



Change detection and urban expansion of Port Sudan, Red Sea, using remote sensing and GIS

Emad Hawash · Adel El-Hassanin ·
Wafaa Amer · Alaa El-Nahry · Hala Effat

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Abstract During the last two decades, Port Sudan City has witnessed major environmental stresses resulting from urban expansion and port extensions. This research aims at analysing land water changes (LWCs), land use land cover (LULC) changes and urban expansion of Port Sudan using remote sensing and GIS. For that purpose, an integrated remote sensing and GIS approach was designed to analyse two Enhanced Thematic Mapper (ETM) and an Operational Land Imager (OLI) Landsat images covering the period from 1999 to 2018. LWCs were detected using mathematical remote sensing and GIS-based procedures, while LULC changes were analysed through a post-classification comparison (PCC) approach using a support vector machine (SVM) classifier for classification. Major detected LWCs include landfill activities in the port area and north lagoon of Kilo Tamanya, and dredging activities in Khor Mog. Areas gained by landfill may have improved the port and transport functions but buried coral reefs and

caused environmental problems as well. Furthermore, the urban areas were twice doubled, which was mostly rapid and uncontrolled, adding more pressure to the already stressed services and administrative sectors. Threats to the agricultural and mangrove areas were also analysed. The agricultural and mangrove areas were decreased by 40% each, which has been shown to have negative impacts on society, food security and biodiversity. Sadly, the lost agricultural lands were changed into bare soil, slums and other industrial uses. In contrast, mesquite forests were naturally increased by 74%. Mesquites have a major role in combating desertification and providing energy for domestic use. The driving forces and constraints of the urban expansion were highlighted. The change information provided by the applied approach will support decision-makers in adopting integrated and compatible land and coast management planning in the studied coastal city.

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E. Hawash (✉) · A. El-Hassanin
Faculty of African Post Graduate Studies, Cairo
University, Giza, Egypt
e-mail: al_hawash@yahoo.com

W. Amer
Faculty of Regional and Urban Planning, Cairo University,
Giza, Egypt

A. El-Nahry · H. Effat
National Authority of Remote Sensing and Space
Sciences, Ministry of Higher Education, Cairo, Egypt

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Introduction

Coastal cities are areas where man's activities are mostly related to land and water together or separately. Between the complex interactions of land, sea and atmosphere on the one hand, and economic development, population growth and resource exhaustion on the other hand, coastal city emerges

as a transparent melting pot that enhances the understanding of coastal, natural socio-economic interactions. These interactions through natural and/or anthropogenic factors could affect the existing land use land cover (LULC) and could be reflected in different types of changes such as LULC change, land water changes (LWCs) (interchangeably with coastline change/shoreline change), urban expansion, agricultural land loss, forest degradation as well as other non-environmental and environmental (inshore-offshore) changes.

Port Sudan is the main coastal city of Sudan. It is very important for the international trade and is the main gate to the Red Sea and the world for Sudan and its neighbouring landlocked countries. The city harbour has witnessed remarkable expansions within the Sea Port Development Phased Plan (1999–2020). This port phased development (PPD) directly resulted in several constructions of new platforms and oil terminals in the southern and northern parts of the harbour (e.g. IMR, 2008; IMR & FMSF, 2014) and indirectly affected the city by attracting more job and settlement seekers. Coastal cities, especially harbour cities, are always challenged by expanding port development, urban and population growth, service stresses, resources attrition, coastal and marine degradation as well as other naturally and anthropogenically caused hazards, which, if not properly managed, can lead to serious environmental and socio-economic problems. High poverty levels (e.g. ADBG, 2017), shortage in water supply and sanitation services (e.g. ADBG, 2017; Elsheikh & Elsayed, 2015), uncontrolled waste management (e.g. IMR, 2008), unplanned settlements (e.g. Abdel Ati et al., 2011), stresses of food supply at the city and the Red Sea State (RSS) levels (e.g. Ali, 2009), dredging and landfilling for the port extension and land-based pollution from the petroleum industry (Nasr, 2015) and mangrove degradation are among the main problems facing Port Sudan. In addition, till the beginning of the 2000s, Port Sudan was still receiving influxes of Sudanese and foreign migrants (e.g. Abdel Ati et al., 2011; Dumper & Stanley, 2007). Furthermore, the city is still spatially extending to fulfil the needs of population growth, which increased from 308,000 in 1993 to 399,000 in 2008 (MoEFUD, 2014) and reached 470,000 in 2018 (WPR, 2020).

Monitoring the spatio-temporal changes of a coastal city during a given period is a basic management

requirement to assess changes that occurred naturally or by human influences, improve understanding of city dynamics and determine the socio-economic impacts on its land and coastal resources. One of the most powerful advantages of remote sensing images is their ability to capture and preserve a record of conditions at different points in time, to enable the identification and characterization of changes over time (Lillesand et al., 2015). Change detection is the process of identifying differences in the status of an object by observing it at different dates (Singh, 1989). Change detection enables the evaluation of subtle changes over a long time as well as the identification of sudden changes in short times due to natural or dramatic anthropogenic impacts (Kuenzer et al., 2011). Examples of sudden and/or rapid changes caused by anthropogenic interferences include land clearing for shrimp pond construction (e.g. Binh et al., 2005), lagoon for fish farm construction (e.g., Gaber et al., 2016) and landfill for urban development (e.g. Dewidar, 2002). Change detection approaches were summarized and categorized based on different viewpoints. Basically, there are two types of change detection methods: (1) detection of the change using various image enhancement methods and (2) extraction of detailed types of land cover change based on the use of classification techniques (Chan et al., 2001; Jensen, 2005; Jensen & Im, 2007). Meanwhile, Lu et al. (2004) categorized change detection into seven types: algebra, transformation, classification, advanced models, remote sensing and GIS integration, visual analysis and other change detection techniques. For traditional remote sensing, change detection techniques that are generally applicable to coarse spatial resolution optical imagery include image algebra multiband differencing (e.g. Coppin & Bauer, 1996), image transformation such as principal component analysis (e.g. Collins & Woodcock, 1996) and the widely used post-classification comparison method (e.g. Jensen et al., 1995). Post-classification comparison (PCC) belongs to classification methods that provide detailed ‘from-to’ change information (Lu et al., 2004). In PCC, two dates of imagery are independently registered and classified, and pixels whose class changed between dates are identified (Lillesand et al., 2015). Meanwhile, PCC requires very good accuracy in the classification stage because the accuracy of the change map is the product of the accuracies of the individual classifications (Singh, 1989). Therefore, the selection of the proper

classifier is of a fundamental importance to address the deficiencies. Two broad categories of classifiers can be identified: parametric or non-parametric classifiers (Abe, 2005). Support vector machine (SVM) is one of the most powerful non-parametric classifiers (Huang et al., 2002). SVMs are based on statistical learning theory and have the aim of determining the location of decision boundaries that produce the optimal separation of classes (Vapnik, 1995). SVM seeks to separate land use cover classes by finding a plane in the multidimensional feature space that maximizes their separation, rather than by characterizing such classes with statistics, and so, they do not need a large training set but just the training samples that are support vectors (Foody & Mathur, 2004). SVM classifiers outperformed other classifiers and produce classification accuracy values as high, if not higher, than other classification methods including neural networks (e.g. Camps-Valls et al., 2004; Dixon & Candade, 2008; Huang et al., 2002; Szuster et al., 2011), maximum likelihood (e.g. Dixon & Candade, 2008; Huang et al., 2002; Kavzoglu & Colkesen, 2009; Keuchel et al., 2003; Oommen et al., 2008; Szuster et al., 2011) and decision tree (e.g. Huang et al., 2002). SVMs are not as sensitive to training sample size and can use small amounts of training samples that are support vectors (e.g. Camps-Valls et al., 2004; Candade & Dixon, 2004; Foody & Mathur, 2004; Ge et al., 2008; Pal & Mather, 2005).

Although a large number of studies have investigated LULC change and LWC for various coastal cities using remote sensing and GIS, only a few of these studies have covered both LULC change and LWC in the same research. First, studies of coastal cities that have investigated LULC changes using remote sensing and GIS include (i) using the PCC approach in monitoring LULC changes in the north-western coastal zone of Egypt (e.g. Shalaby & Tateishi, 2007), assessing coastal LULC change from 1974 to 2008 in the vicinity of Mobile Bay in Alabama (e.g. Ellis et al., 2011), monitoring urban expansion and LULC changes of Shanghai metropolitan in China (e.g. Yin et al., 2011), monitoring LULC change related to shrimp farming in coastal areas of Quang Ninh in Vietnam (e.g. Bui et al., 2014), monitoring coastal LULC change and transformations of Kanyakumari coast in India (e.g. Kaliraj et al., 2017) and tracing LULC change in peri-urban Delhi in India

(e.g. Paul et al., 2021); (ii) using normalized difference vegetation index (NDVI), image differencing and PCC approaches in land cover change dynamics and coastal aquaculture development, East Godavari delta, India (e.g. Rajitha et al., 2010); and (iii) using pre-classification and post-classification change detection approaches in monitoring LULC change in Pisa Province, Italy (e.g. Peiman, 2011).

