find that the population distribution approach is important in determining which SSP leads to the highest exposure to coastal flooding. Though all approaches agree on SSP3 having the highest exposure in 2100, only the basic approach shows SSP3 to lead to the highest exposure throughout the century. The other approaches agree on SSP5 leading to the highest exposure until 2060 (dynamic approach), 2075 (urban approach) and 2090 (coastal approach) (see Figure 4.2). This holds true for all SLR scenarios. This is noteworthy as SSP5 and SSP1 are projected to have considerably lower total populations than the other SSPs (KC and Lutz 2017). We identify two factors leading to this observation. The behaviour in the basic approach can be explained by the underlying global population projections that project population to be highest in SSP3 (KC and Lutz 2017). The higher exposure in SSP5 in the other approaches is due to high urbanisation levels (Jiang and O'Neill 2017). Exposure rises in the coastal approach as coastal areas are assumed to be more attractive than inland areas and decreases in the dynamic approach as high urban sprawl leads to cities expanding to flood proof areas.

Results also show that the absolute difference in exposed population between the basic and the other approaches increases with SLR (see Figure 4.9). We find the highest differences under the high SLR projections in RCP8.5 and the smallest differences under the low SLR projections in RCP2.6. Compared to the basic approach, SSP1, SSP4 and SSP5 show the highest difference and SSP2 and SSP3 the lowest. Different to the urban and the coastal approach, the dynamic approach shows a reduced exposure for SSP3 and a higher difference for SSP2 than for SSP4 for 2090 to 2100, when the basic approach is used as reference. Again, this observation highlights the significance of urbanisation, coastal migration and urban sprawl. As cities are concentrated in coastal areas, the overall population growth in coastal areas is higher than the national average (represented by the basic approach).

Figure 4.4 illustrates the relevance of using socioeconomic scenarios in coastal impact assessments. It shows the share of population exposed to flooding for all SSPs based on the four tested approaches and additionally for a scenario where population remains constant at the year 2000 levels. In this scenario, the share of population exposed to 1 in 100-year coastal floods under medium SLR in RCP 6.0 increases steadily from ~1.6 % in 2000 to ~2.1 % in 2100. In the basic approach, the share decreases or remains constant until 2040 in all scenarios, although the absolute exposed population increases (compare to Figure 4.2). In 2100 the share of population exposed ranges from ~1.2 % in SSP4 to 1.7 % in SSP5. In the coastal approach, the share of exposed population does increase only in SSP1 and SSP5 continuously until 2100 and exceeds the constant scenario. The other SSPs remain at their year 2000 level or decrease. The share of population exposed ranges from 1.5 % in SSP3 to 2.4 % in SSP5. The general patterns of the dynamic approach follow the ones described for the basic approach but the share of exposed population is ~0.05 % higher. The general patterns of the urban approach follow the ones described for the coastal approach but are considerable lower for SSPs 1 and 5.Although the population is not changing in the constant scenario at all, the SLR-related increase of the floodplain leads to an increase in exposure to 1 in 100-year coastal floods.

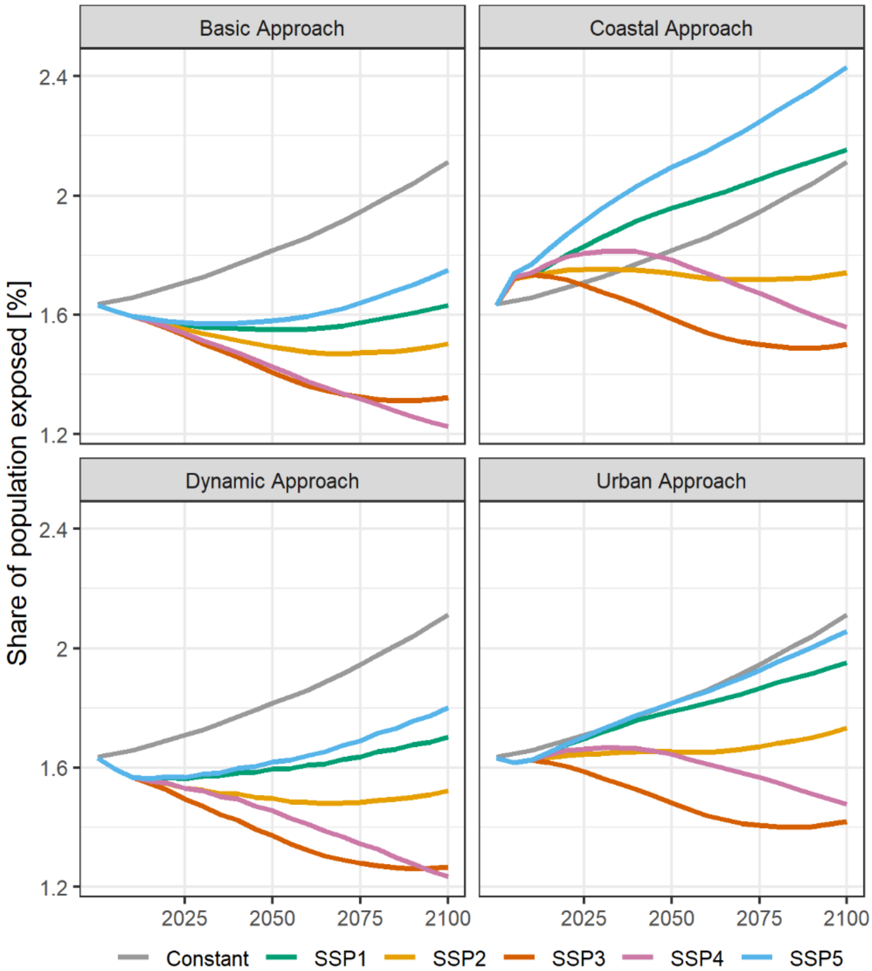

Figure 4.4: Percentage of global population exposed to 1 in 100-year coastal floods for medium SLR projections in RCP 6.0. Constant represents the year 2000 baseline population.

4.3.2 Regional

In this subsection, we focus on the comparison between the basic and the coastal approach, as the coastal approach explicitly considers coastal migration. Exposure under all approaches are shown in Figure 4.5 and the absolute difference to the basic approach in Figure 4.10.

Different to the global patterns, Europe, Northern America and Oceania face the highest exposure under SSP5 for both coastal and basic SSPs. Exposure increases continuously until 2100 under this SSP. For Africa and Latin America and the Caribbean (LAatC), SSP3 shows the highest exposure throughout the century, which also increases continuously with time. This is in line with the underlying national projections of KC and Lutz (2017) that project highest population under SSP5 for the most developed countries and under SSP3 for developing countries. For Asia, we find a notable difference between the coastal and basic approach. In the basic approach, exposure is highest under SSP3 throughout the 21st century. In the coastal approach, exposure is highest under SSP5 until 2075 and under SSP3 afterwards. Asia's high exposure under SSP5 in the coastal approach reflects the high increase of urbanisation levels in the underlying urbanisation projections (Jiang and O'Neill 2017) and the coastward migration in the coastal SSPs. The decrease in Asia's exposure projected after 2050 is due to the decreasing population after 2050 in the underlying population projections (KC and Lutz 2017). This also can also be seen in the basic approach and holds true for all SSPs except SSP3, where the Asia's population is projected to grow after 2050.

The absolute difference in exposure to 1 in 100-year coastal floods on a continental scale follows global patterns and becomes larger with SLR in all SSPs (see Figure 4.10). Accordingly, we find the highest differences in RCP8.5 with high SLR and the smallest differences in RCP2.6 with low SLR. The difference between the coastal and basic approach is highest in SSP5 in all continents except Africa, where SSP4 shows the highest differences. We observe the lowest differences in SSP1 for Africa, LAatC, Northern America and Oceania. For Europe and Asia, we find the lowest differences between the coastal and basic approach in SSP3.

