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Identifying coastal towns and small cities in Denmark using global population data to support climate change adaptation

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ABSTRACT
Coastal settlements face many hazards from climate change. Consequently, there has been extensive focus on developing and implementing adaptation. However, these efforts have prodominantly centred on larger cities. Coastal towns and small cities (urban areas between 1000 and 100,000 people) have received little attention, despite experiencing a number of barriers to adaptation. The absence of information on the global scale of the adaptation challenge within coastal towns and small cities may have contributed to these settlements being overlooked. This paper develops a method that can be used to estimate the numbers, sizes, and locations of coastal towns and small cities worldwide from global population data (Global Human Settlement data). Denmark is used as a pilot for this method with settlements over 1000 people classified with relatively high accuracy. The method developed here represents a potentially fruitful approach to supporting coastal adaptation, as coastal towns and small cities are identifiable globally, they can be classified into types. This will support an assessment of their risk to coastal hazards, and could facilitate knowledge and practice sharing between similar coastal towns and small cities.

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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. These hazards can pose a significant threat to human well-being and cause substantial harm to coastal infrastructure and economic, social, and cultural assets. Climate change is likely to exacerbate the severity and occurrence of these hazards (Werner et al. 2012; Masselink and Russell 2013; Neumann et al. 2015; Vitousek et al. 2017). Consequently, some coastal cities have developed comprehensive adaptation strategies, e.g. New York and Copenhagen, to ensure they are resilient to future coastal hazards (City of Copenhagen 2011; City of New York 2013).

However, it is thought approximately 60% of the global coastal population do not live in large cities (Small and Nicholls 2003). Coastal towns and small cities (CTSC), which are defined here as urban areas at or near the coast and with populations between 1000 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, despite steps for climate change adaptation being taken in many countries at

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the national level, such strategies do not necessarily translate into action and risk reduction in CTSC. For clarity, the terms risk, exposure, vulnerability, and hazard used throughout this article follow the definitions of Cardona et al. (2012), where risk is defined as a function of Exposure (E), Vulnerability (V), and Hazard (H), $R = H \times E \times V$ (Cardona et al. 2012).

To address the challenges of climate change impacts on CTSC worldwide, an exposure assessment is required, i.e. acceptable estimate of their numbers, sizes and locations of CTSC (Major and Juhola 2016). It would be ideal to have reliable census data for small output areas from around the world, but with limited accurate worldwide data on urban boundaries and demographic data, exposure to coastal hazards and climate change adaptation needs may have to be initially approximated by global-scale dataset analysis. 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 knowledge and strategies.

The global coastal population has been estimated to be between 625 m and 1.9 bn (Table 1) depending on the data and coastal criteria used (Small and Nicholls 2003; McGranahan, Balk, and Anderson 2007; Neumann et al. 2015; Kummu et al. 2016). Some of these estimates also describe the size of the settlements located at the coast with Small and Nicholls (2003) stating that the majority of the coastal population lives in smaller settlements, and McGranahan, Balk, and Anderson (2007) assessing the locations of coastal settlements of less than 100,000 people, but limited analysis of these specific urban areas is given.

The recently released Global Human Settlement data (European Commission Joint Research Centre (JRC); Columbia University Center for International Earth Science Information Network – CIESIN 2015) have a higher spatial resolution (ca. 38 and 250 m raster) than the data used within previous global assessments. Hence, an opportunity now exists to focus upon and update the spatial distribution estimates of CTSC. This article presents a possible method to do this, and examines how closely a processed version of population data (Global Human Settlement), together with satellite elevation and distance from the coastline data, approaches to the original input population data.

Table 1. Summary of global coastal population estimates.

Source	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 1000 people per km^2): 480 m (40%) Smaller cities/rural areas (less than 1000 people per km^2): 720 m (60%)	Distance: 100 km from a shoreline Elevation: 100 m above sea level	GPW2 (CIESIN 2000) Spatial resolution of approximately 4.6 km (2.5 arc-minute) at the equator
McGranahan, Balk, and Anderson (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 2004) Spatial resolution of approximately 1 km (30 arc-second) at the equator
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 metres of elevation	GRUMP (CIESIN 2004) Spatial resolution of approximately 1 km (30 arc-second) at the equator
Kummu et al. (2016)	Global total: 1.9 bn	100 km from the coast, and has an elevation lower than 100 m	HYDE (Klein Goldewijk, Beusen, and Janssen 2010) Spatial resolution of approximately 8.3 km (5 arc-minute) at the equator

This examination is undertaken in Denmark, which has excellent census data availability and a large number of CTSC.

The article presents the detailed steps required to undertake such an analysis, and draws appropriate conclusions for further work. Therefore, within this paper we: (a) propose a method to identify coastal towns and small cities using the Global Human Settlement datasets; (b) utilising Denmark as a pilot, compare the outputs of this method with census data from the official Danish statistical authority; and (c) outline a path for future research to facilitate knowledge sharing between similar types of settlements, and improve adaptation knowledge and practice sharing between CTSC.