Second, studies of coastal cities that have investigated LWC, caused by (i) natural effects and/or (ii) anthropogenic influences, are various. LWCs were largely investigated using different remote sensing and GIS approaches of semi-automatic and automatic methods. The primary objective of these studies is to separate the water from the land. Approaches of LWC studies include (i) 'unsupervised classifications' in mapping coastal erosion at the Nile Delta (Egypt) (e.g. Hereher, 2011), and shoreline of Seberang Takir (Malaysia) (e.g. Muslim et al., 2007); (ii) 'thresholding' in extracting water bodies of the Murrumbidgee River in Wagga Wagga (Australia) (e.g. Frazier & Page, 2000), waterline in Gomso Bay (Korea) (e.g. Ryu et al., 2002) and coastline changes of the Yellow River estuary (China) (e.g. Cui & Li, 2011); (iii) 'band ratioing' in detecting coastline change of the Aegean Sea coasts (Turkey) (e.g. Ekercin, 2007) and shoreline change in Medjerda delta coast (Tunisia) (e.g. Louati et al., 2015); (iv) 'a combination of band ratioing and thresholding' in detecting changes of Urmia Lagoon (Iran) (e.g. Alesheikh et al., 2007); (v) 'on-screen digitizing' in evaluating the landfilling, erosion and extension of Jazan (Kingdom of Saudi Arabia, KSA) (e.g. Al-Zubieri et al., 2018); analysing shoreline change between Kanyakumari and Tuticorin (India) (e.g. Mujabar & Chandrasekar, 2013); and detecting shoreline change between Oleron Island and the mouth of the Adour River (France) (e.g. Castelle et al., 2018); and (vi) 'the modified normalized difference water index (MNDWI)' in monitoring coastline change of Hatiya Island in Bangladesh (e.g. Ghosh et al., 2015).

Third, studies of coastal cities that have investigated both LULC changes and LWCs in the same search are very few, which may be referred to the relatively high cost of field work in the coastal and inland areas. Administratively, these studies are very important, because they provide important management

information needed for the coastal city. In general, these studies tend to focus on the city and coast changes (CCCs); their influences, forms, impacts and benefits; and proposed solutions, which are multidirectional but interrelated. Examples of these studies include (i) landfill detection and LULC change (e.g. Dewidar, 2002; Kamh et al., 2012); (ii) landfill detection, LULC change and coral reef composition (e.g. Vanderstraete et al., 2006); and (iii) LULC change and coastline change (e.g. Misra & Balaji, 2015).

This study aims at analysing LWC, LULC changes and urban expansion of Port Sudan using remote sensing and GIS during 1999–2018. The specific objectives of this work include (1) to detect LWC, (2) to produce LULC maps and investigate LULC changes, (3) to explore the spatio-temporal characteristics of urban expansion and (4) to analyse the driving forces and constraints affecting the urban expansion of Port Sudan during 1999–2018.

Study area

Port Sudan City

Port Sudan City (Fig. 1) was established in 1905. Because of the appropriate and importance of the present natural bay, the location of Port Sudan City was chosen and then linked to Khartoum (the capital of Sudan) by a railway in 1906 (Hansman & Hoogeboom, 1992). The city is the main harbour of Sudan and the capital of RSS. It is served by an international airport and connected to Khartoum and Kassala by roads of 800 km and 600 km, respectively. The present study lies between 37° 03' 1.29" E, 19° 45' 30.44" N and 37° 24' 42.84" E, 19° 25' 22.19" N. Port Sudan population was estimated to be 470,000 in 2018 (WPR, 2020). It has a service-based economy and an industrial-based economy linked to shipping, packing, trade, transportation and oil refining. The city is also famous for its diving sites such as Wingate, Towertit and Sanganeb. Port Sudan is a typical arid zone environment. Temperature ranges between 30–47 and 20–27 °C in summer and winter, respectively. Red Sea Hills (RSH) represents a climatic border; only the western part of the hills is affected by the summer rains. The coastal area is affected by the winter

rains from November to January, caused by the NE wind passing over the Red Sea with an average annual rainfall ranges between 34 and 24 mm. Humidity ranges between 42 and 76%. Wind direction at the coast is almost northerly and north-westerly throughout the year (IMR, 2008).

General considerations of the study area

Geological and morphological features have major contributions in determining areas suitable for economic and urban development in coastal areas. In general, the study area can be divided into three geomorphological units (from west to east): RSH, the pediment and the coastal plain. It comprises Basement Complex, Upper Clastic Group, recent deposits and emerged fossil reefs. The Basement Complex in the RSH comprises meta-volcanic, meta-sedimental and magmatic rocks of Neoproterozoic age (Babiker & Gudmundsson, 2004; Vail, 1985; Whiteman, 1971). The hills constitute a semi-desert plateau with a rugged morphology bounding the coastal plain to the west and rising to about 2000 m above mean sea level (amsl) (Haenisch et al., 1996). The Upper Clastic Group represents a clastic sequence, which is mainly composed of coarse gravel and sand (Sestini, 1965). The elevation of the gravel terraces of the study area varies between 6 and 15 m (amsl). Furthermore, the surface of the Upper Clastic Group shows a distinctive drainage system extending from the hills in the west to the coastal plain in the east. Khor (dry wadi) Mog and Khor Salalab are the most famous in Port Sudan after Khor Arabat, which is the main source of drinking water. The recent Sudanese Red Sea coastal plain forms a patchwork of different depositional environments. Its knowledge is important for understanding the geological processes of the past as well as coastal plain management and planning (Hamed, 2015; Schroeder & Mansour, 1994). The coastal plain is covered by recent siliciclastic deposits mainly derived from the RSH and the older sediments cropping out in the area. Extensive wadi systems push the sediments of the RSH onto the littoral zone in the form of a series of fans and deltas, composed of gravel, sand, silt and clay (Whiteman, 1971). The backshore area is mainly covered by sabkha deposits and salt rocks (Al-Imam et al., 2015). The coastal sabkha of the area is almost

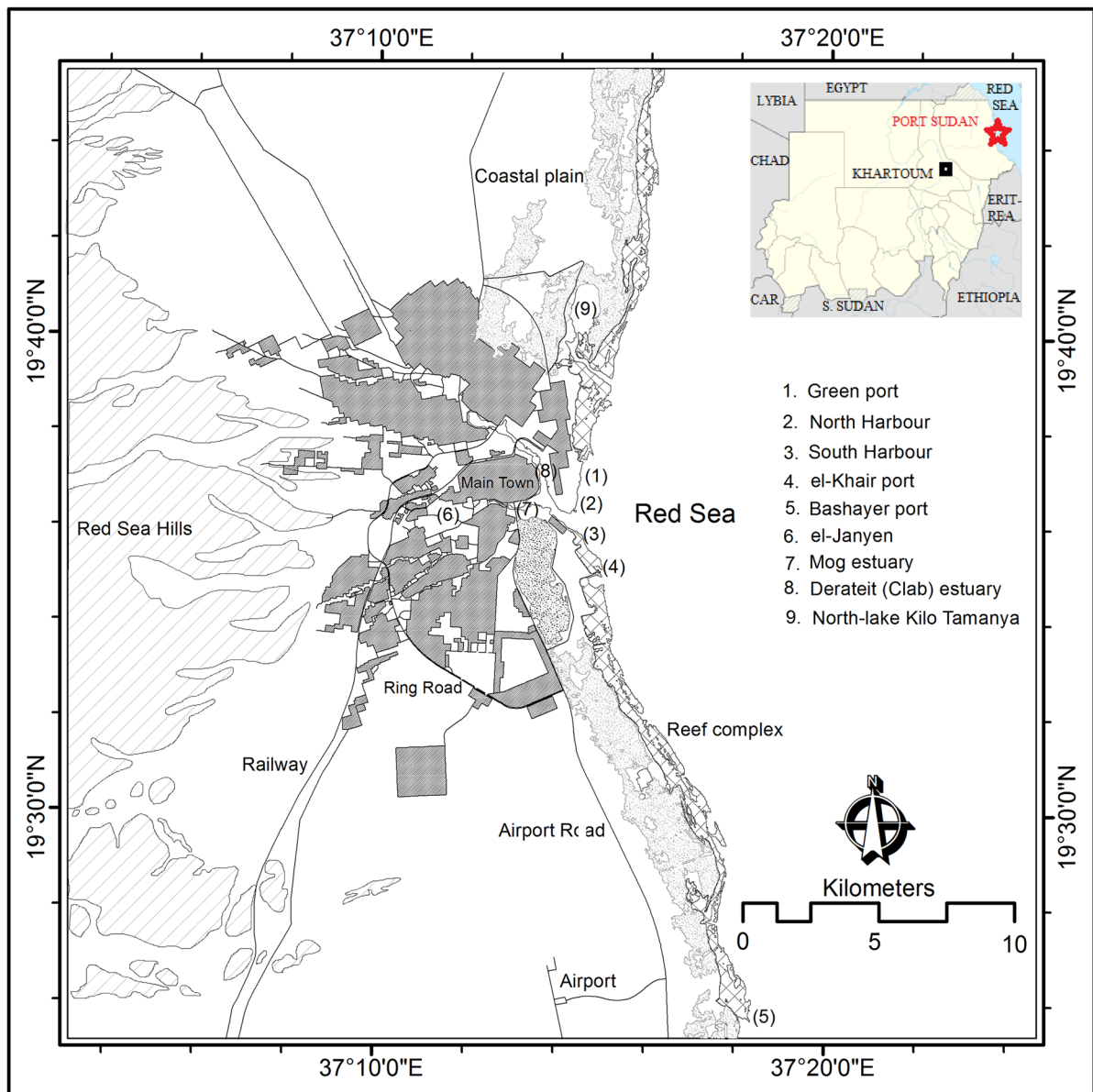


Fig. 1 Study area, Port Sudan

bare, but some of its northern and southern areas are covered by vegetation (mesquite forests and patches of mangroves) and sand. The emerged reef deposits occur at a lower elevation south of Port Sudan. Furthermore, the thickness of the emerged reefs is fairly constant with a maximum of 10–13 m north of Port Sudan (Hamed, 2015). Furthermore, Sestini (1965) identified four distinct reef terraces occur at 2 m, 4 m, 7 m and 9–10 m (amsl).