The relative difference in exposed population is heterogeneous and does not follow the global patterns. For Africa, which shows overall the highest values, we find the relative difference to decrease with rising sea levels (see Table 4.2). The highest difference in exposure is in SSP4 (coastal approach is up to 64 % higher than the basic approach) and lowest in SSP2 and SSP3 (coastal approach 24 % higher than basic approach). For Asia, we find the highest relative differences between coastal and basic approach in SSP5 (48 %) and the lowest in SSP3 (~12 %). For Europe, which shows overall the closest agreement between coastal and basic approach, the relative difference in exposure increases slightly with SLR. SSP5 exhibits the highest relative difference in exposure (~20 %) and SSP3 the lowest (<1 %). For Northern America, the relative difference in exposure increases with SLR in SSP1 and decreases in SSP2-5 while the opposite is the case in Asia. For LAatC and Oceania we do not find a relation between SLR and relative difference in exposure based on the basic and coastal SSPs.

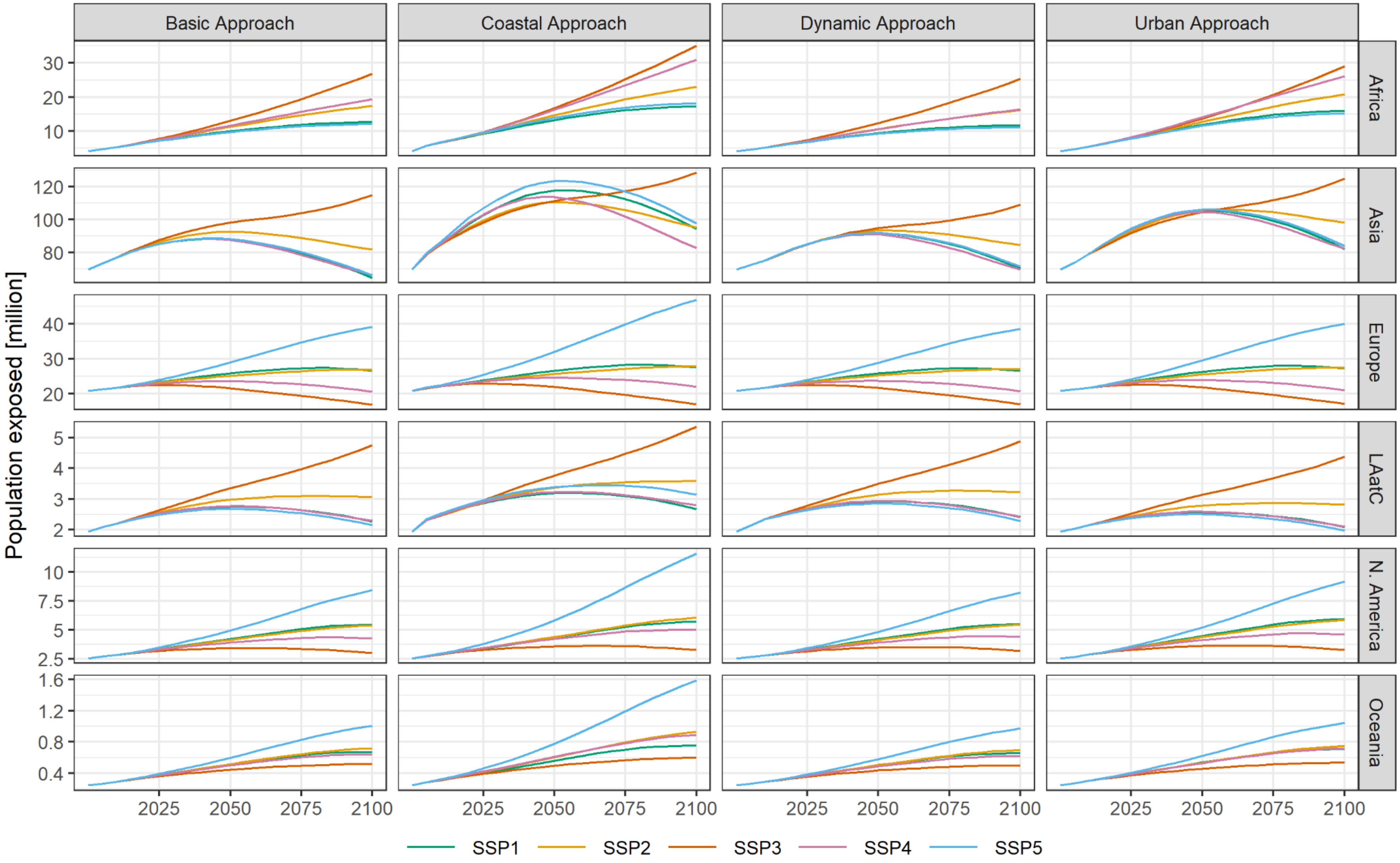

Figure 4.5: Population exposed to 1 in 100-year coastal floods per continent based on different regionalisation approaches under medium SLR in RCP 6.0

Table 4.2: Relative difference in population exposed to 1 in 100-year coastal floods in 2100 between coastal and basic approach per continent [in %].

		RCP 2.6			RCP 4.5			RCP 6.0			RCP 8.5		
	SLR	low	med	hig	low	med	hig	low	med	hig	low	med	hig
Africa	SSP1	40.7	38.3	36.1	39.5	37.2	34.8	39.2	36.9	34.6	37.2	34.4	32.0
	SSP2	35.4	33.2	30.5	34.4	32.0	28.6	34.0	31.7	28.2	32.0	28.0	24.3
	SSP3	31.0	30.6	30.1	30.8	30.4	29.6	30.8	30.4	29.5	30.4	29.4	28.4
	SSP4	64.3	61.9	58.7	63.2	60.6	56.0	62.9	60.2	55.5	60.6	55.2	49.8
	SSP5	57.5	54.1	50.2	55.9	52.3	47.4	55.4	51.8	46.9	52.3	46.7	41.4
Asia	SSP1	45.7	45.7	45.7	45.7	45.7	45.6	45.7	45.7	45.6	45.7	45.6	45.5
	SSP2	16.6	16.7	16.8	16.6	16.7	16.8	16.6	16.7	16.8	16.7	16.8	17.0
	SSP3	11.8	11.8	11.8	11.8	11.8	11.8	11.8	11.8	11.8	11.8	11.8	11.9
	SSP4	24.4	24.5	24.7	24.5	24.6	24.8	24.5	24.6	24.8	24.6	24.8	25.0
	SSP5	47.7	47.7	47.8	47.7	47.8	47.9	47.7	47.8	47.9	47.8	47.9	48.0
Europe	SSP1	3.6	3.7	3.7	3.6	3.7	3.8	3.6	3.7	3.8	3.7	3.8	3.8
	SSP2	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.3	3.4
	SSP3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.5	0.5
	SSP4	7.0	7.0	7.0	7.0	7.0	7.1	7.0	7.0	7.1	7.0	7.1	7.2
	SSP5	19.8	19.9	20.1	19.8	20.0	20.2	19.9	20.0	20.2	20.0	20.2	20.4
Latin America and the Caribbean	SSP1	18.3	18.0	17.7	18.1	17.9	17.6	18.1	17.8	17.6	17.9	17.5	17.2
	SSP2	16.3	16.8	17.1	16.6	17.0	17.2	16.6	17.1	17.2	17.0	17.1	16.6
	SSP3	12.7	12.8	12.8	12.7	12.8	12.7	12.7	12.8	12.7	12.8	12.7	12.2
	SSP4	21.4	21.8	22.1	21.6	22.0	22.1	21.7	22.0	22.0	22.0	22.0	21.3
	SSP5	45.0	45.5	45.9	45.3	45.8	46.0	45.3	45.8	45.9	45.8	45.9	45.2
Northern America	SSP1	4.3	4.3	4.4	4.3	4.4	4.4	4.3	4.4	4.4	4.4	4.4	4.5
	SSP2	12.9	12.6	12.4	12.7	12.5	12.3	12.7	12.5	12.3	12.5	12.3	12.0
	SSP3	8.3	8.3	8.2	8.3	8.2	8.2	8.3	8.2	8.1	8.2	8.1	8.0
	SSP4	17.2	16.9	16.7	17.0	16.8	16.6	17.0	16.8	16.6	16.8	16.5	16.2
	SSP5	37.9	37.6	37.3	37.7	37.5	37.2	37.6	37.4	37.1	37.5	37.1	36.8
Oceania	SSP1	11.3	11.4	11.6	11.3	11.5	11.6	11.4	11.5	11.6	11.5	11.6	11.4
	SSP2	28.2	28.2	28.2	28.3	28.3	28.2	28.3	28.3	28.2	28.3	28.2	28.2
	SSP3	13.6	13.7	13.7	13.7	13.7	13.8	13.7	13.7	13.8	13.7	13.8	13.9
	SSP4	39.0	39.1	39.0	39.1	39.1	39.0	39.1	39.1	39.0	39.1	39.0	38.7
	SSP5	57.0	57.0	57.0	57.0	57.0	56.9	57.0	57.0	56.9	57.0	56.9	56.8

4.3.3 National

Urbanisation projections, costal migration and data inconsistencies have a considerable influence on exposure. To demonstrate this, we analyse the difference in exposure between approaches on national level for the United States of America, India, China and Cote d'Ivoire. The differences in these four countries result from distinct patterns across three continents.