2. Data and methods

In brief, the method to identify CTSC used global population and urban footprint data (Global Human Settlement) which was subsequently classified into urban areas based on their population. This classification was compared to the official Danish settlement boundary and population data. The coastal populations were then identified using elevation and proximity to the coast data to identify the populations at the coast. The data and methods are described in detail below. ArcGIS 10.5 (ESRI 2017a) was used, hence any mentions of tools in this section are found within this software.

2.1. Study area

Denmark was chosen as a test case for development of the methodology to identify CTSC for four reasons. Firstly, Denmark has an extensive coastline (7300 km) and it is estimated that 40% of the Danish population lives within 3 km of the coast (Sørenson 2013, 96). The coast includes urban areas, holiday homes, and recreational areas, but substantial lengths remain natural (Kappel, Rasmussen, and Waneck 2010).

Secondly, Denmark is a 'data-rich' environment, which means that a number of national and continental data sets, such as population statistics, are current and readily available, allowing the accuracy of the CTSC identification methodology outputs to be established using supporting datasets.

Thirdly, the Danish coast is complex and subject to current and future climate change, with active measures already in place. Morphologically, the Danish coast is classed predominantly as 'sand/littoral dune coasts' and 'soft cliff coast', with rock coast found only on the small island of Bornholm in the east (Sørenson 2013, 97). Consequently, coastal erosion and flooding have affected the coast, and substantial management in the form of sea walls, revetments, groins, shore parallel breakwaters, and sand nourishment have been used (Sørenson 2013). With climate change, relative sea levels are expected to rise to between 0.3 and 0.5 m by 2099 compared to 1990–1999 baseline levels (Grinsted 2015) potentially resulting in the increase in coastal erosion extent and rates (Leatherman, Zhang, and Douglas 2000; Zhang, Douglas, and Leatherman 2004; Masselink and Russell 2013). Existing coastal erosion, relative sea level rise, and likely increases in the maximum wind speed (Olesen et al. 2014) mean that coastal erosion, flooding, and saline intrusion are significant issues that need to be addressed in Denmark currently and in the future.

Finally, Denmark has a range of city sizes on which to trial the accuracy of the CTSC identified. Four cities in Denmark have a population over 100,000 (Copenhagen, Aarhus, Odense, Aalborg) with 32% (1.9 m) of the population living within these cities (Statistics Denmark 2017). The methodology should identify these cities, and exclude them for being too large, but identify the remaining 68% of the population that live in the smaller towns and cities.

2.2. Input data

A summary of the input data and datasets used in this research is shown in Table 2. In the following two sections, we outline in further detail the input data on population and coastal classification, respectively.

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

Type	Data	Description	Source
Raster	GHS Pop (250 m)	Global population for 2015 Cell value equates to the number of people living within the 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 (0–1 scale)	Freire et al. (2015)
	DHM-2007 DSM (10 m)	LiDAR derived Denmark elevation model. Cell value equates to height in metres above sea level	Miljøministeriet Kort & Matrikelstyrelsen (2014)
Polygon	City Statistics (Byopgørelsen)	Boundaries of Danish towns and cities and their populations. Used for accuracy assessment	Danmark Statistik (2015)
Polyline	EEA Coastline	Coastline at 1:100,000 scale for geographical Europe	European Environment Agency (2015)
	OSM Roads	Road data from Open Street Map (OSM). Only the major roads were used: Motorway, trunk, and primary	OpenStreetMap Contributors (2018)

2.2.1. Population

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 urban area boundaries and their populations. The GHS assesses global human presence in the form of built-up (urban footprint) and population density. This is output as the GHS Built-Up raster (at 38 and 250 m resolution), which represents the proportion of each cell that is covered with a building footprint (Pesaresi 2015). Population data from the Gridded Population of the World (GPW) v4 (CIESEN 2017), 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 (at 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). The 2015 GHS Pop and Built-up data are used here, which uses population data for Denmark from 2010.

Within the GHS Built-Up and Population data some of the major roads in Denmark were classified with a population due to errors in the initial built-up classification. To reduce the impact of this on the final towns and cities classification some of the erroneous data were removed. The major roads (motorways, trunk, and primary roads) data were extracted from OpenStreetMap (OpenStreetMap Contributors 2018) and converted to a 250 m raster snapped to the GHS Pop raster. OpenStreetMap data was used rather than national mapping data as to allow the potential expansion of the methodology to continental and global scales in the future.

2.2.2. Coastal classification

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 than the low-elevation coastal zone utilised by McGranahan, Balk, and Anderson (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 can occur via subterranean hydrological connectivity and is therefore not dependent on hydrological connectivity at the surface.

For the coastal elevation criteria, a digital surface model (DSM) with a 10 m cell size from the DHM-2007 dataset produced by the surveying department of the Danish Environment Ministry (Miljøministeriet Kort & Matrikelstyrelsen 2014) was used. The DSM is derived from LiDAR data, and has a horizontal accuracy of 1.0 m and a vertical accuracy of 0.1 m (Miljøministeriet Kort & Matrikelstyrelsen 2014). For the coastal distance criteria, 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 Pop raster.