Data and field work

Data

The used Landsat data were of the path (171) and row (046). They include two Enhanced Thematic Mapper (ETM) Landsat images and an Operational Land Imager (OLI) Landsat image, acquired at 05–10-1999, 27–09-2008 and 01–10-2018, respectively. They were

freely obtained from the Earth Resources Observation and Science (EROS) (<https://earthexplorer.usgs.gov>), US Geological Survey (USGS). The datasets were selected with similar calendar dates to eliminate the effects of external sources such as Sun angle and seasonal and phenological differences (e.g. Lillesand et al., 2015; Lu et al., 2004). For this research, only the 30-m and 15-m bands were used. The method relies on image processing techniques using the ENVI 5.3 and ArcGIS 10.5 software.

Field work

The field work was undertaken through several visits during 2012–2018, most of them were within August–October. To document the regions of interest (ROIs), extensive field surveys were conducted throughout the study area, using Garmin 38 global positioning system (GPS). For safety and security reasons, some areas were inaccessible. With the aid of supervised classified maps of Port Sudan 2002 and 2013 (e.g. Hawash, 2013) as well as false colour composite (FCC) maps of 1999, 2008 and 2018, the ROIs were collected. The collected field sampling sheet was divided into two parts: the first will be used in the classification stage, and the second will be used in the accuracy assessment. Further, ground control points (GCPs) and the boundaries of slum areas were determined using GPS. Furthermore, information from the locals (most of them are the emigrants or their offspring) regarding landfill, urban development, green cover change and mangrove degradation was also collected.

Methods

The relationship between land and humans in terms of land use land cover change and human growth for development is a complex issue (Ganasri et al., 2013). A descriptive statistical approach, using the integration between remote sensing and GIS, was used to analyse the city and coast changes of Port Sudan. For that purpose, the PCC approach and the proposed ratio, masking and overlay (RMO) procedures were used to fulfil the objectives of the current study. The methodology begins with a main pre-processing stage, followed by two main procedures, i.e. LWC

and LULC change, and ends with the analysis of the changes and urban growth (Fig. 2).

Digital images pre-processing

A square of 1252×1252 pixels (30.0 m), i.e. 1410.75 km², covering Port Sudan and its surroundings was used to extract the study subsets. To get ideal results, all data were atmospherically corrected using Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) (e.g. Adler-Golden et al., 1999). The datasets used in this study were ortho-rectified products and were indeed in the World Geodetic System (WGS 84) datum and the Universal Transverse Mercator (UTM) projection system, Zone 37 North. For the most accurate change detection results, all the images must be co-registered. Accurate spatial registration of the various dates of imagery (ideally to within 1/4 to 1/2 pixel) is a requirement for effective change detection (Lillesand et al., 2015). Through the collected GCPs and GPS tracks, the geometric accuracy was assessed for the OLI-2018 subset where misalignments of 0.2 pixel were found. Then, using twelve tie points, the OLI-2018 subset was used as a base file, while the other subsets were used as warp files to perform image-to-image registration for each of them. The resulted total RMS error of the ETMs for 1999 and 2008 were 0.162 and 0.154, respectively.

Land water change detection

The proposed procedures of RMO are based on using remote sensing in separating the land from the water for each image followed by using GIS tools to obtain the changes between each two consecutive dates. In band-ratio methods, two bands from a multispectral image are used and take advantage of the differences in the spectral response of different land cover types (Boland, 1976; Sun et al., 2012). Wavelengths of NIR and SWIR bands are highly absorbed by water and exhibit higher reflectance characteristics from soil and healthy vegetation, providing a context for land/water interface (Alesheikh et al., 2007; Braud & Feng, 1998; Frazier & Page, 2000; Guariglia et al., 2006; Kuleli, 2010).

To extract LWC, the following steps were performed: (i) ratio, by discriminating water pixels from land pixels using the band ratio of shortwave infrared/green, i.e. b5/b2 of the ETM (e.g. Ekercin, 2007;

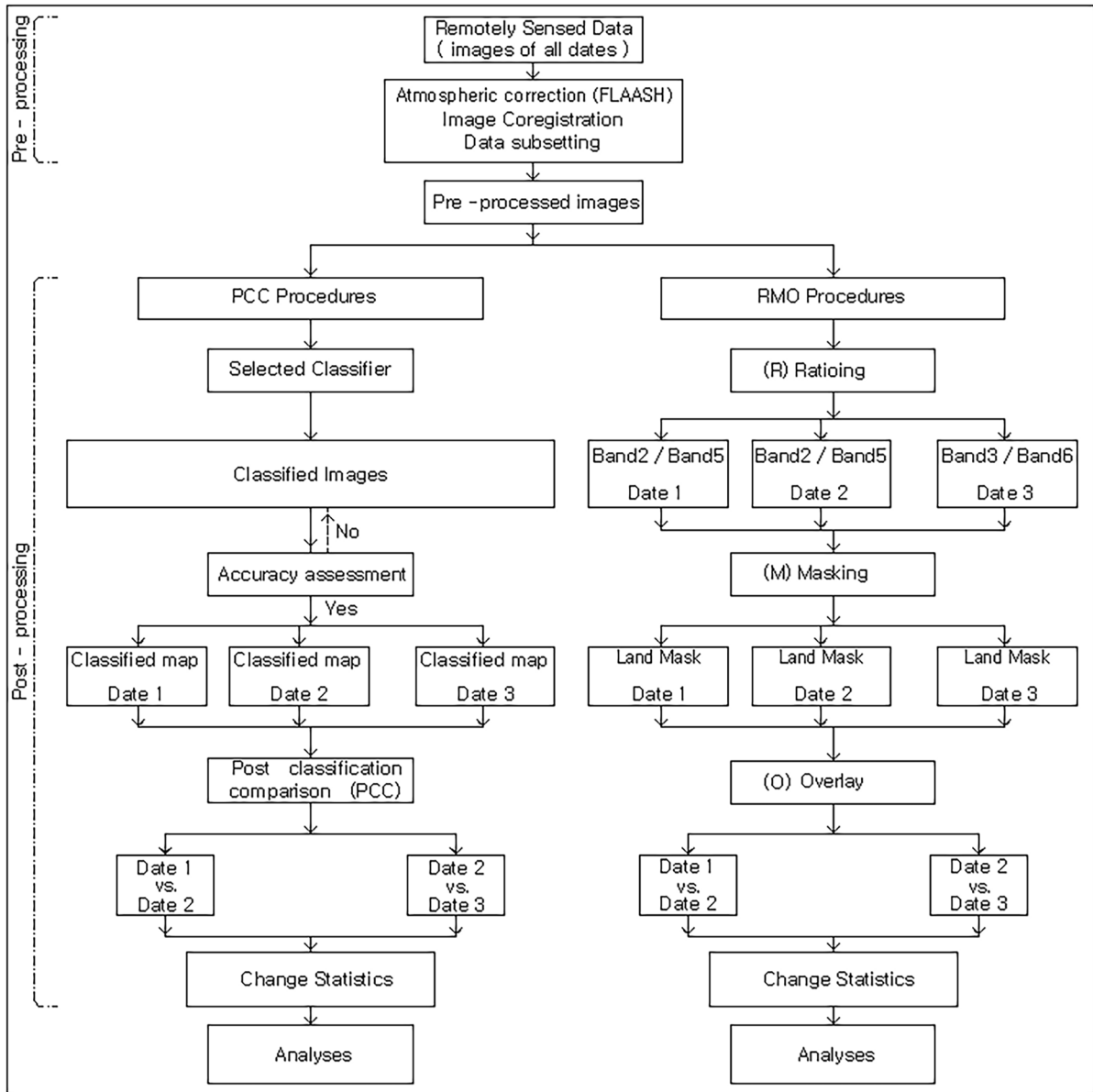


Fig. 2 Methodology. Date 1=ETM+, 1999. Date 2=ETM+, 2008. Date 3=OLI, 2018. PCC, post-classification comparison; RMO, ratio, masking and overlay

Guariglia et al., 2006; Kuleli, 2010; Louati et al., 2015) and their corresponding b6/b3 of the OLI; (ii) masking: by reclassifying the resulted ratios having values less than 1 for water pixels and more than 1 for land pixels, the land pixels were extracted and then converted to a vector to obtain a binary land-body mask of each date; and (iii) overlay: by using the overlay tool in GIS, the resulted land-body masks

were analysed in consecutive pairs to determine the coast changes in the studied intervals.