For the United States of America the difference between the approaches in SSPs 1-4 is < 350,000 (6.5% relative difference) (see Figure 4.6 for absolute numbers on exposure and Figure 4.11 for differences to the basic approach). In SSP5 the absolute difference between the approaches is up to 2 million, which translates into a relative difference of 25%. These high differences in SSP5 result from the assumption in the coastal approach of coastal areas being more attractive than inland areas thus attracting more population (Merkens et al. 2016). The good agreement in exposure between the approaches for the other SSPs results from a high urbanisation level of 80% in the base year (UN 2015) and a low urbanisation gain of 17% until 2100 in all SSPs (Jiang and O'Neill 2017), which also leads to relatively small urban sprawl (difference between dynamic and urban approach).

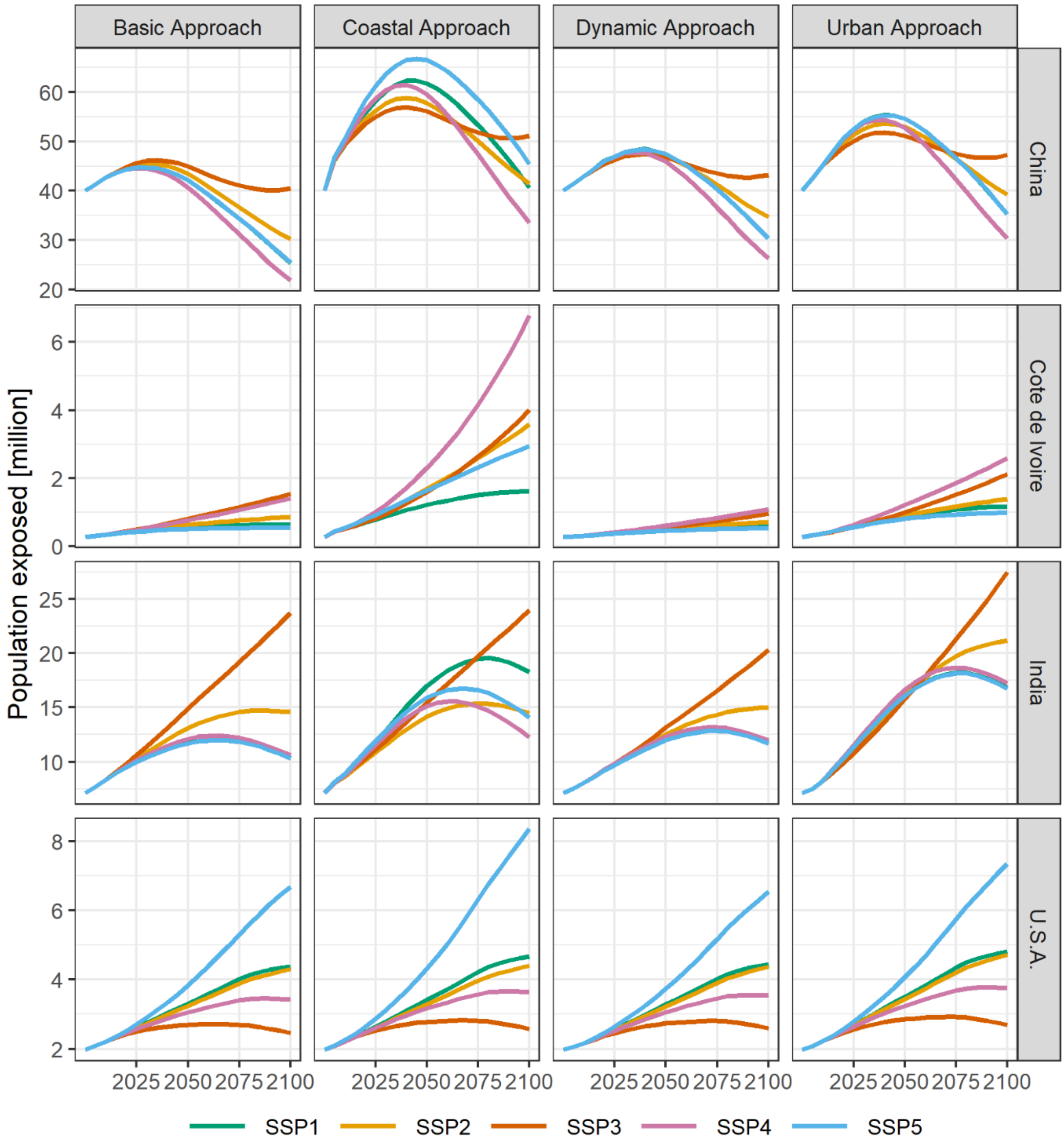

Figure 4.6: National population exposed to 1 in 100-year coastal floods based on different regionalisation approaches under medium SLR in RCP 6.0.

For India, exposure in 2100 is projected to be highest under SSP3 for all approaches with ~20 to 27 million people. Different to the United States of America, we find the urban approach leading to higher estimates in exposure than the coastal approach. This is due to a negative observed GD, which means that for India coastal areas were less attractive than inland areas. In the coastal approach, this observation is assumed to persist. The high difference between the urban and the dynamic approach illustrate that urban sprawl leads to a considerable reduction of exposure compared to the assumption of static urban extents. As both, urban sprawl and migration to the inland lead to a reduction of exposure; we expect all regionalised approaches to overestimate exposure, whereas we assume that the dynamic approach leads to the best estimates in this case.

The opposite applies to Cote d'Ivoire. The exposure in 2100 based on the coastal approach is up to 5.5 time higher than based on the other approaches. We find the highest absolute differences in SSP4 (~5 million). This is partly due to the high gain in urbanisation level (increase from 43% in 2000 to 94% in 2100) and a high projected increase of population from 16.5 million in 2000 to 53 million in 2100 (Jiang and O'Neill 2017; UN 2015). We suspect a high positive observed GD to be the major driver of the considerably higher exposure in the coastal approach (high difference between coastal and urban approach), which is maintained for SSPs 2-5. In SSP1 the urban GD for coastal and inland areas is set to zero, which implies no differences in growth rates for cities and leads to the lowest difference to the other approaches. We consider that in the coastal approach overestimates the exposed population for Cote d'Ivoire. Although other studies project the population of Abidjan (a coastal city) to grow by 4.7 times between 2010 and 2100 (Hoornweg and Pope 2016), the comparison between the dynamic and the urban suggests, that the city will extent to less flood prone areas.

For China, we find the highest differences between the coastal and basic approach in 2100 with ~25 million (up to 80% relative difference) under SSP5. This is due to an increase in urbanisation level (35% in the base year to 94% in 2100) and, as already discussed for the United States of America, the assumption of a high attractiveness of coastal areas in the coastal approach. The difference between the urban and dynamic approach of ~8 million suggests that cities expand to less flood prone areas, what leads to a considerable reduction of exposure compared to static urban extents. The difference of ~5 million in exposure for 2005 is due to inconsistencies in the UN (2015) and CIESIN et al. (2011b) data used to determine base year urbanisation in the coastal SSPs. However, even if the absolute differences in exposure for years later than 2010 were reduced by 5 million, the differences between the coastal and the other approaches would still be notable.