2.3. Coastal population statistics

The identification of the coastal population, regardless of settlement size, was created for comparative purposes. 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). The output is a point dataset with attributes for population, elevation, and distance to the coast, and is termed the 'GHS Pop Points' dataset. Statistics reporting the total and coastal population were then produced.

2.4. Identification and classification of towns and cities

To identify CTSC firstly requires identification of settlement boundaries and their population size. A summary of the GIS workflow is shown in Figure 1. The GHS Pop data was initially filtered before processing (area A in Figure 1) 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

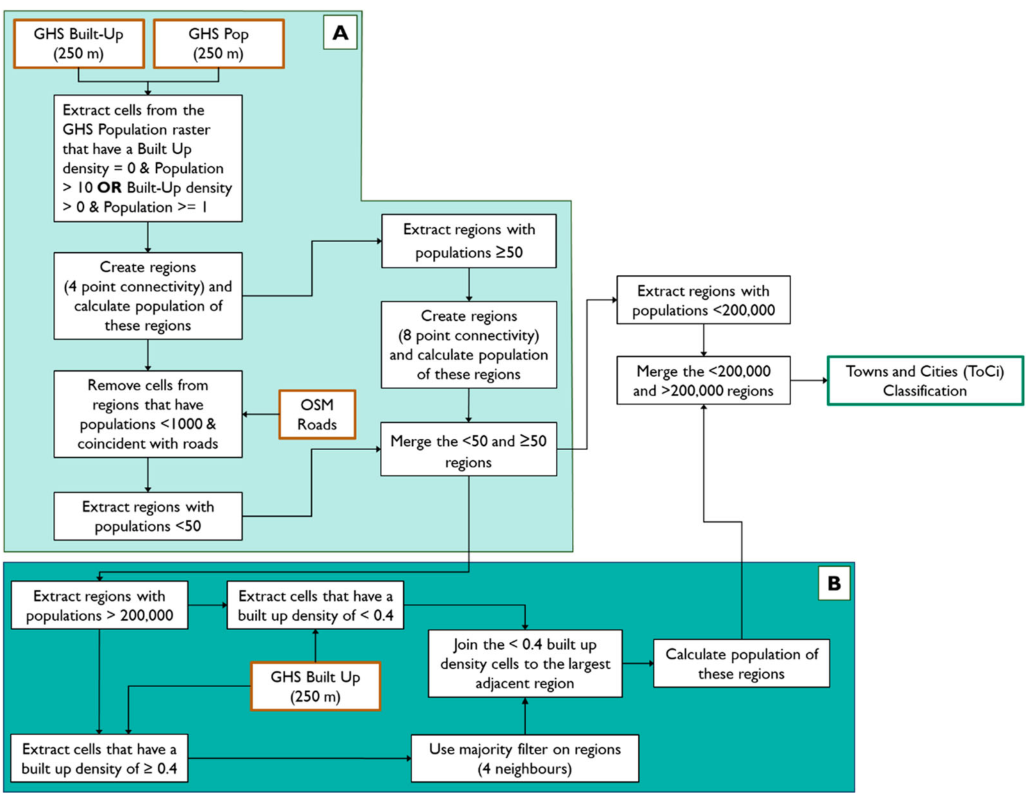

Figure 1. GIS workflow used to identify coastal towns and small cities. All processes refer to tools within ArcGIS 10.5.

used to include 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 cells that were located within regions that had a population of <1000 and coincident with the OSM Road data were removed. The population of the affected regions was then recalculated.

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 Pop 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 proportion higher or equal to 0.4 (i.e. 40% of a 250 m pixel were classed as urban) were extracted and regions created using four-point connectivity (area B in Figure 1). The cells which had an urban density proportion below 0.4, were then joined to the largest (by area) adjacent region using the 'Eliminate' tool (ESRI 2017e). The population of these regions were 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 Points* dataset (Section 0) 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 *GHS Pop Points* outside the boundaries of the *ToCi Classification* polygons were excluded. Summary statistics reporting the total population, coastal population, and summary of coastal population by settlement size were then produced.

2.5. Accuracy of the towns and cities classification

In order to assess the accuracy of the *ToCi Classification* the output was compared against the City Statistics (Byopgørelsen) dataset produced by Denmark Statistics (Danmark Statistik 2015). This is a dataset that delineates the boundaries of settlements based on surveying and their populations in 2012 from the Civil Registration System (CPR) database. The CPR database ties key demographic information of every resident in Denmark with an address, therefore, an accurate count of populations within the boundaries of settlements can be established.

Within the development of GPWv4, the CPR data for 2010 provided the population data for Denmark. The data had been amalgamated to an output area, in this case the 'Parish' (Sogne) boundaries.