Classification change detection

Each classification is made to suit the needs of the user, and few users will be satisfied with an inventory that does not meet most of their needs (Anderson

et al., 1976). Compatibly, Port Sudan, as a Red Sea coastal city (RSCC), has some distinguished and special LULC characteristics that must be highlighted in the classification outputs. Based on a modified list of Anderson classification system (Anderson et al., 1976), the field work and the previous knowledge of the study area, twenty classes were recognized (Fig. 3 and Table 1).

Four SVMs named, linear (e.g. Vapnik, 1995), polynomial (e.g. Vapnik, 1995), radial basis function (RBF) (e.g. Vapnik, 1995) and sigmoid (e.g. Evgeniou et al., 2000), are the most and commonly used in classifying remote sensing datasets. The current work used the four SVMs to classify the study images. The training areas collected at the field were carefully examined to select the ROIs intended to be used. The spectral separability between each ROI pair was computed using Jeffries-Matusita (J-M). J-M values range from 0 to 2.0, where values greater than 1.9 indicate that the ROI pairs have good separability (Richards, 2013). For the current study, J-M separability between each ROI pairs ranged between 2.0 and 1.90. Using the ROI accuracy sets, the classified

images were checked and confusion matrices were computed (e.g. Congalton & Green, 2019).

The PCC approach is used to analyse the changes between each consecutive independently classified pair of images of a given study area in a pixel-based comparison to produce information about the changes. These procedures were used to analyse the changes of Port Sudan during 1999–2008 (first interval) and 2008–2018 (second interval). This study used the accuracies of the individual classifications to calculate the overall change detection accuracy (e.g. Stow et al., 1980).

Results and discussion

LWC of Port Sudan, 1999–2018

Using RMO procedures, the ratio stage was employed for each image to produce a ratio map of each date (Fig. 4a-c), followed by the masking stage, which was performed for the ratio maps, to extract the land mask of each date (Fig. 5a-c) and overlay, which was

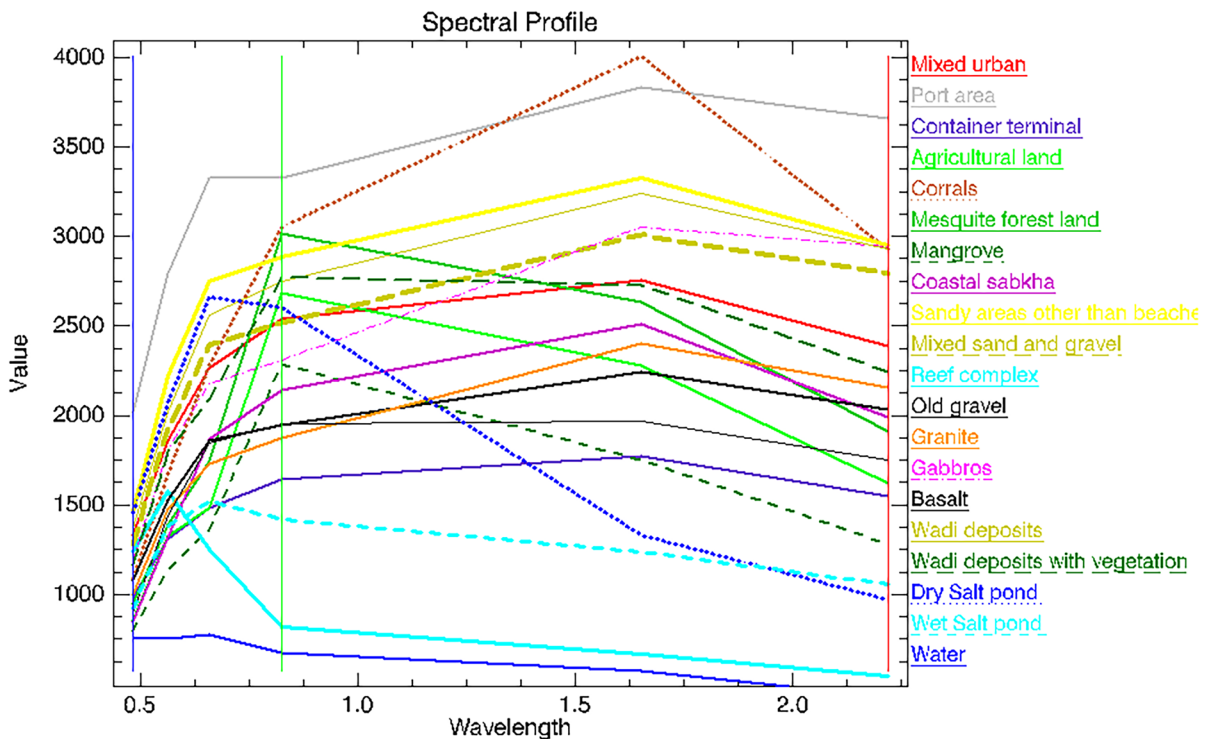


Fig. 3 Spectral signatures of LULC classes in Port Sudan

Table 1 Scheme and definition of LULC classes of Port Sudan

	Land use land cover class	Description
1	Mixed urban/built-up areas	Residential, commercial, industrial, services and utilities
2	Port area	Docks, drydocks, locks and waterway control structures
3	Container terminal	A specialized facility where ocean container vessels dock to discharge and load containers, always full of containers
4	Agricultural land	Crop land, farm land and other agricultural uses
5	Corrals	Holding areas for livestock
6	Mesquite forest land	Lands covered by mesquite trees (<i>Prosopis</i>)
7	Mangrove	Coastal wetland composed of forest and scrub dominated by <i>Avicennia marina</i>
8	Coastal sabkha	A flat salt-encrusted desert that usually lacks any significant plant cover due to the high concentration of salts and sediments
9	Sandy areas other than beaches	Sand and silt deposits with sparse vegetation
10	Mixed sand and gravel	Combination of sand, pebble and gravel field outcrops
11	Reef complex	Coral reef complexes
12	Old gravel	Old gravel rock
13	Granite	Granite rock
14	Gabbros	Gabbros rock
15	Basalt	Basaltic rock
16	Wadi deposits	Quaternary sediments
17	Wadi deposits with vegetation	Quaternary sediments covered with seasonal vegetation
18	Dry salt pond	Shallow artificial salt pan designed to extract salts from sea water filled, with dry salt
19	Wet salt pond	The same as dry salt pond but filled with sea water
20	Water	Sea water and estuaries

employed by using each pair of masks in consecutive dates to obtain the changes of the first and second intervals (Fig. 6a, b).

When comparing RMO results with the three studied FCC images, most of the detected changes could be attributed to anthropogenic activities, while other

small areas might be attributed to natural processes (Fig. 7). Landfill areas were related to (i) Port constructions at the port area (e.g. 1.04 km² in the first interval and 1.21 km² in the second interval), (ii) highway construction at the north lagoons of Kilo Tamanya (e.g. 0.22 km² in the first interval and 0.13