4.4 Discussion

One of our key findings is that under all scenarios the coastal approach projects higher population located in the floodplain of 1 in 100-year coastal floods than the basic approach. In agreement with previous studies that identified urbanisation as a key component in coastal population development, we explain most of the differences with the projected growing urbanisation levels in the coastal approach (see Figure 4.7 and Figure 4.8). Coastal areas today show a higher concentration of cities than inland areas. Kummu et al. (2016) show that 105 out of 256 cities with a population of more than 1 million are located in the near coast zone (proximity to coast < 100 km and altitude < 100 m). According to Brown et al. (2013), in 2010 20 out of 31 megacities (cities with more than 8 million inhabitants) were located in the low-elevation coastal zone (LECZ; altitude ≤ 10 m and hydrological connection to the ocean). Neumann et al. (2015) assume that the number of megacities in the LECZ will increase to 25 until 2025. Hoornweg and Pope (2016) project the population development of the 101 largest cities under three SSPs. They show that the percentage of population living in these cities will increase from 11 % in 2010 to 15 % in SSP3, 20 % in SSP2 and 23 % in SSP1 until 2100. As the coastal approach accounts for urbanisation (Merkens et al. 2016) and the basic approach does not, coastal population tends to be underestimated in the basic approach.

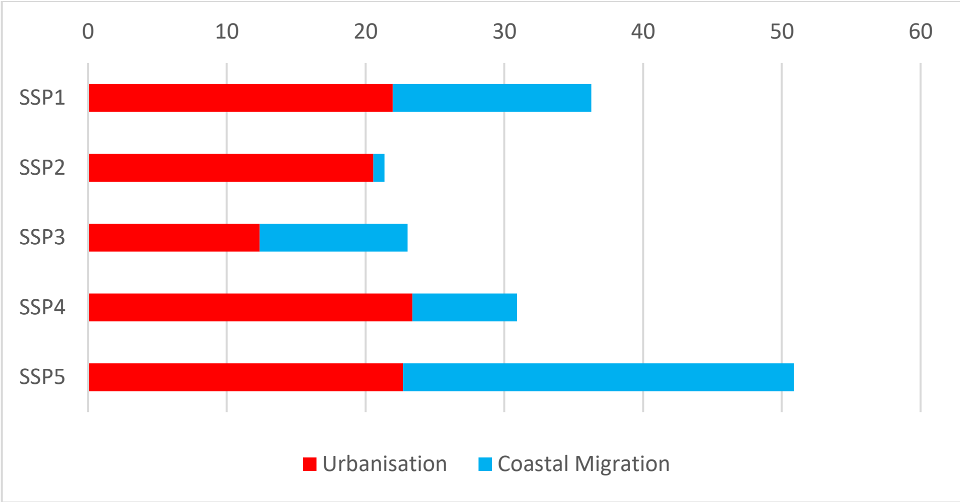

Figure 4.7: Components of the absolute difference between the coastal and basic approach in population exposed to 1 in 100-year coastal floods under medium SLR in RCP 6.0 (in million).

The basic approach shows similar results to the study of Jongman et al. (2012) that also used a homogeneous population growth approach on national level. They found an increase in population exposure to 1 in 100-year coastal floods between 2010 and 2050 of 25 % on a global scale. In the basic approach, we find an increase of population's exposure to 1 in 100-year coastal floods between 19 % in SSP4 and 28 % in SSP3. The exposure based on the coastal approach grows from 2010 to 2050 between 33 % in SSP3 and 50 % in SSP5 and exceeds the projections of Jongman et al. (2012). In agreement with Jongman et al. (2012), both approaches analysed in context of this paper project the highest absolute growth in exposed population until 2050 for Asia and the highest relative growth for Africa. However, the comparison of results to other studies proofs difficult, as the underlying population projections are different. For example, Jongman et al. (2012) used the medium Fertility projection of the 2006 Revision by the UN Population Division while this study is based on the work of KC and Lutz (2017).

The differences in population exposure between the approaches for the years 2005 and 2010 are due to using differing definitions of 'urban' in the underlying data. The urbanisation projections rely on Jiang and O'Neill (2017), which used the world urbanisation prospects (UN 2015) as input data that retains the urban definitions used by each country. Across countries, the definitions are inconsistent. The coastal SSPs of Merkens et al. (2016) used the GRUMP urban extents grid, which tends to underestimate urban extents in developing regions (see subsection 4.2.1). Hence, urban population is concentrated in the remaining settlements with nightlights, leading to higher estimated population counts in these areas. As coastal areas in eastern and northern Africa are heavily populated (Hinkel et al. 2012) and western Africa hosts important port cities with growing population (Hanson et al. 2011), the inconsistencies in data trigger an offset in the initial exposure. In SSP4, which shows the highest relative differences between the coastal and basic approach for Africa, the African population grows more than threefold (KC and Lutz 2017) and the urbanisation level almost doubles until 2100 (Jiang and O'Neill 2017). This leads presumably to an overestimation of exposure in the coastal approach. With SLR, the effects of the initial inconsistencies in the data decrease, leading to a reduction of the relative differences of exposed population.

This study has focused on the differences in exposure that arise from using different approaches to regionalise population projections. We interpret the differences in exposure between the approaches as uncertainty that is related to regionalisation, as the underlying population projections on national level do not differ between the approaches. Other uncertainties arise from elevation data and the base year population datasets used to assess the exposure to 1 in 100-year coastal floods. Elevation and population datasets can potentially be improved if data availability improves and the need for modelling decreases. The uncertainties that arise from the downscaling approach can be reduced to some extent, if the differences between reported urbanisation level and the urbanisation levels based on remote sensing products find a better agreement. Other parts of the uncertainty cannot be removed, as the projections are made for long timeframes and human behaviour cannot be predicted.

4.5 Conclusion

This study compared different approaches to account for population change in coastal impact assessment in order to assess the exposure of population to 1 in 100-year coastal floods under different SLR and socioeconomic scenarios. All approaches were based on the same population projections on national level. We found that urbanisation and coastal migration lead to increased exposure whereas urban sprawl leads to reduced exposure. This emphasises the need for taking into account population dynamics on subnational level in exposure assessments. We believe that the exposure estimates obtained from approaches accounting for regional variations in population distribution, such as urbanisation, coastal migration and urban sprawl, are more reliable than the approaches not accounting for such variations. As coastal areas host a disproportionately large number of cities, sub-national population dynamics are of particular relevance for coastal exposure studies and should not be ignored. With rapidly growing cities in developing countries, the need to provide improved assessments of population exposure to coastal flooding is important for global and national planning, both in terms of allocating human and financial resources on national level and climate change adaptation funding on international level.

Acknowledgments

The authors would like to express their thanks to the editor and the reviewers for their valuable comments. We also would like to thank Maureen Tsakiris for illustrating Figure 4.1.

4.6 Appendix

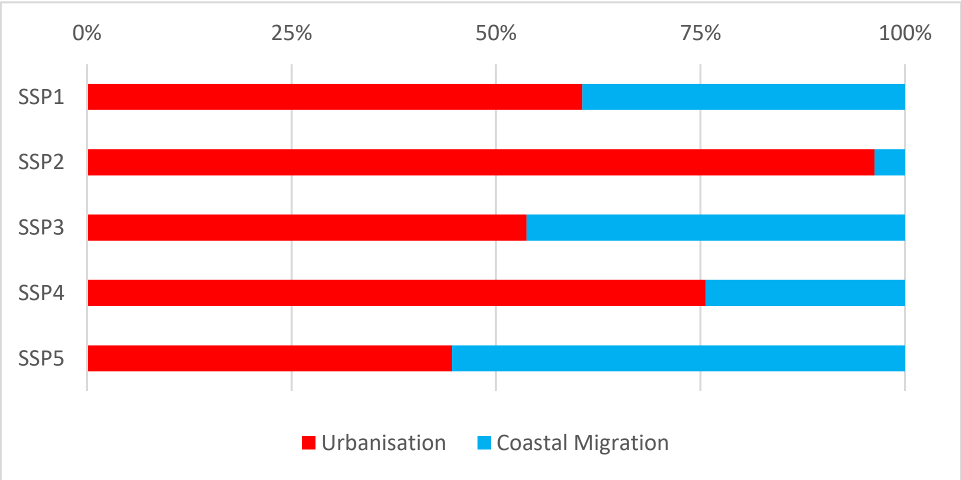

Figure 4.8: Share of urbanisation and coastal migration on the relative difference between the coastal and basic approach in population exposed to 1 in 100-year coastal floods under medium SLR in RCP 6.0.