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

Population	Description
<10	Isolated
10–1000	Village
1000–100,000	Town or small city
>100,000	Medium/large city

These data were then used to produce the GPWv4 and consequently, the GHS Pop output. Therefore, the *ToCi Classification* is not compared to an independent dataset, rather what is being tested here is whether given all the processing that have been applied here and elsewhere to the CPR population data the *ToCi Classification* can estimate a reliable estimate of the population when compared to the City Statistics data.

The towns and cities within the City Statistics dataset were classified based on population size according to Table 3. The City Statistics dataset also included areas with 0 population, mainly areas of holiday homes (Sommerhusbebyggelse). These settlements were excluded, resulting in 7945 settlements used for comparison (Table 4).

To assess the accuracy of the settlement population estimate, each of the City Statistics polygons were converted to a single point in the centre of each polygon. Then, the distance to the nearest *ToCi Classification* polygon was calculated. If the nearest polygon was within 250 m, they were considered a matching pair. Of the original 7945 settlements in the City Statistics dataset, 6364 were matched with a *ToCi Classification* polygon. Some settlements were not paired as the size of the Isolated population polygons in the City Statistic dataset have a mean area of 0.02 km^2, which is much less than smallest settlement in the *ToCi Classification* (0.0625 km^2). Therefore, the matching of these small settlements is often not possible without error. Where multiple City Statistic points were within a *ToCi Classification* polygon, the population from the City Statistic points were summed. The population size and the size classes of the matching settlements were then compared.

To assess the accuracy of the boundaries of the settlements, 400 points per class were randomly generated. A 'Rural' class was added to the City Statistics and *ToCi Classification* to any area not classified as urban, to assess the accuracy of the classification outside of the urban areas. In total 2000 points were used to asses the accuracy of the classification. The class from both the City Statistics and *ToCi Classification* classifications was extracted at the point location, and a confusion matrix generated.

3. Results

The results for the comparison of the City Statistics and the *ToCi Classification* settlement population and class are firstly presented. Secondly, the accuracy of the settlement boundary are described. Finally, results for the *GHS Pop ToCi Classification* that establish the number and settlement size distribution of the coastal population in Denmark are presented. An example of the *ToCi Classification* is shown in Figure 2, however, the classification can be viewed via a webmap at https://goo.gl/chmSwq.

3.1. Population and class comparison

The *ToCi Classification* identified a total of 31,464 settlements in Denmark (Table 5), considerably higher than the 7945 in the City Statistics dataset. This figure is due to a large number of settlements within the Isolated and Village classes.

Figure 3 shows the population sizes of the City Statistic settlements estimated by the *ToCi Classification* within the settlements paired. The $r^2 = 0.99$, however a Wilcoxon signed rank test showed that there is a significant difference ($p < .001$) between the populations, with considerable differences in

Table 4. Summary of the settlements within the City Statistics dataset used for comparison.

Class	Number	Mean area (km^2)
Isolated	1900	0.02
Village	5076	0.12
Town or small city	965	2.37
Medium/large city	4	77.7
Total	7945	0.41

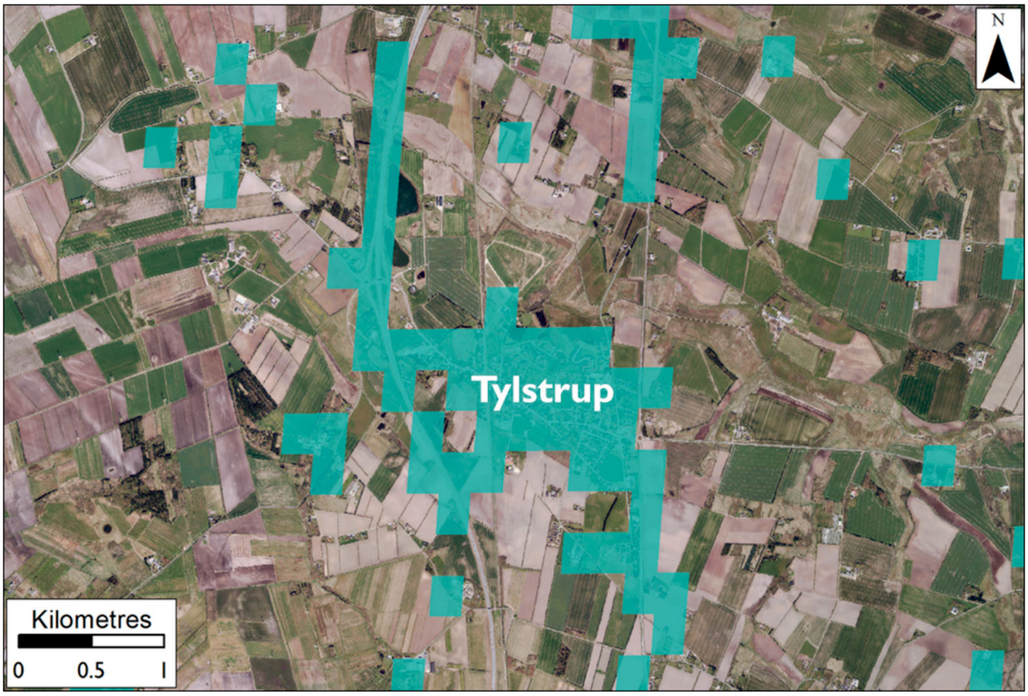

Figure 2. An example of the town of Tylstrup (estimated population of 1697) and surrounding Villages and Isolated settlements delineated by the *GHS Pop ToCi Classification* in northern Jutland. Contains data from the Agency for Data Supply and Efficiency (Dataforsyningog Effektivisering (SDFE)), Ortofoto–GeoDanmark, January 2018.