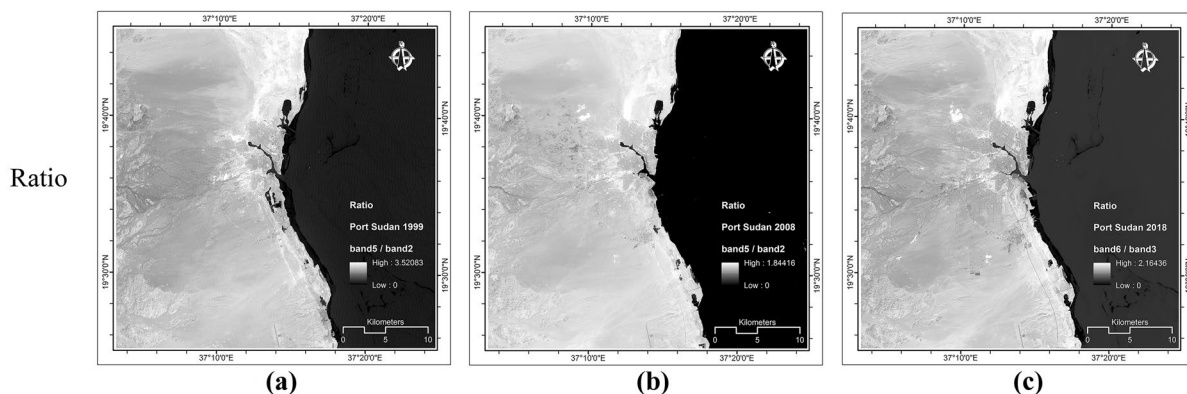


Fig. 4 Ratio maps of Port Sudan. **a** 1999, **b** 2008 and **c** 2018

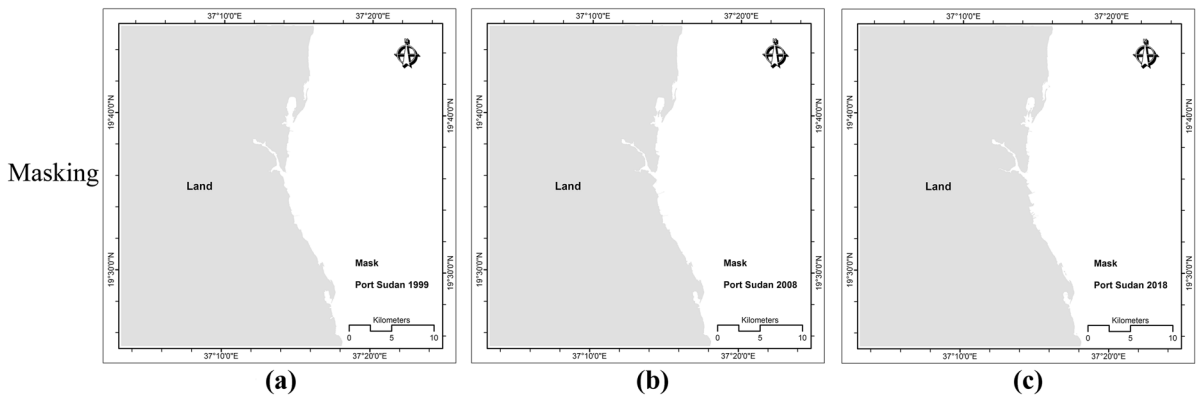


Fig. 5 Land masks of Port Sudan. **a** 1999, **b** 2008 and **c** 2018

km² in the second interval) and (iii) solid marinas and jetties at Derateit estuary (e.g. 0.12 km² in the first interval). In addition, in the second interval, sedimentation accretion of about 0.01 km² took place in areas south of el-Khair port, with no evidence of associated anthropogenic activities. For dredged areas, they occurred at the extension of Mog estuary (e.g. 0.04 km² and 0.05 km² in the first and second intervals, respectively). Figure 7 shows the detected LWC, which includes the sudden changes that occurred at Port Sudan's coast in 19 years. Meanwhile, establishing hard structures along the coast, for either the development of ports and harbours or protection, significantly modifies the shoreline and the erosion/accretion trend (Mohanty et al., 2012). After finishing the port phased development of Port Sudan, it is important to conduct an in-depth study to (i) assess the impacts of all the coastal structures on the shoreline and (ii) assess the natural longshore sedimentation and alongshore processes in a 30–50-year study period.

Globally, 60% of reefs are currently threatened by a combination of ocean warming, acidification and other anthropogenic impacts (United Nations, 2017). Locally, anthropogenic activities such as landfills and dredging are among the most negative impacts threatening reefs in Port Sudan, which indicate the need for additional studies to monitor the changes in the composition of coral reefs offshore. Since coral reefs are a major tourist attraction, burying coral reefs is expected to become a complicated socio-economic issue for the city in the

future. Through the fieldwork of Derateit and Mog estuaries, FCC maps as well as RMO outputs, the main detected hazardous processes include (i) landfill and dredging in the port area and Derateit estuary: dumping huge quantities of imported fill materials in the Red Sea resulting in burying large areas of coral reefs and coastal habitats; (ii) landfill in the north lagoons of Kilo Tamanya: dumping quantities of imported fill materials instead of establishing piles to construct a highway; and (iii) excavating activities in el-Khair port and Mog estuary: removing huge quantities of sediments and corals to fulfil the needs of el-Khair inlet and the extension of the estuary (Fig. 6a, b). Furthermore, the huge shipping and harbouring of Port Sudan and the operating of Bashayer and el-Khair oil terminals are expected to add more impacts on the southern coastal areas, which indicate the need for additional coastal hazards research.

The accuracies of the applied RMO in detecting LWC need reliable ground truth maps (GTMs), which were not available. Because of the lack of a reliable ground truth map, an image-driven reference data is utilized (Alesheikh et al., 1999, 2007). By fusing each studied image with its corresponding 15-m panchromatic band, GTM was obtained. Using the fused images, the land body of each date was extracted by on-screen digitizing. Then, each land body extracted by RMO was compared with its corresponding land body extracted by GTM, where the accuracies were between 1 and 1.5 pixel (pixel size = 30 m).

Fig. 6 Overlay of Port Sudan's masks. **a** 1999–2008 and **b** 2008–2018

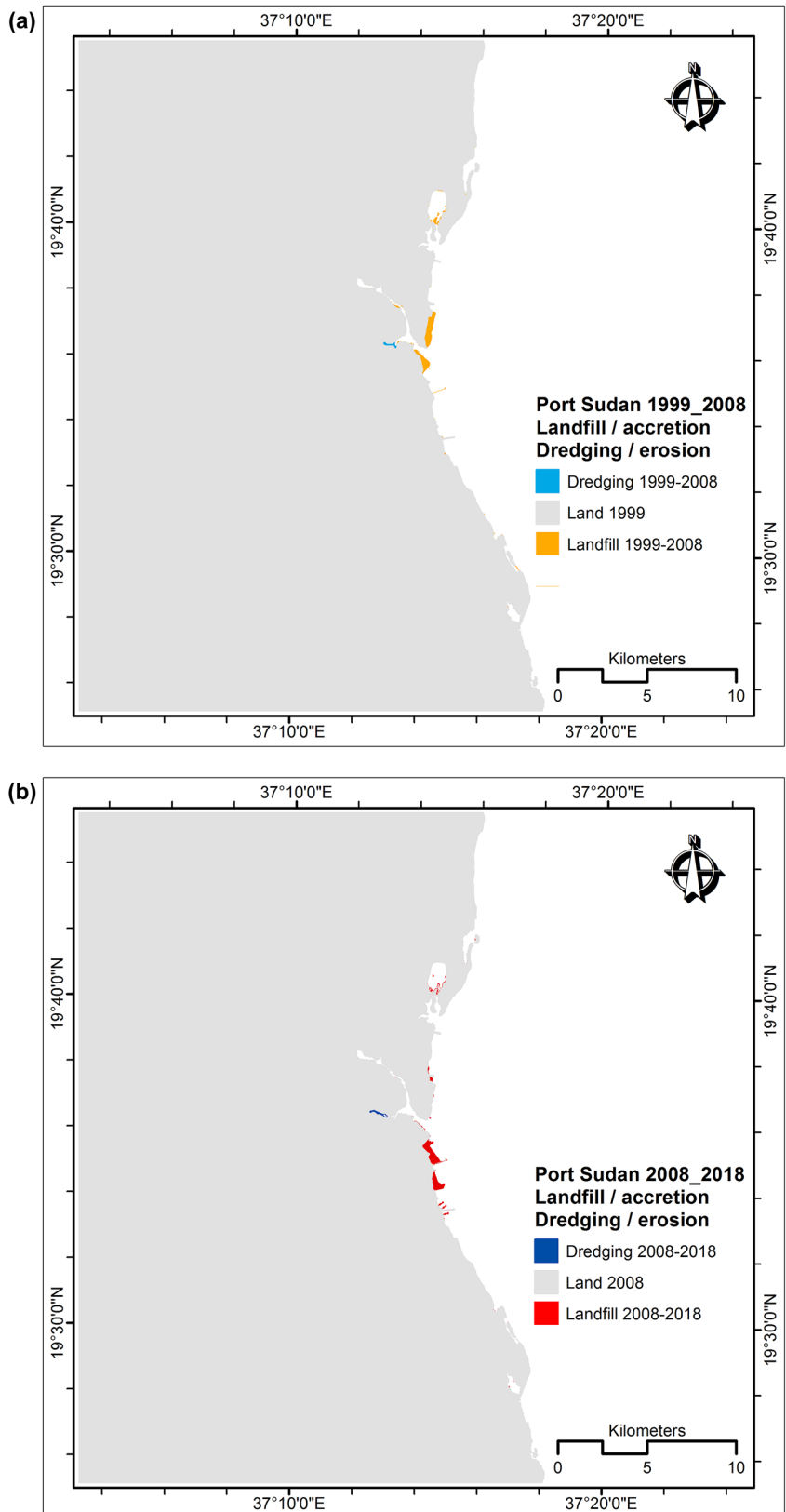
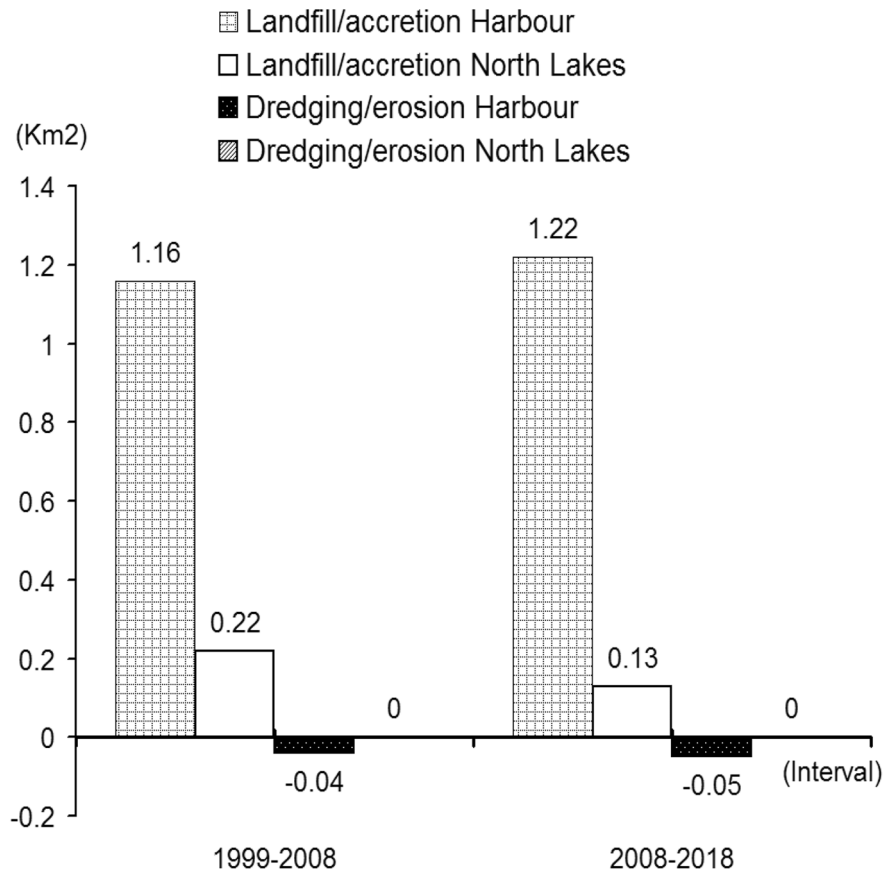