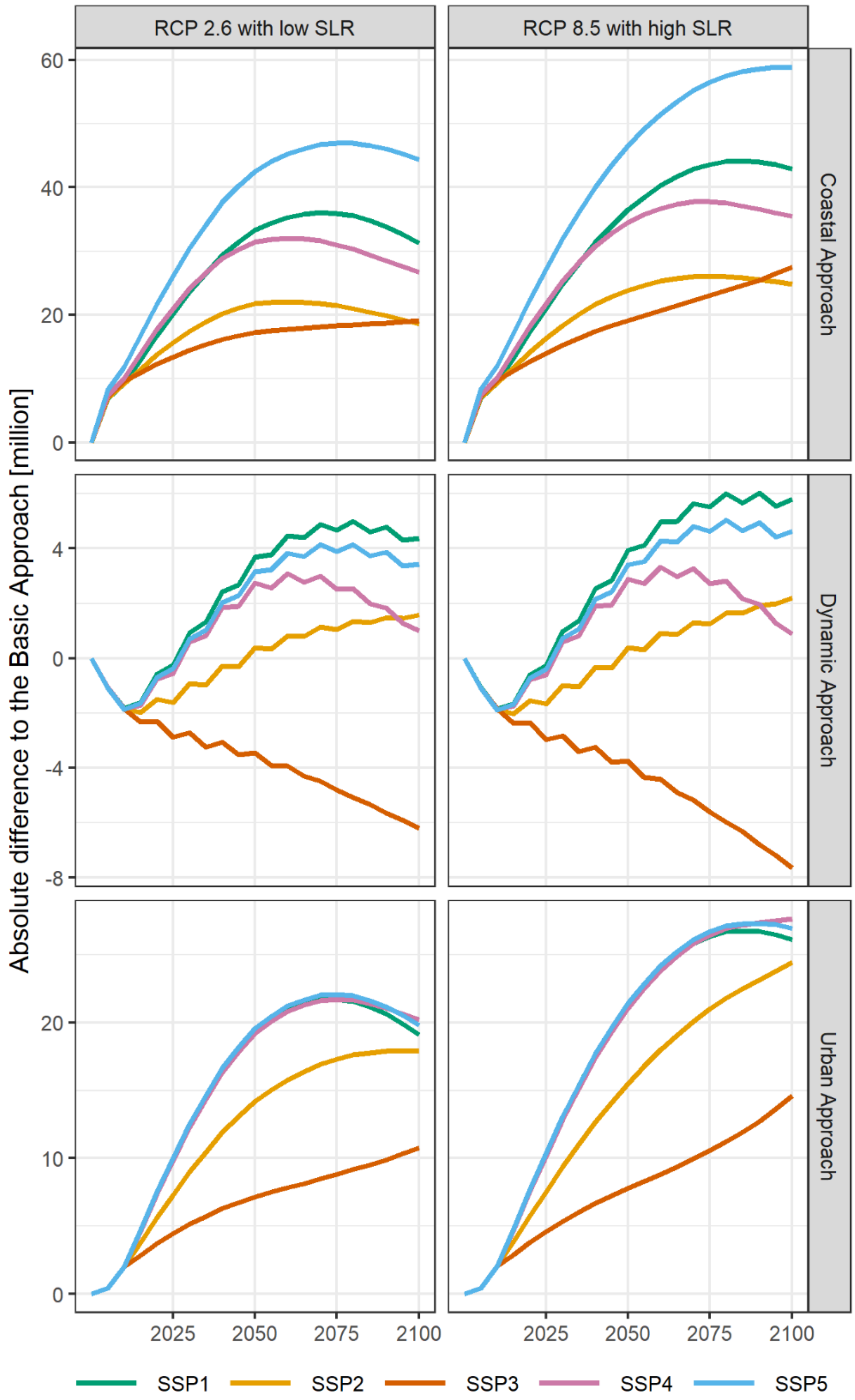

Figure 4.9: Absolute Difference (respective approach minus basic approach) in population exposed to 1 in 100-year coastal floods under the lowest and highest SLR variant (in million). Note the different scales of the y-axis.

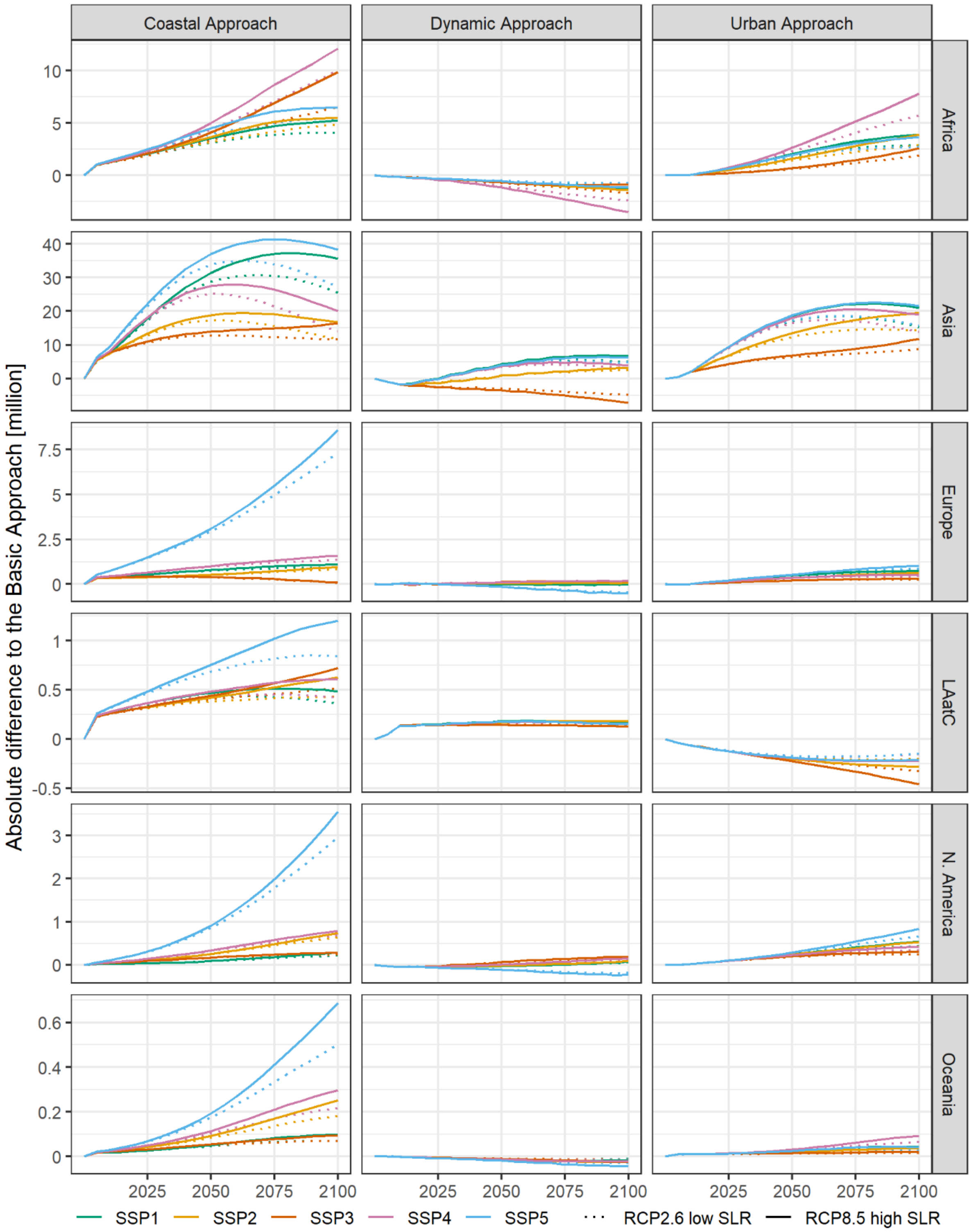

Figure 4.10: Absolute difference (respective approach minus basic approach) in population exposed to 1 in 100-year coastal floods per continent under low and high SLR projections.

