Adapting Coastal Towns and Small Cities to Climate Change: Assessing the Scale of the Challenge

James Fitton[1*], David C. Major[2], Martin Lehmann[1]

[1] Aalborg University, Denmark, [2]Columbia University, USA

A paper prepared for the Sixth Annual International Conference on Sustainable Development on 26-28 September, 2018, at Columbia University in New York City. This paper, in expanded form, is a planned contribution to the Journal of Applied Geography.

Abstract

This analysis examines how global population datasets can be used to identify the location and population of coastal towns and small cities. This is important as many areas of the world, where well-defined local census information is not available, climate change adaptation needs may have to be approximated by global dataset analysis. Coastal settlements face many impacts from climate change, including sea level rise, storm surges, increased flooding, erosion, and salt water intrusion. Small coastal towns and cities (urban areas between 400 and 100,000 people) often have limited information about local climate change impacts and often lack both the financial resources and the engineering/planning bases to develop appropriate adaptation measures, stifling adaptation progress. A method is presented here that uses global population and built-up density data, to identify the coastal towns and small cities within Europe. The analysis identified some 21.2 m people living at the coast, of which 10.8 (51%) are located within 4,800 small towns and cities. This shows that there is a adaptation knowledge and practice need to be developed in order to ensure that a significant number of people are fully adapted to climate change. The next phase of this research is to establish the suitability of expanding this assessment to a global scale, and to assign further hazard, climate, and economic data so that areas or locations that are most at risk to the impacts of climate change can be identified. This information could facilitate knowledge sharing between similar settlements, and improve adaptation knowledge and practice within coastal towns and small cities globally.

Key words: climate change adaptation, global data, coastal hazards, Denmark, small urban areas.

1. Introduction

Settlements situated at or the near the coast are exposed to hazards such as sea level rise, storm surges, flooding, erosion, and salt-water intrusion. Climate change is likely to exacerbate the severity

*Corresponding Author: james@plan.aau.dk, Department of Planning, Aalborg Unviersity, Aalborg, Denmark

and occurrence of these hazards (Masselink and Russell, 2013; Neumann et al., 2015; Vitousek et al., 2017; Werner et al., 2012). These hazards pose a significant current and future threat to human life and can cause substantial harm to coastal infrastructure and economic, social, and cultural assets.

Consequently, some coastal cities have invested considerably to develop adaptation strategies, e.g. New York and Copenhagen, to ensure they are 'future proofed' (City of Copenhagen, 2011; City of New York, 2013). However, it is thought approximately 60% of the global population do not live in large cities (Small and Nicholls, 2003). Coastal towns and small cities (CTSC), which are defined here as urban areas with between 400 and 100,000 people, often have limited information about local climate change impacts, and lack the financial resources to develop appropriate adaptation measures (Major and Juhola, 2016). Furthermore, the lessons learnt and best practices developed for the larger cities are not necessarily suitable or applicable within CTSC. Therefore, even though steps for climate change adaptation are being taken in many countries at the national level, such strategies for adaptation do not necessarily translate into action in CTSC.

There is limited information available on estimates of the number and types of CTSC worldwide likely to be impacted by climate change (Major and Juhola, 2016). This information is key, as by assessing the global scale of the challenge required to adapt CTSC to climate change it will highlight the importance of the issue and promote research and development of appropriate adaptation strategies. Additionally, once the CTSC have been identified, supplementary data can used to classify the CTSC into 'types'. This will allow the key challenges for CTSC to be recognised, as well as support knowledge sharing between CTSC of similar types.

This paper outlines a method that uses global datasets to identify CTSC in Europe. The model was initially developed and tested within Denmark, and has been up-scaled here. The suitability and limitations of the method and consideration of the appropriateness of expanding the CTSC identification method to a global scale assessment are discussed. The paper has sections in addition to this Introduction: Section 2, Methodology; Section 3, Results; Section 4, Discussion; and Section 5, Conclusions.