Fig. 7 LWC of Port Sudan, 1999–2018



LULC of Port Sudan, 1999–2018

Port Sudan ETM-1999, ETM-2008 and OLI-2018 Landsat images were classified using SVMs (Fig. 8a-c). Classification accuracy was used by this study as a measure of quality (e.g. Lu & Weng, 2007). For the three dates, all four SVMs attained high overall accuracy (over 90.0%), which met the minimum accuracy stipulated by Anderson et al. (1976) (at least 85.0%). Among the four SVMs, sigmoid gave the highest accuracy for the 1999, 2008 and 2018 images with overall accuracies equal to 91.7, 92.3 and 92.8, respectively. Classified images resulted from this work will fulfil the lack of LULC maps and can help in improving the outputs of future studies of the study area. In addition, the classification results revealed the usefulness of SVM in producing LULC maps of an arid area like Port Sudan. Furthermore, using a limited number of training samples that are support vectors (e.g. Foody & Mathur, 2004; Tzotsos et al., 2008)

was one of the main advantages of using SVM classifiers for the current work, which compensated for the shortage of collecting sufficient representatives of some LULC types.

LULC changes of Port Sudan, 1999–2018

Employing PCC for a consecutive pair of registered and independently classified images assures descriptive and quantified information about the changes that occurred during the investigated interval. Using the approximation of Stow et al. (1980), PCC accuracy for the first and second intervals was 84.6% and 85.6%, respectively. Furthermore, by using the resulted 1999, 2008 and 2018 LULC-classified images, the areas of each class were computed (Table 2). Results of urban changes will be presented after outlining the changes of the other LULC types.

Agricultural lands (ALs) of Port Sudan (located mainly in el-Janayen [small deltas of Khor Mog] and in areas attached to the airport road) were changed

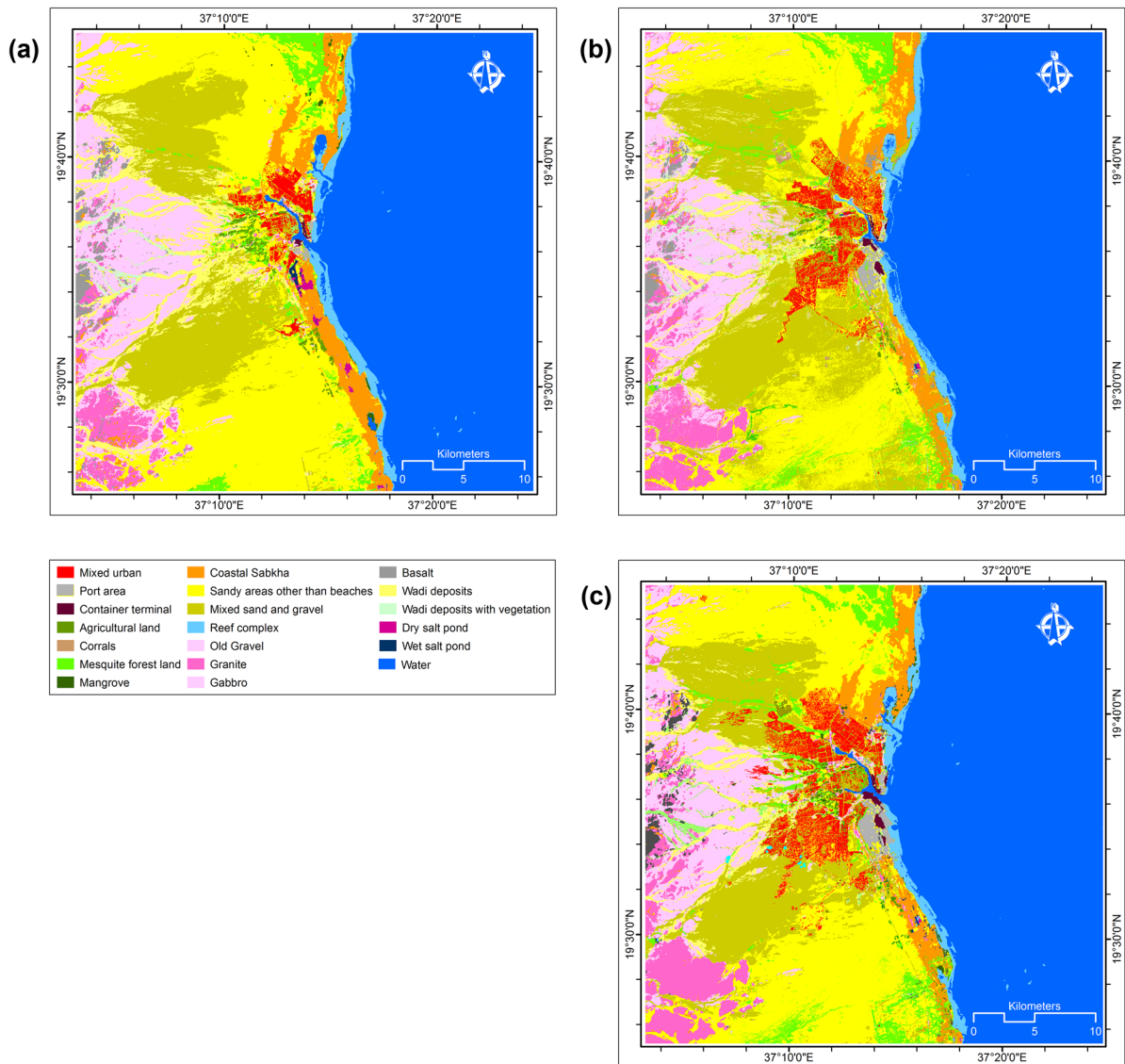


Fig. 8 LULC of Port Sudan. **a** 1999, **b** 2008 and **c** 2018

dramatically. In general, the total area of ALs was decreased from 5.18 to 3.84 and 3.13 km² (Table 2) in 1999, 2008 and 2018, respectively, i.e. about 0.11 km² year⁻¹ along the 19-year period. Relatively, the total area of ALs was decreased by a relative change of about 25.9% and 18.5% during the first and second intervals, respectively, which represent about 40% of the AL primary area in 1999 (Table 2 and Fig. 9a). When distributing the total area of AL over its two locations in el-Janayen and airport road, they were decreased from 3.40 km² and 1.78 km² in 1999

to 2.52 km² and 1.52 km² in 2008 and to 2.21 km² and 0.92 km² in 2018. During the entire study period, more than a third (35%) of el-Janayen AL was lost and changed into bare land (ready to build) or urban (most of them are slums) areas. Not only do these slums occupy AL, but they also narrowing the khors and negatively affect the local environment through their solid waste. In addition, almost half (48%) of airport road AL was lost and changed into services and industrial activities (related to refinery). According to the World Bank Group (2020), agriculture is

Table 2 LULC areas extracted from classified images of Port Sudan (1999, 2008 and 2018)