the smaller population settlements. On average, the *ToCi Classification* overestimates the population size by 76%.

Within this research, we are primarily interested in towns and small cities, therefore, when we limit the analysis to only settlements that are over 1000 people in either dataset a stronger relationship is observed (Figure 4). The correlation remains the same ($r^2 = 0.99$), and the Wilcoxon signed rank test still shows there is a significant difference ($p < .001$) between the populations. However, within this sample of data the *ToCi Classification* overestimates the population size by only 4.5%.

3.2. Settlement boundary accuracy

Table 6 shows the confusion matrix with Producer Accuracy (PA) and User Accuracy (UA) generated from the 2000 points plotted within each of the classes. Overall, in 55% of cases, the *ToCi Classification* matches the classification of the City Statistics data, with a kappa of 0.44. This average accuracy is lowered by the Isolated (PA: 7%, UA: 44%), Village (PA: 43%, UA: 57%) and Rural (PA: 53%, UA: 27%) classes, with accuracies within the Town or Small City (PA: 75%, UA: 76%) and

Table 5. The number and population of the settlement size classes according to the *GHS Pop ToCi Classification*.

Class	Number	Population
Isolated	16,094	67,845
Village	14,471	639,947
Town or small city	895	3,070,748
Medium/large city	4	1,753,967
Total	31,464	5,532,507

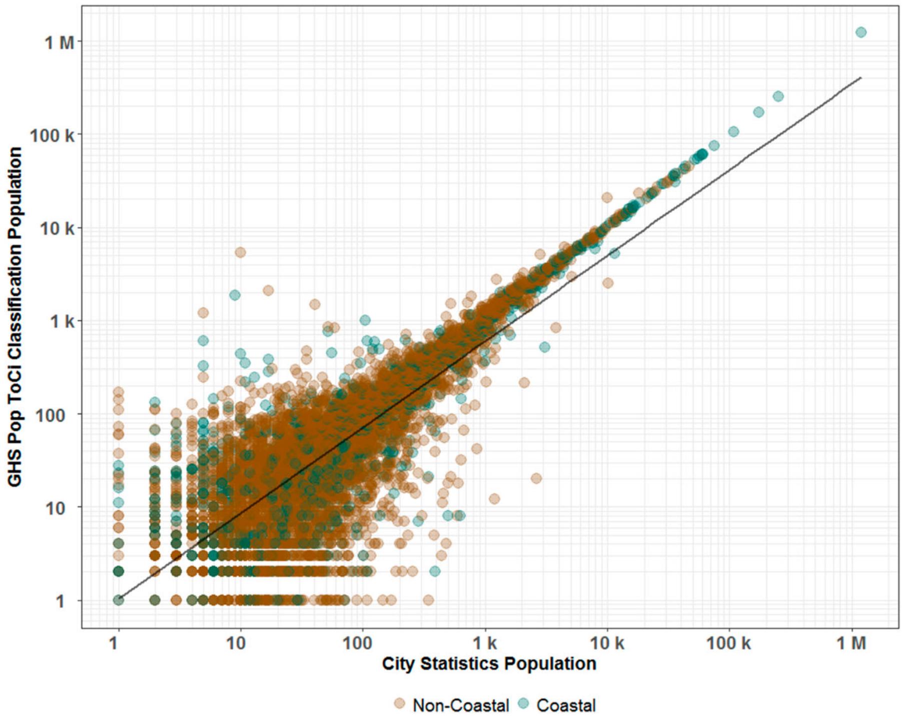

Figure 3. Comparison of population sizes estimated by the City Statistics dataset and the *GHS Pop ToCi Classification* for all settlements. $r^2 = 0.99$, and a Wilcoxon signed rank test shows there is a significant difference ($p < .001$) between the two populations.

Medium/Large City classes (PA: 97%, UA: 86%) much higher. Approximately, 80% and 48% of the PA errors within the Isolated and Village are associated with urban areas being misclassified as rural, and 47% of the PA error within the Rural class associated with the opposite.

3.3. Coastal population

The *GHS Pop Point* data identifies that there are almost 5.7 m people in Denmark (Table 7). When these populations are assigned a settlement classification by the *ToCi Classification*, the population decreases slightly to just over 5.5 m. The number of people identified as living at the coast was 1.2 m (21.9%), within *GHS Pop ToCi Classification* (Table 7).