1.1. Identifying Coastal Populations

To date, the number of people living at the coast has been estimated using global population data and a criterion based on proximity to the coast and/or elevation. Global coastal populations are estimated from 625 m to 1.9 bn (Table 1) depending on the data and criteria used (Kummu et al., 2016; McGranahan et al., 2007; Neumann et al., 2015; Small and Nicholls, 2003). Some of these coastal population estimates have been separated into urban/rural estimates. In the case of McGranahan et al. (2007) the proportion of the coastal population that are coastal within settlements less than 100,000 people is provided, however, no global summary of the population or count of settlements is given. Small and Nicholls (2003) acknowledge that the majority of the coastal population lives in smaller settlements, yet there has been limited attempts to specifically develop a global assessment to identify and assess these types of settlements. This is possibly due to the low resolution of the data previously available. For example, the Global Urban Mapping Project (GRUMP, CIESIN, 2000) population and urban extent classification used by McGranahan et al. (2007) is a 30 arc-seconds (ca.1 km) raster. However, higher resolution satellite derived global urban footprint datasets have recently become available, such as the Global Human Settlement data (ca. 38 m and 250m raster)(European Commission Joint Research Centre (JRC); Columbia University Center for International Earth Science Information Network - CIESIN, 2015). This has allowed global population datasets to be allocated to smaller areas of urban development than was previously feasible. Therefore, it is now possible to identify and classify small urban areas based on their population and urban density at global scales with higher accuracy.

Table 1: Summary of coastal population estimates.

Reference	Coastal Population Estimates	Coastal Definition	Population Data Source
Small and Nicholls (2003)	Global Total: 1.2 bn Large Cities/main urban areas (population densities greater than 1,000 people per km^2: 480 m (40%) Smaller cities/rural areas (less than 1,000 people per km^2): 720 m (60%)	Distance: 100 km from a shoreline Elevation: 100 m of sea level	GPW2 (CIESIN, 2000)
McGranahan et al.(2007)	Global Total: 634 m Urban: 360 m (57%) Rural: 274 m (43%)	Contiguous area along the coast that is less than 10 metres above sea level	GRUMP (CIESIN, 2000)
Neumann et al.(2015)	Global Total: 625 m Urban: 147 m (23.5%) Rural: 478 m (76.5%)	Contiguous and hydrologically connected zone of land along the coast and below 10 m of elevation	GRUMP (CIESIN, 2000)
Kummu et al. (2016)	Global Total: 1.9 bn	100 km from the coast, and has an elevation lower than 100m	HYDE (Klein Goldewijk et al., 2010)

2. Methodology

The CTSC were identified using a method that utilises global population and urban footprint data, along with national scale elevation and continental scale coastline data. This method has been developed and validated using Denmark as a test case. This paper uses the same method, which is outlined in detail below, however in brief, global population and urban footprint data were utilised to classify urban areas based on their population. The coastal populations were identified using elevation and proximity to the coast data. The population and coastal datasets were combined to identify the populations within towns and small cities that are coastal. Data were processed within GIS using ArcGIS 10.5 (ESRI, 2017a), hence, any mentions of tools in this section are found within this software.

2.1. Coastal Definition

There are multiple definitions that can be used for 'coastal' depending on the application (Boak and Turner, 2005). In this paper, populations are classified as coastal when they are located within 2 km of the coast and have an elevation of equal to or less than 10 m. This approach was used rather the low-elevation coastal zone utilised by McGranahan et al. (2007) and Neumann et al. (2015) as within the definition is a parameter for hydrological connectivity to the coast (Table 1). This is highly relevant for flooding and coastal erosion, however, within this research we are also interested in populations that may be impacted by the intrusion of saline water into freshwater aquifers. Saline intrusion requires subterranean hydrological connectivity but is not necessarily dependent on hydrological connectivity at the surface.