No	Land use land cover	1999 areas		2008 areas		2018 areas	
		km ²	%	km ²	%	km ²	%
1	Mixed urban/built-up areas	26.84	3.27	51.49	6.27	81.21	9.87
2	Port area	1.01	0.12	3.57	0.43	7.34	0.89
3	Container terminal	0.68	0.08	1.77	0.22	2.47	0.30
4	Agricultural land	5.18	0.63	3.84	0.47	3.13	0.38
5	Corrals	0.79	0.10	1.76	0.21	1.79	0.22
6	Mesquite forest land	16.26	1.98	22.13	2.69	28.37	3.45
7	Mangrove	1.81	0.22	1.31	0.16	1.08	0.13
8	Coastal sabkha	52.51	6.40	50.21	6.11	47.19	5.73
9	Sandy areas other than beaches	275.84	33.64	268.42	32.69	252.94	30.74
10	Mixed sand and gravel	176.64	21.54	158.87	19.35	141.43	17.19
11	Old gravel	103.32	12.60	102.71	12.51	102.13	12.41
12	Granite	54.82	6.68	56.69	6.90	56.15	6.82
13	Gabbros	17.68	2.16	16.63	2.03	16.97	2.06
14	Basalt	15.6	1.90	14.93	1.82	15.13	1.84
15	Wadi deposits	55.8	6.80	54.16	6.60	53.42	6.49
16	Wadi deposits with vegetation	12.36	1.51	11.61	1.41	11.09	1.35
17	Dry salt pond	2.12	0.26	0.91	0.11	0.81	0.10
18	Wet salt pond	0.82	0.10	0.15	0.02	0.27	0.03
	Sub-total (land)	820.08	100.00	821.16	100.00	822.92	100.00
19	Reef complex	24.18		23.47		21.86	
20	Sea water	566.49		566.12		565.97	
	Total (land and sea)	1410.75		1410.75		1410.75	

the backbone of the Sudanese economy, generating one-third of GDP, having a labour share of more than 50% and providing livelihood to approximately two-thirds of the population. The expanded urban areas of Port Sudan had an adverse impact on agriculture, which was neglected and left to deteriorate further, leading to reduced food and livestock production, job loss for the farmers and reduced income and raising poverty-environment problems. More efforts and policies are needed to preserve the limited existing AL.

Regarding forests, the mesquite forests (located in the northern and southern areas of the coastal plain, khors and along the airport road) were increased by about 36% and 28% during the first and second intervals, respectively (e.g. 74% along the entire study period) (Table 2 and Fig. 9b). Mesquite trees affect the local surroundings in three directions: (i) combating desertification (positive impacts for the local environment), (ii) reducing water availability (negative impacts for farmers) and (iii) income source as a source of charcoal (positive impacts for nomads) (e.g. Abdalla, 2015). The increase in mesquite forests in

Port Sudan is shown as an important natural resource for combating desertification and energy. Conversely, mangrove patches located in the northern and southern coastal areas were decreased by a relative change of more than 27% during the first interval and further decreased by about 17% during the second interval (Table 2 and Fig. 9c). The lost mangrove areas may be referred to as sedimentation or dredging processes of el-Khair Oil Terminal (e.g. IMR & FMSF, 2014) or overgrazing (e.g. El-Feky & Ahmed, 2015). Due to the inaccessibility of some areas along the city coast, a distinction between the estimated causes of mangrove decline is not possible, illustrating the need for an authorized study to cover this issue. Globally, an estimated 20% of global mangroves have been lost since 1980 (United Nations, 2017). At a local scale, the loss of mangrove areas in Port Sudan with such a high rate of decline (e.g. 2.10% year⁻¹) is very serious and negatively affects livestock, natural habitats and biodiversity in the coastal areas and may lead to coastal erosion. When comparing the case of mesquite increase with that of mangrove decrease in the

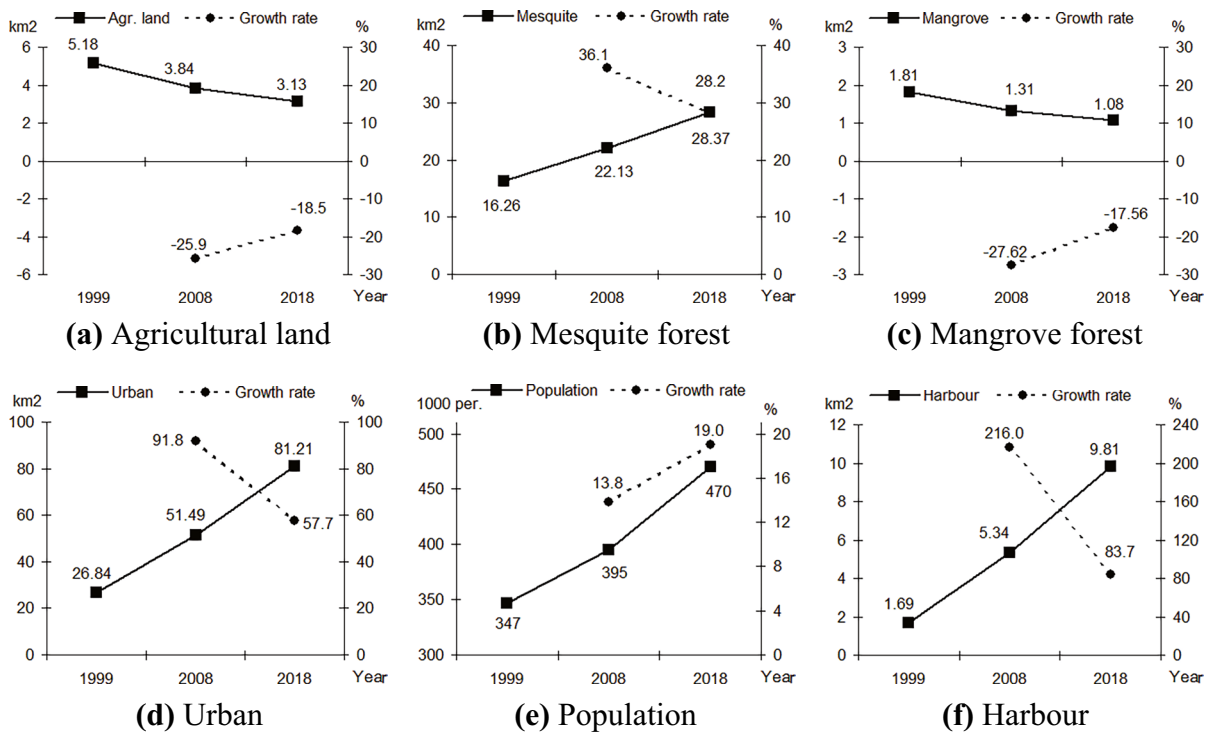


Fig. 9 Relative changes of some LULC types and population. **a** Agricultural land, **b** mesquite forest, **c** mangrove forest, **d** urban, **e** population and **f** harbour

same study area/period, most of the reasons could be attributed to the characteristics of the two plants. Mesquite is characterized by (i) abundant long-lived seed that is disseminated by livestock and wildlife, (ii) the root system can reach 50 m long and extended in a radius of approximately 30 m around the trunk, (iii) the high rate of seed germination in almost all environmental conditions and (iv) the ability to re-sprout (e.g. Abdalla, 2015). Moreover, when adding the factors of the landfill, dredging and shipping activities that are negatively affecting mangroves (e.g. IMR & FMSF, 2014) to the comparison, the case mesquite increase/mangrove decrease could be clearly identified.

Urban of Port Sudan (Table 2) was increased by an average rate of 2.74 km² year⁻¹ and 2.97 km² year⁻¹ during the first and second intervals, respectively. The urban area was the only LULC type that has increased rapidly from 26.84 to 81.21 km², which is more than twice its primary area in 1999 with an average rate of 2.86 km² year⁻¹ over the entire 19-year study period. The urban areas in Port Sudan mainly expanded over

sand, sand and gravel and agricultural lands along the study period (Fig. 8a-c). Of the 54.37 km² of growth in urban areas (1999–2018), about 59.0% was converted from sand and gravel, 37.0% from sand and 2.0% from agricultural lands and the remaining 2.0% was converted from other LULC types. From 1999 to 2018, the relative change of the urban areas was about 203.0%, where the greatest increase was during the first interval of about 92.0% (10.2% annual urban growth rate) followed by about 58.0% (5.8% annual urban growth rate) during the second interval (Fig. 9d). This rapid pace of urbanization in Port Sudan means more infrastructure challenges, health and environmental hazards, competition over job opportunities as well as high poverty rates, thus adding more stresses to the already stressed city.

The spatial patterns of urban expansion

Due to the presence of Derateit and Mog estuaries, the urban mass of Port Sudan is divided into three regions boarded by the coastal area to the east and RSH to

the west (Fig. 8c). The city is characterized by a distinctive pattern of urban sprawl in the form of a maple leaf. The spatial patterns of the urban expansion were mainly northwest, southwest, south and west. As one of the main advantages of PCC, changes from one LULC type to another can be spatially obtained (e.g. Lu et al., 2004). In the southeast coastal areas, some areas of the harbour were expanded to cover areas of coastal sabkha and buried salt ponds. Construction of permanent structures on sabkha is not recommended unless soil enhancement, replacement or piling is considered (Ahtchi-Ali & Vitiello, 2012), which are costly operations. Furthermore, the northeast coastal area is pristine (far away from the harbour and current urban problems) and remained unaffected by the negative changes that occurred in other coastal cities such as Hurghada and Safaga in Egypt (e.g. Dewidar, 2002; Moufaddal, 2005; Vanderstraete et al., 2006; Kamh et al., 2012) and Jazan in KSA (e.g. Al-Zubieri et al., 2018). These areas are considered a great opportunity for the local authorities to regulate tourism development under a sustainable umbrella to preserve the future wealth of the community.