The GHS Pop *ToCi Classification* identifies 9.3% of the national population as living within CTSC, in 229 settlements (Table 8), which is equal to 42.5% of the coastal population. This analysis shows that the minority (48.2%) of the coastal population live within ‘Medium/Large Cities’ in Denmark.

4. Discussion

The aim of this paper was to develop a scalable methodology that could identify towns and small cities at a national level utilising global population data. The *ToCi Classification* correctly identifies towns and small cities in 75% of instances (Table 6). The *ToCi Classification* output supported the analysis of the coastal population and settlement distribution that identified 229 CTSC. In total, there is a combined coastal population of 1.2 m, with the majority of the population living outside ‘Medium/Large Cities’. These results suggest that despite the processing of the census data within the GPWv4, and the GHS outputs, the data are still useable to identify coastal towns and small cities.

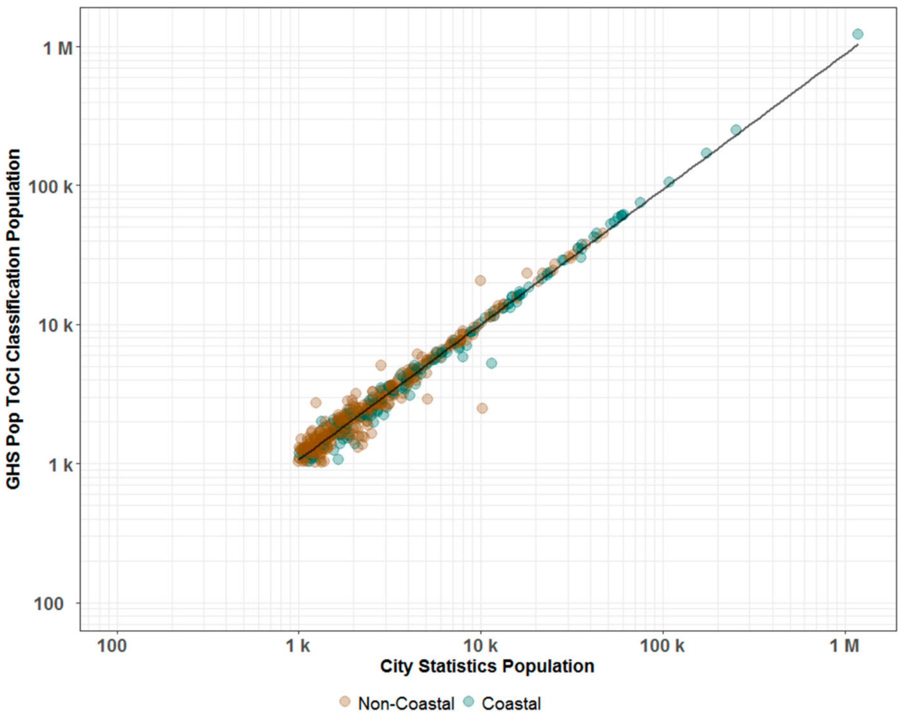

Figure 4. Comparison of population sizes estimated by the City Statistics dataset and the *GHS Pop ToCi Classification* for settlements with populations over 1000. $r^2 = 0.99$, and a Wilcoxon signed rank test shows there is a significant difference ($p < .001$) between the two populations.

Table 6. Confusion matrix comparing the City Statistic data with the *ToCi Classification*.

		City Statistics						
		Isolated	Village	Town or small city	Medium/large city	Rural	Total	User accuracy
ToCi Classification	Isolated	29	25	1	0	11	66	44%
	Village	45	170	23	0	60	298	57%
	Town or small city	6	13	299	0	74	392	76%
	Medium/large city	0	0	22	388	43	453	86%
	Rural	320	192	55	12	212	791	27%
	Total	400	400	400	400	400	2000	0
	Producer accuracy	7%	43%	75%	97%	53%	0	55%

Additionally, these results are aligned with those of the global scale study of Small and Nicholls (2003) in that the majority of people living at the coast inhabit smaller settlements. The implications of this are that a large proportion of the exposed population will not benefit from the adaptation

Table 7. Total population and coastal population for Denmark within the *GHS Pop Point* and *GHS Pop ToCi Classification*.

	GHS Pop Point		GHS Pop ToCi Classification	
Total population	5,668,997	–	5,532,507	–
Coastal population	1,221,628	21.5%	1,212,125	21.9%

Note: Population in both datasets is derived from GHS Pop data.

Table 8. Coastal population by settlement size derived from the *GHS Pop ToCi Classification*.