2.2. Input Data

The population and the urban footprint data from the Global Human Settlement (GHS) project (http://ghsl.jrc.ec.europa.eu/index.php) were used to generate the town and city boundaries and their populations. The GHS assesses global human presence in the form of built-up (urban footprint), population density, and settlement classification data. These data are based upon LANDSAT satellite imagery that are classified to extract the areas that are built-up. This is output as the GHS Built-Up raster (at 38 m and 250 m resolution), which represents the proportion of each cell that is covered with a building footprint (Pesaresi et al., 2015). Population data from the Gridded Population of the World (GPW) v4 (CIESEN, 2017), which is at census tract level, is then assigned to the built-up areas identified in the GHS Built-Up data, to produce the GHS Pop raster (250 m and 1 km resolution) (European Commission Joint Research Centre (JRC); Columbia University Center for International Earth Science Information Network - CIESIN, 2015; Freire et al., 2015). These data are available for four epochs, 1975, 1990, 2000, and 2015, with the most recent dataset used for this research.

To determine whether settlements are located at the coast a classification of elevation and distance to the coast is required. SRTM30 (Shuttle Radar Topography Mission Global 30m), an elevation model derived from satellite data which extends to 60°N (Farr et al., 2007), was used to allocate elevation, as used by McGranahan et al. (2007) and Neumann et al. (2015). For areas above 60°N, the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) GDEM (Global Digital Elevation Model) was used. The European Environment Agency (EEA) Coastline was used to establish the distance to the coast (European Environment Agency, 2015). The EEA coastline is 1:100,000 scale and covers geographical Europe. A 250 m raster of the distance to the coastline was produced using the 'Euclidean distance' tool (ESRI, 2017b), and snapped to the GHS Population raster.

Table 2: Summary of the datasets used to identify the coastal towns and cities in Denmark.

Format	Data (Spatial Resolution)	Description	Source
Raster	GHS Population (250 m)	Global population for 2015. Cell value equates to the number of people living within that cell.	European Commission Joint Research Centre (JRC); Columbia University Center for International Earth Science Information Network – CIESIN (2015)
	GHS Built-Up (250 m)	Global urban footprint for 2015. Cell value equates to the proportion of the cell which has an urban footprint (0 to 1 scale)	Pesaresi et al. (2015)
	SRTM30 Global Elevation (1 arc-second, ca. 30 meters)	Elevation model to 60°N.	Farr et al. (2007)
	ASTER GDEM v2	Elevation model for between 60°N and 83°N.	Tachikawa et al. (2011)
Polyline	EEA Coastline	Coastline at 1:100 000 scale for geographical Europe.	European Environment Agency (2015)

2.3. Identification and Classification of Towns and Cities

To identify small towns and cities firstly requires identification of settlement boundaries and their population size regardless of whether they are located at the coast or not. The GHS Population data was initially filtered before processing as areas with a built- up value of 0, were still sometimes assigned a population. Therefore, only population data was used that either had a built-up value equal to 0 and a population greater than 10, or a built-up value > 0 and a population > 1. These values were used as a balance of including as much of the original data as possible, but without including data which created erroneous settlement classifications.

Regions of contiguous cells (ESRI, 2017d) using four-point connectivity were created that had the effect of assigning a unique identification number to contiguous groups of cells that are directly left, right, above, or below neighbouring cells. The populations of these regions were then calculated. This process established the initial boundaries and populations of the towns and cities.

The regions that had populations of ≥50 were extracted, and the regions recalculated, this time using eight-point connectivity method (cells to the right, left, above, below, and diagonally adjacent are considered contiguous). The populations of these regions were recalculated, and the regions with populations less than 50 were merged with this new dataset. Four-point connectivity was used on regions with populations less than 50 to further limit the influence of the road networks identified with the GHS Population data as urban areas. This approach allows the benefits of the eight-point connectivity for towns and cities but minimises the false positives of the road network.