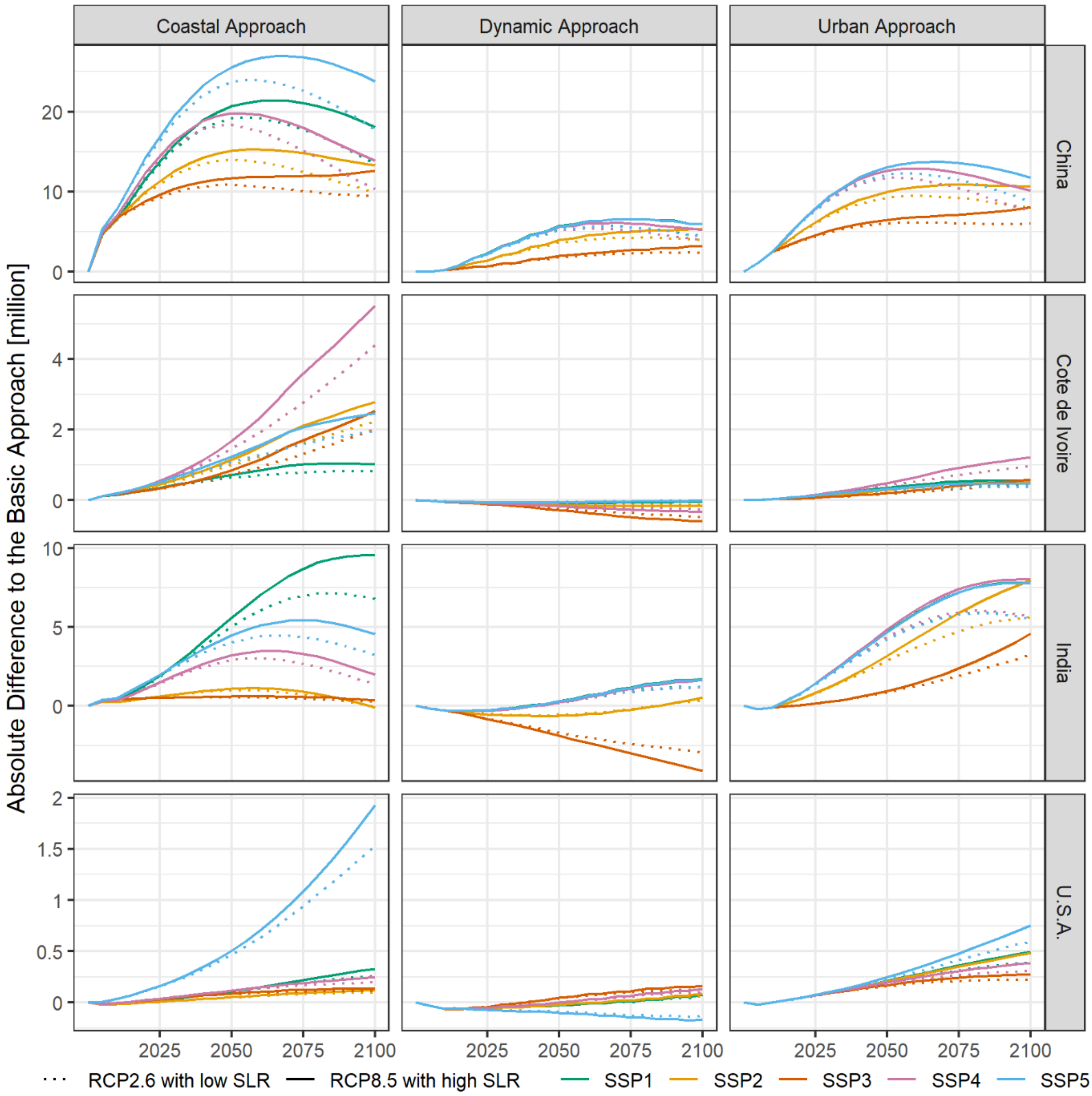

Figure 4.11: Absolute difference (respective approach minus basic approach) in population exposed to 1 in 100-year coastal floods for four countries under low and high SLR projections.

5 Synthesis

The synthesis summarises the findings of chapters 2 to 4 with regard to improving the distribution of current population (subsection 5.1.1) and population growth projections (subsection 5.1.2) for coastal impact and vulnerability assessments. Subsection 5.2 takes up the main findings to answer the research questions of this thesis. Finally, subsection 5.3 points out limitations and discusses approaches to enhance the proposed methods for distributing current and future population.

5.1 Summary and main achievements

5.1.1 Allocation of population within census units

Chapter 2 addresses the limitation of homogeneously distributed population within census units by using satellite derived settlement extents to heterogeneously allocate population within these units. Population per census unit is the most detailed source of information that global population datasets use as input data (Doxsey-Whitfield et al. 2015). As more detailed spatial information is not available, the population is assumed to be homogeneously distributed within a respective census unit. Hence, the size of census units is the determining factor which affects the usability of the population data in exposure analysis. Some countries, e.g. the member states of the European Union, use administrative boundaries to define census units, whereas other countries, such as the United States of America, define census blocks, which are usually smaller than the finest administrative unit (municipalities). The uncertainty of the actual distribution of population increases with the size of census units. Ancillary data can be used to reduce this uncertainty by a) defining areas that cannot be populated (e.g. water bodies) or by b) defining areas that are suitable for human settlement. Unlike other studies that use several ancillary datasets to redistribute population within census units (e.g. Stevens et al. 2015; Dobson et al. 2000), the approaches tested in Chapter 2 are exclusively based on GUF settlement extents. These have spatial resolutions of 0.4 arc-seconds (approximately 12 m at the equator) and 2.8 arc-seconds (approximately 84 m at the equator) and cover the entire globe, which is why the approaches can also be applied in other study areas as well as globally. This work evaluates the usability of the GUF for regionalising population in three ways: (i), by calculating a confusion matrix comparing the presence of settlement extents and population, (ii), by downscaling population information from district level to municipality level and (iii), by assessing the population living in flood prone areas.

First, the confusion matrix compares the actual location of population, which is extracted from a population raster with a spatial resolution of 100 m provided by the German Census, to the settlement extents provided by the GUF. These are aggregated to a spatial resolution of 100 m to match the spatial resolution of the population raster. GUF0.4 captures ~95 % of the population in the study area, overestimates populated areas by ~46 % and fails to capture ~18 % of all populated areas. GUF2.8 captures ~83 % of the population, overestimates populated areas by ~31 % and fails to capture ~44 % of all populated areas. Second, the performance of the regionalisation approaches is tested on municipality level. In a reference approach, the population within districts is homogenously resampled, leading to the same population density in all municipalities located in the respective district. This approach leads to a RTAE of ~0.5 and a %RMSE of ~100 % (see Table 2.3), indicating the limitations of assuming a homogenous population distribution. Employing the GUF in resampling population reduces the error metrics (RTAE ranging from 0.14 to 0.21 and %RMSE ranging from 29 % to 46 %), suggesting that both, GUF0.4 and GUF2.8, lead to a considerable improvement in allocating population within administrative units. Third, the German Census raster is used to validate and quantify the performance of the regionalisation approaches in assessing the exposure of population living in flood prone areas (elevation below 3 m). Again, the reference approach leads to the highest errors and overestimates exposure by 120 % to 140 %. All tested approaches reduce the overestimation of population exposure, ranging from 23 % to 29 %. Furthermore, the comparison between the approaches indicates that GUF2.8 leads to slightly lower errors than GUF0.4.