	GHS Pop ToCi Classification			
Class (population)	Coastal population	Proportion of total population	Proportion of coastal population	Settlement count
Isolated (<10)	12,512	0.2%	1.0%	3006
Villages (10–1000)	99,956	1.8%	8.2%	2622
Towns and small cities (1,000–100,000)	515,508	9.3%	42.5%	229
Medium/large cities (>100,000)	584,149	10.6%	48.2%	4
Total	1,212,125	21.9%	100%	5851

Note: Population derived from GHS Pop data and coastal classification based on DHM-2007 DSM and EEA Coastline.

plans and practices of the larger cities, such as Copenhagen, as they are unlikely to be transferable to these many, smaller settlements. Therefore, there is a pressing need for adaptation approaches that are suitable for the size and scale of coastal towns and small cities to be identified and/or developed, in Denmark and elsewhere.

Despite the successes in identifying CTSC in Denmark, there are some discrepancies between the *ToCi Classification* and City Statistics classification, which are discussed below to establish limitations within the methodology and identify improvements for future iterations.

4.1. Isolated and village settlements

The population estimated within settlements by the *ToCi Classification* is statistically significantly different from the City Statistics population, with the *ToCi Classification* overestimating populations, particularly within the smaller settlements (<1000 people). This is further confirmed by the low accuracy of the classification in the smaller classifications within the confusion matrix (Table 6). This suggests that the methodology is unable to adequately process the data from very small settlements, and often overestimates their population. This is unsurprising considering the global nature of the dataset, and the contrast in scale between the GHS Pop and City Statistics data. For example, the smallest settlement the GHS Pop data could theoretically identify is $0.0625\ km^2$ ($0.25\ km \times 0.25\ km$), however, the smallest settlements in the City Statistics data have a mean area of $0.02\ km^2$. This demonstrates the difficulty in accurately modelling the boundaries of settlements using a 250 m global dataset compared to a highly accurate local boundary dataset. It is necessary to assign a boundary to settlements using the global data, however it is highly unlikely that these will precisely match the local data, therefore some error is expected in this regard.

The potentially greater issue is false positives, i.e. areas that are not urban but have been identified as such. Due to the land use classification of the GHS Built-Up data there are likely areas such as roads and industrial areas, which are given a permanent residential population. This is potentially why the number of small settlements identified within the *ToCi Classification* is very large. There are estimated to be just over 30,000 'Isolated' and 'Villages' by the *ToCi Classification*, in contrast, the City Statistics data suggest there are just under 7000 settlements of this size in reality. This misclassification could be avoided if information on building use was included within the classification, which may be relatively straightforward at the national scale, but more problematic at continental and global scales due to availability of data at sufficient spatial resolutions. This is a minor problem in the Danish context, and should not alter the overall conclusions here, but, it is worthy of consideration when countries with large areas of industrial land, e.g. container ports, oil refineries, at the coast are studied. When this method is expanded to other geographical contexts, it may be the case that using populations of 1000 or more may be too low, and the lower boundary of the Town or Small City classification may have to be increased in order to minimise error.

4.2. Settlement classification

Despite the population size discrepancies highlighted above, it is important to remember why this research was conducted; to identify towns and small cities that can be analysed and researched further to support climate change adaptation. Therefore, while establishing a highly accurate population estimate for settlements is desirable, the more important output is whether the towns and small cities were correctly identified as such.

For settlements with populations of more than 1000 people, the average PA is 86% and average UA 81%. Indicating that the methodology is able to identify these larger settlements. Errors are produced due to the boundary and scale issues highlighted above, but also, a number of errors are attributed to some towns and small cities that were classified as being larger than they are in reality. This is related to the way the methodology works within large sprawling cities and the reliance upon the connectivity of the urban footprint. For example, within the *ToCi Classification*, a single polygon identifies Copenhagen. In contrast, the City Statistics utilises administrative boundaries to assist with delineating settlement boundaries and as a result 33 separate settlements are identified within Copenhagen (Figure 5).

The methodology therefore underestimates the number of settlements within larger sprawling settlements. Ideally, to improve the classification administrative boundaries would be included, however accurate data at a global scale to represent this may be difficult to obtain. Furthermore, the focus here is to find CTSC that require support and further research to support adaptation. The *ToCi Classification* classifies Copenhagen as a single settlement, which is not how the administration of the city is structured, however there is and will be considerable cooperation concerning climate change adaptation between these administrative centres. The *ToCi Classification* therefore, may not truly reflect the reality of governance in the larger cities, however, CTSC which are not