Dense urban settlements, such as Copenhagen, contain many contiguous cells, and as a result sprawl over a large area and include towns and cities that in reality are outside the boundaries of the main city. Therefore, to minimise the effect of this sprawl, settlements with populations greater than 200,000 were extracted and any cells that had an urban density (based on the GHS Built-Up data) of ≥0.4 were extracted and regions created using four point connectivity. The cells which had an urban density of <0.4, were then joined to the largest (by area)adjacent region using the 'Eliminate' tool (ESRI, 2017e). The population of these regions was then recalculated.

The regions of less than 200,000 were then merged together with this dataset to create the final output. The raster dataset of towns and cities (ToCi) was converted to a polygon dataset (termed the '*ToCi Classification*') and assigned a classification based on their population (Table 3). The GHS Pop raster was converted to a point dataset, then an elevation and proximity to the coast value assigned to these points using the 'Extract values to points' tool (ESRI, 2017c) and the SRTM30 and ASTER global elevation and EEA coastline distance raster. The output is a point dataset with attributes of population, elevation, and distance to the coast. This data is termed the '*GHS Pop Points*' dataset. The *GHS Pop Points* dataset was intersected with the *ToCi Classification* polygons, to create a point dataset with attribute information for population, the size of the settlement the population resides, an elevation, and a proximity to the coast (this dataset is termed the '*GHS Pop*

ToCi Classification' dataset). Any of the *GHS Pop Points* outside the boundaries of the *ToCi Classification* polygons were excluded.

Table 3: Classification of towns and cities in the ToCi Classification dataset.

Population	Description
<10	Isolated
10 - 400	Village
400 - 100,000	Town or Small City
>100,000	Medium/Large City

3. Results

Approximately, 3% of the European population is estimated to be coastal, equating to 21.2 m people. Of this population, the *ToCi Classification* identified a total of 11 m people who live within coastal towns and small cities across Europe, which equates to 52% of the coastal population (Table 4). The 10.8 m people are distributed within approximately 4,800 CTSC. The distribution of the coastal population is uneven, with 24 countries (of 35 with a coastal population) that have 50% or more of their coastal population living within CTSC.

Table 4: Analysis on the coastal population in geographical Europe. The table is sorted on the proportion of coastal population. Coastal is defined as within 2 km of the coast, and below 10 m elevation. The following countries are not included within the table as they do not have a coastal population: Andorra, Austria, Belarus, Czech Republic, Hungary, Liechtenstein, Luxembourg, Republic of Macedonia, Republic of Moldova, San Marino, Serbia, Slovakia, Switzerland.

Country	Coastal Population	Proportion of population that is coastal (%)	Coastal population within small towns and cities	Proportion of coastal population within small towns and cities (%)	Number of coastal small towns and cities
Gibraltar	19,638	61	19,501	99	1
Guernsey	29,905	47	29,224	98	2
Åland Islands	11,375	44	5,742	50	3
Jersey	23,574	24	23,394	99	2
Denmark	1,102,420	20	507,102	46	233
Iceland	61,549	20	27,924	45	21
Isle of Man	10,560	13	9,167	87	7
Norway	510,582	11	331,755	65	405
Sweden	967,090	10	583,569	60	301
Greece	1,085,094	10	629,146	58	440
Finland	513,571	10	261,128	51	100
Estonia	115,686	10	72,640	63	25
Montenegro	48,180	8	46,094	96	20
Ireland	344,184	8	152,591	44	124

Country	Coastal Population	Proportion of population that is coastal (%)	Coastal population within small towns and cities	Proportion of coastal population within small towns and cities (%)	Number of coastal small towns and cities
Latvia	141,315	8	130,071	92	20
Spain	3,051,766	7	1,318,440	43	445
Albania	194,947	7	101,530	52	32
Malta	27,152	7	10,186	38	11
Croatia	254,799	6	162,132	64	134
Italy	3,615,783	6	1,859,548	51	580
United Kingdom	2,566,696	4	1,260,211	49	505
Netherlands	662,987	4	373,955	56	126
Faroe Islands	810	4	810	100	2
Lithuania	104,956	4	12,390	12	5
Portugal	292,612	3	155,123	53	97
France	1,617,880	3	800,087	49	399
Slovenia	35,868	2	35,748	100	4
Belgium	146,265	1	142,316	97	20
Russian Federation	1,864,950	1	774,463	42	360
Ukraine	582,096	1	281,630	48	140
Bulgaria	74,860	1	24,859	33	20
Germany	710,422	1	503,321	71	188
Poland	353,579	1	179,488	51	76
Romania	52,949	<1	36,725	69	13
Bosnia and Herzegovina	484	<1	484	100	1
Total	**21,196,584**	**3%**	**10,862,494**	**51%**	**4,862**