5.1.2 Regionalisation of population growth projections

Riahi et al. (2017) state sectoral extensions of the SSPs to be one of the critical next steps for the climate change research community. This thesis addresses this call by presenting the coastal SSPs, which extend the SSPs to the coastal zone (see Chapter 3). Based on a literature review, this work identifies factors affecting coastal migration and develops qualitative narratives for five coastal SSPs while ensuring consistency with the global SSPs. Besides the narratives, the coastal SSPs involve the quantification of future coastal population and its regionalisation to a spatially explicit level. This quantitative component of the coastal SSPs utilises existing population and urbanisation projections on a national level. Furthermore, the quantitative component modifies observed population GD between coastal and inland areas based on the interpretation of the qualitative costal SSP narratives. The regionalisation of the population projections is based on the initial distribution of population in the year 2000 and on the derived growth rates for coastal urban, coastal rural, inland urban and inland rural areas for each country and SSP. The spatial resolution of the coastal SSPs (0.5 arc-minutes; ~1 km at the equator) is 15 times finer than the existing spatially explicit population projections of Jones and O’Neill (2016) (7.5 arc-minutes; ~15 km at the equator). Their resolution is suitable for both climate modellers and global scale land use modellers (Riahi et al. 2017). However, the usability in coastal exposure analysis is limited as many floodplains do not expand 15 km inland and are not resolved at a spatial resolution of 7.5 arc-minutes.

This work assesses 637 million people living in the LECZ for the year 2000 (Table 3.3), which is comparable to the findings of previous studies ranging from 557 million to 702 million (Table 1.3). Until 2050, the five coastal SSPs indicate a considerable increase in exposure (Table 3.3), which ranges from 58 % (SSP2) to 71 % (SSP5) compared to the year 2000. Between 2050 and 2100, the LECZ population increases under SSP3 and decreases in the other four SSPs. Its share on the total population between 2000 (10.5 %) and 2100 increases in SSP1 (12.3 %) and SSP5 (12.3 %) and decreases in SSP2 (9.7 %), SSP3 (9.4 %) and SSP4 (9.0 %). In absolute numbers, the LECZ population increases from 637 million (year 2000) to 830 million in SSP4 (lowest 2100 LECZ population) and 1184 million in SSP3 (highest LECZ population). The LECZ population based on the coastal SSPs is 85 million (SSP2) to 239 million (SSP5) higher than based on national average growth rates (Table 3.5).

Exposure based on regionalised population growth in the coastal SSPs provides more plausible estimates than exposure based on national average growth rates. Urbanisation levels have considerably increased since 1950, when 30 % of the population worldwide lived in urban areas. In 2010, more than 50 % of the global population lived in urban areas (UN 2015). This trend is projected to continue und also considered in the urbanisation projections of the SSPs (Jiang and O’Neill 2017). Urbanisation is a highly relevant process in coastal areas, as the density of cities at the coast is much higher compared to inland areas (Kummu et al. 2016). In 2010, 20 out of 31 mega-cities were located in the LECZ (Brown et al. 2013). The population of large cities is expected to increase under the SSPs (Hoornweg and Pope 2016), which will also result in an increase of mega-cities in the LECZ (Brown et al. 2013). National average population growth projections do not represent these urbanisation trends (McGranahan et al. 2007), leading to an underestimation of future population in the LECZ. Furthermore, the coastal SSPs differentiate between coastal and non-coastal areas. The population growth rates at the coast differ from the population growth rates in inland areas in most countries (Figure 3.2). This affects future population if the observed GD hold true under future conditions. For countries in which population in coastal areas grows faster than in inland areas, national average growth rates underestimate future population in the LECZ. In contrast, for countries in which coastal urban or coastal rural population grows more slowly than in inland areas, future population exposure is overestimated. The regionalised population growth projections overcome this limitation, as they differentiate between growth rates for urban and rural as well as coastal and inland population.

Chapter 4 investigates to which extent coastal migration, urbanisation and urban sprawl affect future exposure to coastal flooding by assessing the exposure to 1 in 100-year coastal floods in DIVA. It compares four regionalisation approaches: (i), a basic approach that does not differentiate population growth on national level, (ii), an urban approach that accounts for different population growth in urban and rural areas on a national level, (iii), a dynamic approach that is based on the spatially explicit population projections of Jones and O'Neill (2016) and (iv), a coastal approach that utilises the coastal SSPs (Figure 4.1). The dynamic approach considers changes in urbanisation levels and urban extents whereas the coastal approach includes changes in urbanisation levels and coastal migration. The national population totals across the four approaches do not differ. Differences between the basic and the urban approach result from changes in the urbanisation level being the only difference in the input data. Similarly, differences between the urban approach and the coastal approach are due to coastal migration. Lastly, the difference between the urban approach and the dynamic approach results from urban sprawl.

For the year 2000, this work estimates 100 million people living in areas exposed to 1 in 100-year coastal floods (Figure 4.1). Previous studies assessed considerably higher exposure of up to 190 million for the year 2000 and 290 million for 2010 (Table 1.3). As those studies used different data on population, elevation or ESL, the information value of this comparison is limited. For 2100, the coastal approach shows the highest exposure to coastal flooding under all SSPs, ranging from 145 million under SSP4 to 190 million under SSP3 (Figure 4.2). In SSP3, the dynamic approach shows the smallest exposure (~160 million), whereas the basic approach leads to the smallest exposure for the other four SSPs with a minimum of 112 million people exposed under SSP1. The differences between the basic and the dynamic approach are small, with the basic approach exceeding the dynamic approach by ~7 million under SSP3 and the dynamic approach exceeding the basic approach by not more than 5 million under the other four SSPs. For individual countries, these differences are higher (Figure 4.11). In SSP3, exposure in the urban approach is about 12 million people higher than in the basic approach and between 20 million and 25 million people higher than under the other four SSPs. The coastal approach exceeds exposure based on the urban approach in all SSPs ranging from 1 million under SSP2 to 28 million people under SSP5.

5.2 Answers to research questions

Chapter 2 assesses the usability of settlement extents for allocating population within census units for the German Baltic Sea region. Different to previous studies that developed approaches requiring a large number of input datasets to redistribute population, the presented approaches use solely the GUF settlement extents for redistributing population. This addresses the first research question:

Can satellite derived global settlement extents be used to improve the representation of population living in flood prone areas?

In the German Baltic Sea region, GUF0.4 successfully identifies 95 % of the population and 82 % of inhabited areas, whereas GUF2.8 identifies 83 % of the population and 56 % of populated areas. These numbers suggest that the finer resolved GUF0.4 identifies populated areas with a notably higher accuracy than the coarser resolved GUF2.8. Both, GUF0.4 and GUF2.8, do not differentiate between inhabited and uninhabited buildings, such as industrial plants or barns, leadings to an overestimation of populated areas by 46 % (GUF0.4) and 31 % (GUF2.8). Although GUF does not capture all population or all populated areas in the study area, it considerably improves the redistribution of population within census units. If GUF is used to regionalise population from district to municipality level instead of distributing population homogenously within districts, errors on municipality level are reduced by 50 % to 70 %. This also affects the estimates of population living in areas exposed to coastal flooding. Assuming a homogenous population distribution on district level leads to an overestimation of exposure by 120 %. If GUF is used to regionalise population on a district level, the overestimation is reduced by 23 % to 29 %, with GUF2.8 showing slightly smaller errors than GUF0.4. Assuming homogeneous population distribution on municipality levels overestimates the exposure of population to coastal flooding by 143 %. Employing GUF to redistribute population on municipality levels reduces the error by 40 % to 50 %. All tested approaches that use GUF to allocate population within census units lead to a considerable reduction of errors compared to approaches distributing population homogeneously. In summary, employing satellite derived settlement extents to allocate population both improves the representation of population within census units and reduces the error in assessing the population living in flood prone areas.