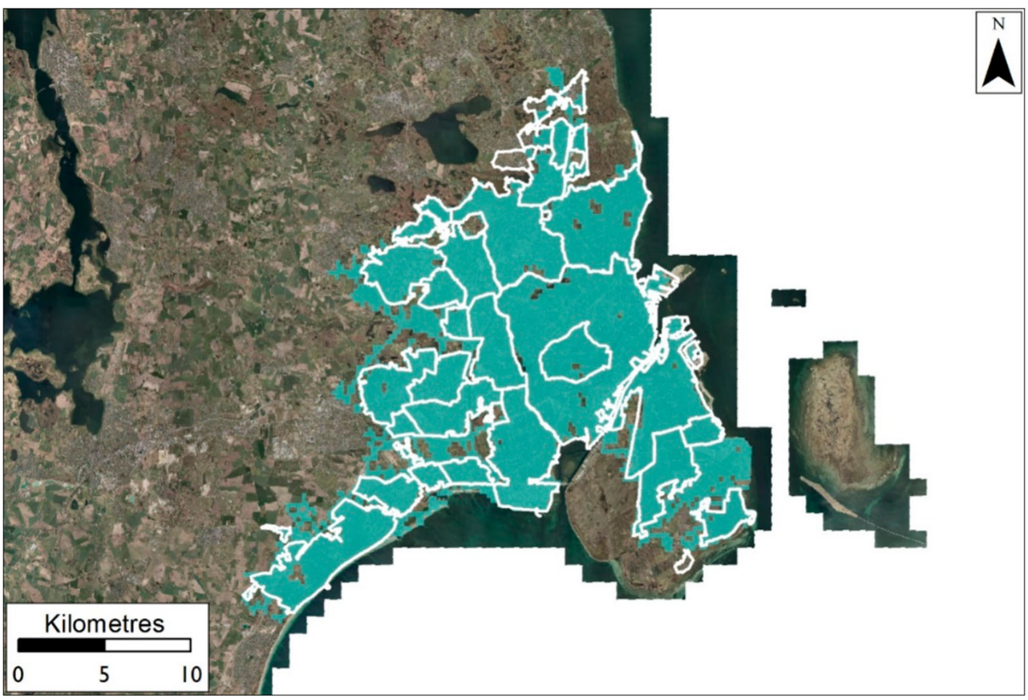

Figure 5. Example of Copenhagen identified as a single city by the *ToCi Classification* (green area) and the 33 separate settlements identified within the City Statistics dataset (polygons with white border). Contains data from the Agency for Data Supply and Efficiency (Dataforsyningog Effektivisering (SDFE)), Ortofoto–GeoDanmark, January 2018.

necessarily able to rely on close cooperation with neighbouring local government partners, are still identified.

4.3. Future development

The methods and analysis presented here have been applied to Denmark as a pilot to establish whether it would be possible to expand this work to continental and global scales as a practical way to identify coastal settlements where no local census data are available. The results of this pilot indicate that it would be worthwhile expanding this method to include other data-rich countries that offer a range of contrasting settlement, economic, and cultural settings, e.g. a country dominated by archipelagos. This will support further testing of outside of Denmark, and further development of the method. Developing the methodology to work within the Google Earth Engine platform (Gorelick et al. 2017), which will support rapid global scale assessments will also be explored. If this is successful, the next step will be to apply this method to data-poor countries and, working with local partners, further assess the accuracy of the CTSC classification using independent datasets and local knowledge. Different population datasets can drastically affect the results of coastal flooding assessments (Mondal and Tatem 2012). Therefore, further confidence in the CTSC classification (in both data-rich and data-poor countries) could be achieved by comparing a CTSC classification using the WorldPop (Tatem 2017) data (global population estimates at a 100 m spatial resolution) to assess whether similar CTSC classifications are achieved when the GHS data is used.

The method developed here to identify CTSC is the first stage in supporting coastal adaptation. It is important to assess exposure, vulnerability, and risk of hazards (Oppenheimer et al. 2014); therefore using supporting hazard data, the number of CTSC that are exposed to coastal hazards can be estimated. This approach is similar to the work of Neumann et al. (2015), however with a focus on smaller urban areas. Additionally, CTSC can be classified into types based on their physical, social, economic, and cultural characteristics. This will enable a high-level assessment of the relative degree of vulnerability to coastal hazards, of who or what (e.g. economic, cultural, historical, and environmental assets) may be impacted, and of the ability of the CTSC to cope and adapt to current and future coastal hazards. There are two reasons to conduct this assessment: firstly, it allows the prioritisation of adaptation within the settlements that could be potentially the most harmed by coastal hazards. Secondly, the CTSC can be categorised into types, similar in characteristics and the hazards that they face, and adaptation networks can be fostered amongst these settlements to encourage adaptation practice sharing. This will in turn increase access to and proliferation of highly relevant adaptation information, but also share the financial burden of generating such knowledge.

5. Conclusions

This paper has demonstrated a scalable method that uses global population data to identify the coastal towns and small cities within Denmark. This research has shown that 21.9% of the population live at the coast, of which 9.3% live in small towns and cities. There are limitations of the data and the methodology; however, these can be overcome with the likely future improvements within the accuracy of the input datasets. Despite these limitations, when compared with local scale data, the results are comparable and produce useable outputs for the purposes of supporting coastal climate change adaptation in towns and small cities.

As the methodology is developed further it can eventually be used to assess the scale and characterise the coastal adaptation challenge in locations where data to test the accuracy of the results does not exist. The next phases of this work will focus on method development with overall aim to identify CTSC on a global scale.

This research has identified the need for Denmark to 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. Consequently, this may contribute to an even further depopulation of areas outside larger cities and thus reinforce the current trends of migration and urbanisation.

Disclosure statement

No potential conflict of interest was reported by the authors.

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