4. Discussion

The results demonstrate that there is a significant population (21.2 m) living at the coast in Europe, which is equivalent to the population of Beijing, China, or almost three times the population of London, UK. However, this population is distributed within settlements of various sizes, with 51% of this population located within 4,800 separate small (<100,000 people) settlements across Europe. This represents a huge task for adaptation, as these smaller settlements have difficultly obtaining expertise and knowledge to support their adaptation. Furthermore, acquiring the financial support to enact any plans that are developed is even more arduous. With this research showing that the majority of coastal people in Europe do not live in large cities, increased focus on the adaptation needs of smaller settlements by governments, researchers, and non-governmental organisations is necessary.

To overcome some of the adaptation barriers within these settlements, there needs to be increased efficiency in knowledge development and sharing between CTSC. The next phase of this research aims to support this by classifying these CTSC into types based on their physical, social, economic, and cultural characteristics. Towns and cities that are similar in both characteristics and the hazards that they face allows for fostering of adaptation networks amongst these settlements to encourage adaptation practice sharing that will in turn support access to highly relevant adaptation information, and also share the financial burden of generating such knowledge. This will then allow an assessment of their relative degree of exposure, vulnerability, and risk to coastal hazards, and establish their ability to adapt.

The methods and analysis presented here have been applied to Europe, however, it is worthwhile expanding this work to include other countries that offer a range of contrasting settlement, economic, and cultural settings, e.g. a country dominated by archipelagos. This will test the suitability of the methodology at a global scale, and provide a global analysis of the scale of the climate adaptation challenge.

5. Conclusions

This paper has demonstrated that a significant population live within coastal towns and small cities in Europe, which are facing many barriers to adaptation. The outputs and methods developed within this research can be used to assess the scale and characterise the coastal adaptation challenge, and act as a catalyst focus adaptation research and practice within coastal towns and small cities if the impacts of climate change are to be sufficiently reduced. It is important to highlight this discrepancy if it exists in other countries, as if larger cities continue to be the focus of adaptation research and practice, potentially the majority of the global coastal population will not be sufficiently adapted to minimise the impacts of climate change.

6. References

Boak, E.H., Turner, I.L., 2005. Shoreline Definition and Detection: A Review. J. Coast. Res. 214, 688–703. https://doi.org/10.2112/03-0071.1

Center for International Earth Science Information Network - CIESIN Columbia University, International Food Policy Research Institute - IFPRI, The World Bank, and C.I. de A.T.-C., 2000. Global Rural-Urban Mapping Project, Version 1 (GRUMPv1): Population.

CIESIN, 2000. Gridded Population of the World (GPW), version 2.

CIESIN (Center for International Earth Science Information Network), 2017. Gridded Population of the World, Version 4 (GPWv4). https://doi.org/10.7927/H4DZ068D

City of Copenhagen, 2011. Copenhagen Climate Adaptation Plan.

City of New York, 2013. A Stronger More Resilient New-York 445.

ESRI, 2017a. ArcGIS Desktop: Release 10.5.1 Redlands, CA: Environmental Systems Research Institute.

ESRI, 2017b. Euclidean Distance [WWW Document]. URL http://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/euclidean-distance.htm (accessed 3.1.18).

ESRI, 2017d. Region Group [WWW Document]. URL http://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/region-group.htm

ESRI, 2017e. Eliminate [WWW Document]. URL http://desktop.arcgis.com/en/arcmap/10.5/tools/data-management-toolbox/eliminate.htm (accessed 5.16.18).