Chapter 4 compares different approaches to regionalise population growth projections and utilises the coastal SSPs (Chapter 2) that account for urbanisation and coastal migration and the population projections of Jones and O'Neill (2016) that consider urbanisation and urban sprawl. This addresses the second research question:

How does accounting for coastal migration, urbanisation and urban sprawl affect the estimates of future population exposure to coastal flooding?

Population growth and SLR lead to increasing exposure of population to coastal flooding. Urbanisation and coastal migration intensify this trend. Until 2100 coastal migration leads to increasing exposure in all SSPs, ranging from 1 % (SSP2) to 22 % (SSP5). In the same period of time, urbanisation increases exposure between 7 % (SSP3) and 20 % (SSP1, SSP4 and SSP5). This is consistent with the urbanisation projections of the SSPs that project the highest urbanisation levels for SSP1, SSP4 and SSP5 (>90 %), followed by SSP2 (~80 %) and SSP3 (~55 %) (Jiang and O'Neill 2017). Compared to coastal migration, urbanisation is the dominant process for SSPs 1-4, whereas coastal migration is the dominant process in SSP5. In contrast, urban sprawl leads to a reduction of exposed population to coastal flooding ranging from 12 % (SSP3) to 20 % (SSP4). The net effect of urbanisation and urban sprawl (without coastal migration) leads to a reduction of exposure under SSP3 and to an increase of exposure under the other four SSPs. The number of coastal cities in relation to inland cities, the magnitude of the projected increase in urbanisation levels and the observed GD between coastal and inland areas can lead to deviations compared to these global findings on a national level. To summarise, accounting for urbanisation, and coastal migration leads to higher estimates of population exposure to coastal flooding compared to national average growth rates, whereas considering urban sprawl leads to lower estimates of population exposure.

5.3 Conclusions and future challenges

This thesis demonstrates that considering heterogeneity in the spatial distribution of population improves the estimates of exposure to coastal flooding. Within census units, spatial information of settlement extents can be used to create a more heterogeneous distribution of population, which reduces the error in assessing the number of people currently living in flood prone areas. For assessing future exposure of population, the developed coastal SSPs provide more plausible estimates than non-regionalised population projections, as they account for urbanisation and coastal migration.

The projection method developed for the quantitative component of the coastal SSPs is flexible and can be applied on updated base year population data or utilise updated population or urbanisation projections. Reimann et al. (2018) adopt the method and develop regionalised coastal SSPs for the Mediterranean. They use GPW v4 as base year population (2010) and define coastal areas by combining the LECZ with a 20 km coastal buffer.

However, some components of the coastal SSPs show limitations and need to be enhanced. First, the observed GD that differentiate population growth between coastal and inland areas are derived from a relatively short period of 10 years (1990 to 2000) compared to the 100-year period they predict. Shocks in the observation period, such as wars, diseases or economic crises, can lead to a bias in the observed GD for individual countries. A longer and more recent observation period would be more robust and allow to account for trends on national and subnational level instead of using static GD. Furthermore, the observed GD are modified based on expert judgement (Table 3.2), which would also benefit from more comprehensive baseline data.

Second, the heterogeneous definition of ‘urban’ across countries but also across datasets is a data related limitation. Among others, national statistical offices use administrative or economic criteria, the presence of infrastructure or minimum population thresholds to define urban population (UN 2015). The minimum population threshold across countries varies considerably and ranges from 200 to 50,000 inhabitants (UN 2015). The urban mask of GRUMP defines urban areas based on population counts, settlement points and night-time lights (CIESIN et al. 2011b). For regions with limited coverage or access to electricity, this can lead to a mismatch between reported and modelled urban population (Balk et al. 2006). This limitation is difficult to resolve, unless the UN introduces a clear definition of urban population that has to be adopted by all countries.

Third, Chapter 4 shows that urban sprawl is a relevant process in coastal areas, which is not considered in the coastal SSPs. This limitation can be addressed by combining the coastal SSPs with the work of Jones and O’Neill (2016), who propose a gravity-based approach to distribute population based on the distance to existing urban areas and current population densities. This combination could lead to more plausible estimates of future exposure to coastal flooding as the processes of urbanisation, urban sprawl and coastal migration would be included.

Fourth, the assessed population of the LECZ in Chapter 2 and the population in the 1 in 100-year floodplain in Chapter 4 are based on the assumption of homogeneous population distribution within census units. A homogeneous distribution of population can lead to an over- or underestimation of exposure as demonstrated in Chapter 2. This limitation applies to all global studies using GRUMP or GPW as input data for population. Other datasets that utilise more complex dasymetric approaches to allocate population within census units, are either not reproducible (LandScan) or do not cover the full globe consistently (Worldpop), restricting their usability in impact assessment on a global scale (Lloyd et al. 2019).

The coastal SSPs and also the gravity-based approach of Jones and O'Neill (2016) would benefit from a globally consistent dataset allocating population heterogeneously within census units, as existing urban areas are used for both approaches. Employing the GUF settlement extents to allocate population has the potential to address this demand, as it proves to work well for the German Baltic Sea region. The study site has predominantly rural characteristics. Before the GUF can be applied to the entire globe, it needs to be validated in other regions with different settlement patterns or building structures (e.g. areas with high urban sprawl or areas with apartment blocks).

The tested approaches in Chapter 2 can be refined by adding data on building heights and building structures, once these are available for the entire globe. Building heights help to differentiate population densities within settlements whereas building structures serve to identify industrial or commercial districts that reduce population density. This can contribute to create a globally consistent population dataset of high spatial resolution as demanded by Lloyd et al. (2019), which allows more robust estimates of the exposure to natural hazards and diseases. However, accounting for building heights and building structures increases the complexity of the dasymetric mapping approach.

An interesting aspect that future coastal flood assessments could account for are seasonal differences in the number of people located on flood prone areas. Both, ESL (Dangendorf et al. 2013) and population are not evenly distributed throughout the year. Coastal areas are popular for touristic activities (Scott et al. 2012). The actual number of people located in flood prone areas is thus the sum of domestic population and tourists. Domestic population is represented in census data, whereas no official data on tourism with sufficient spatial and temporal resolution exist. Deville et al. (2014) show that mobile phone data have the potential to fill this gap. The location of cell phones can be used to develop population grids of high spatial and temporal resolution, which could allow to differentiate exposure of population for seasons, working days and weekends or even over a day independently from census data. If these population grids can be processed in real time, or near real time, they can be used to assess the number of people that need to be evacuated in case of ESL.

The aim of this thesis was to improve the representation of population for coastal exposure analysis. For risk assessments, it could be useful to divide 'population' in more detailed groups. Besides exposure to hazards, risk assessments also need to account for vulnerability, which is determined by the adaptive capacity of population (Cardona et al. 2012). Among others, adaptive capacity depends on age, economic income and education of population (Koerth et al. 2017). Hauer (2019) shows that the regionalisation of age-structures is not limited to assessing current risk but can also be used to assess future risk. The study downscales the SSP population projections to county-level for the United States of America, providing regionalised information on the age-structure of population. Thus, population grids differentiating 'population' in more detail can contribute to improved estimates of the risk associated to coastal flooding.

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Erklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation, abgesehen von der Beratung durch meine Betreuer, nach Inhalt und Form selbständig verfasst habe und keine weiteren Quellen und Hilfsmittel als die hier angegebenen verwendet habe. Diese Arbeit hat weder ganz noch in Teilen bereits an anderer Stelle im Rahmen eines Prüfungsverfahrens vorgelegen. Als kumulative Dissertation sind Kapitel 2 bis 4 wie zu Beginn der Kapitel vermerkt in den genannten Zeitschriften veröffentlicht. Ich erkläre, dass die vorliegende Arbeit unter Einhaltung der Regeln guter wissenschaftlicher Praxis der Deutschen Forschungsgemeinschaft entstanden ist. Weiterhin versichere ich hiermit, dass mir bisher kein akademischer Grad entzogen wurde.

Kiel, 17.12.2019