ESRI, 2017c. Extract Values to Points [WWW Document]. URL http://desktop.arcgis.com/en/arcmap/10.5/tools/spatial-analyst-toolbox/extract-values-to-points.htm# (accessed 3.1.18).

European Commission Joint Research Centre (JRC); Columbia University Center for International Earth Science Information Network - CIESIN, 2015. GHS population grid, derived from GPW4, multitemporal (1975, 1990, 2000, 2015). European Commission, Joint Research Centre (JRC) [Dataset].

European Environment Agency, 2015. EEA coastline for analysis [WWW Document]. URL https://www.eea.europa.eu/data-and-maps/data/eea-coastline-for-analysis-1 (accessed 9.5.17).

Farr, T., Rosen, P., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., Alsdorf, D., 2007. The shuttle radar topography mission. Rev. Geophys. 45, 1–33. https://doi.org/10.1029/2005RG000183.1.INTRODUCTION

Freire, S., Kemper, T., Pesaresi, M., Florczyk, A., Syrris, V., 2015. Combining GHSL and GPW to improve global population mapping, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, pp. 2541–2543. https://doi.org/10.1109/IGARSS.2015.7326329

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Klein Goldewijk, K., Beusen, A., Janssen, P., 2010. Long-term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1. The Holocene 20, 565–573. https://doi.org/10.1177/0959683609356587

Kummu, M., de Moel, H., Salvucci, G., Viviroli, D., Ward, P.J., Varis, O., 2016. Over the hills and further away from coast: global geospatial patterns of human and environment over the 20th–21st centuries. Environ. Res. Lett. 11, 034010. https://doi.org/10.1088/1748-9326/11/3/034010

Major, D.C., Juhola, S., 2016. Guidance for Climate Change Adaptation in Small Coastal Towns and Cities: A New Challenge. J. Urban Plan. Dev. 142, 02516001. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000356

Masselink, G., Russell, P., 2013. Impacts of climate change on coastal erosion. MCCIP Sci. Rev. 1.

McGranahan, G., Balk, D., Anderson, B., 2007. The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. Environ. Urban. 19, 17–37. https://doi.org/10.1177/0956247807076960

Neumann, B., Vafeidis, A.T., Zimmermann, J., Nicholls, R.J., 2015. Future coastal population growth and exposure to sea-level rise and coastal flooding - A global assessment. PLoS One. https://doi.org/10.1371/journal.pone.0118571

Pesaresi, M., Ehrilch, D., Florczyk, A.J., Freire, S., Julea, A., Kemper, T., Soille, P., Syrris, V., 2015. GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000, 2014). European Commission, Joint Research Centre (JRC) [Dataset].

Small, C., Nicholls, R.J., 2003. A global analysis of human settlement in coastal zones. J. Coast. Res. 19, 584–599.

Tachikawa, T., Hat, M., Kaku, M., Iwasaki, A., 2011. Characteristics of ASTER GDEM version 2, in: Geoscience and Remote Sensing Symposium (IGARSS). pp. 3657–3660. https://doi.org/10.1109 / IGARSS.2011.6050017

Vitousek, S., Barnard, P.L., Fletcher, C.H., Frazer, N., Erikson, L., Storlazzi, C.D., 2017. Doubling of coastal flooding frequency within decades due to sea-level rise. Sci. Rep. https://doi.org/10.1038/s41598-017-01362-7

Werner, A.D., Ward, J.D., Morgan, L.K., Simmons, C.T., Robinson, N.I., Teubner, M.D., 2012. Vulnerability indicators of sea water intrusion. Ground Water 50, 48–58. https://doi.org/10.1111/j.1745-6584.2011.00817.x

Wessel, P., Smith, W.H.F., 1996. A global, self-consistent, hierarchical, high-resolution shoreline database. J. Geophys. Res. Solid Earth 101, 8741–8743. https://doi.org/10.1029/96JB00104