Driving forces and constraints influencing the urban expansion of Port Sudan

Urban growth and expansion are temporally and spatially influenced by a combination of factors and constraints that are specific to each city. For the current work, natural environment, socio-economic, physical and technological conditions are presented.

Natural environment

The site and location of coastal cities, especially harbour and tourism cities, ensure their strong economic base. The geology of Port Sudan as well as its harbour (the mouth of a gulf continuing seaward through a coral-free 18–26-m-deep channel) assures its harbouring advantages. Furthermore, the vital location of Port Sudan (middle of the maritime route of Europe, East Africa-Asia) facilitates its function as an important international trade point. Furthermore, the unique natural inshore and offshore sites and the distinguished environmental conditions of Port Sudan facilitate its function as a city, diving and recreational site and as a resource provider, thus attracting inhabitants, investors and tourists to settle and invest.

Economy

The economy of Port Sudan is highly connected to the harbour and its related activities, which play a major role in the Sudanese economy. Meanwhile, after Sudan-South Sudan's secession in 2011 (Twijnstra, 2015), the economic co-operation between the two Sudans decreased, which largely affected the development booming. Fortunately, the PPD had started in 1999 and was planned to continue until 2020 (e.g. IMR & FMSF, 2014). Among the indicators of the state of optimism in that era are the following: (i) the increase in the volume of Khartoum-Port Sudan transportation (e.g. Ranganathan & Briceño-Garmendia, 2011) and (ii) the construction of an oil pipeline, a new refinery and a terminal in Port Sudan (e.g. Berry, 2015). The current study revealed that an area of 8.12 km² was added to the harbour (port area plus container terminals) during 1999–2018 (Table 2). This means that each 1.0 km² added to the harbour area corresponds to 6.7 km² added to the urban area, indicating high expectations of the roles of the harbour in the future. To enhance society and reduce poverty, it is of utmost importance to keep the ports' equipment maintained and modernized and their manpower well trained. In general, the oil economic activities, the PPD and transportation growth that began after the mid-1990s positively affected Port Sudan and Sudan's economy, which subsequently led to a large migration to the city and urban growth.

Population

The estimated population of Port Sudan increased from 347,000 to 395,000 and 470,000 in 1999, 2008 and 2018, respectively (e.g. WPR, 2020). When comparing population growth with the resulted urban and harbour areas (Table 2) during the two intervals, important conclusions are drawn. During the first interval, Port Sudan's population grew by about 13.8% (Fig. 9e), while the harbour (Fig. 9f) and urban (Fig. 9d) areas expanded by 216.0% and 91.8%, respectively, which represent more than 15 and 6 times the population growth rate, respectively. In the following interval, Port Sudan's population grew by about 19.0%, while the harbour and urban areas expanded by about 83.7% and 59.7%, respectively, which represent more than 4 and 3 times the rate of population growth rate, respectively (Fig. 9d-f). The

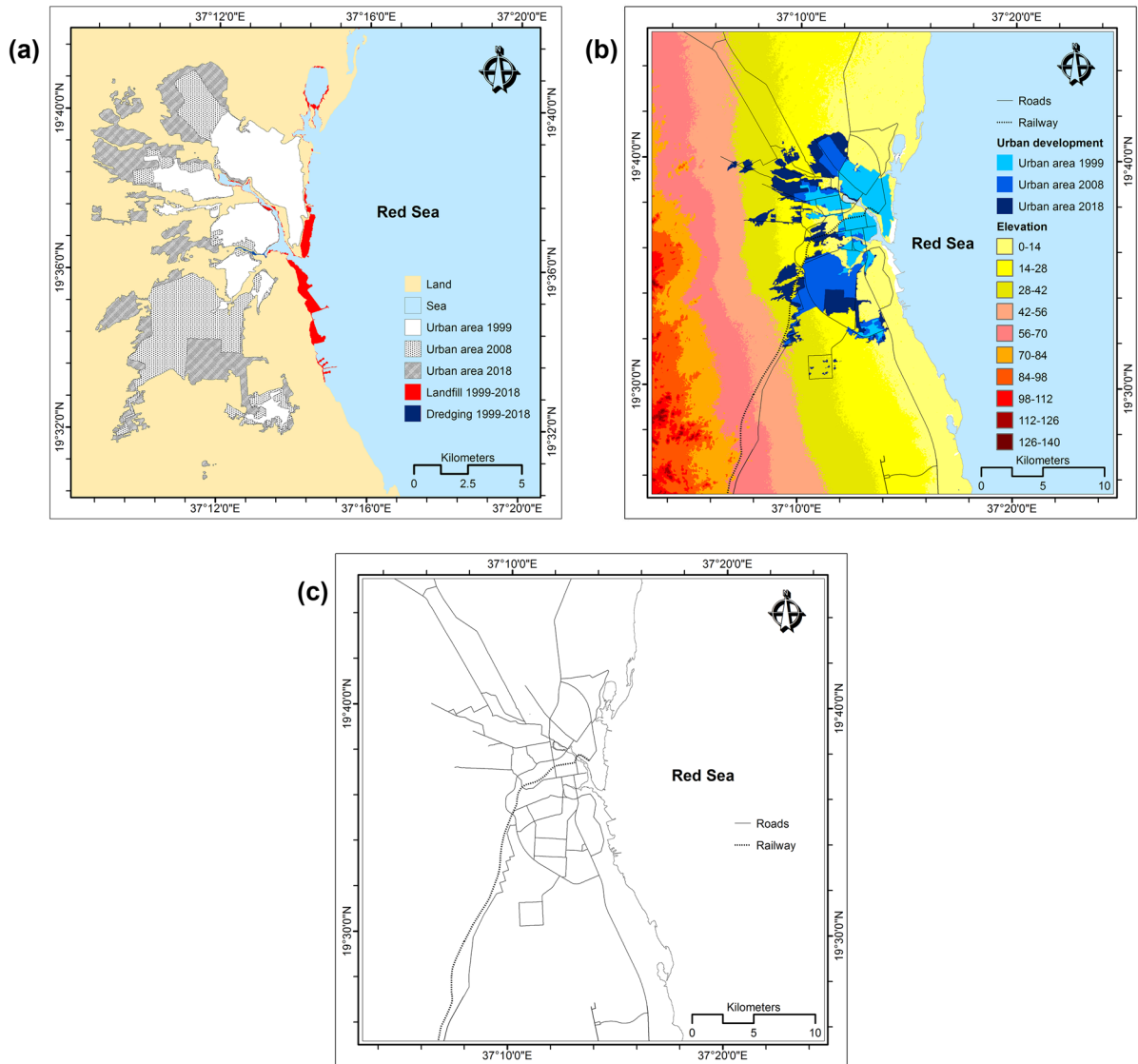


Fig. 10 Urban expansion of Port Sudan. **a** Urban development 1999–2018, **b** urban development draped over a digital elevation model and **c** main roads' network

results show that the rate of urban development has outstripped the rate of population growth along the entire study period. This can be explained as a rapid expansion of housing combined with soft regulatory hands and the availability of diverse and low-cost building materials, resulting in the land being used for urbanization at a faster rate. Obviously, the rapid population growth in Port Sudan is a result of natural increase, in-migration from Sudan (impact of drought and conflict) and the neighbouring countries seeking

security, job opportunities or extended migration to other countries.

Topographical and geological factors

The topography of Port Sudan influenced its urban expansion directions, which tended to follow flat areas. The current urban areas of Port Sudan generally have a gentle slope of 0°–8° (Fig. 10a, b). Geologically, the coastal plain area (recent deposits) has

good potential for urban expansion in the future, but it should be under proper management plans.

Road network

Using the 15-m panchromatic band of the OLI-2018, the main roads and the railroad of Port Sudan were digitized (Fig. 10c). Through field visits, information about the development of the internal road network during the study period was obtained. During that era, the city administration used to use its heavy machinery to divide land areas into planned plots, which were then handed over to the people (residents, internally displaced persons (IDPs) or refugees) to be developed. These simple and straightforward administrative procedures in road construction represent a major managerial effort that provides an initial stage for future development when the necessary funds are available. The implemented road network (asphalted, gravel or sand) was the backbone of shaping the spatial pattern of Port Sudan's urban areas.

The road network has replaced the railway's role in transportation, which has been declining due to operational and socio-economic problems. Furthermore, during 2000–2008, the length of Sudan's roads almost doubled from 3400 km to more than 6200 km, which include the development and raise the efficiency of the major arterial route of Khartoum-Port Sudan (e.g. Ranganathan & Briceño-Garmendia, 2011). Furthermore, the regional road connectivity of neighbouring landlocked countries (e.g. South Sudan, Chad, Central Africa and Ethiopia) to Khartoum and with the coastal gateway of Port Sudan received considerable attention during 2011–2018 (MoFEP, 2019). In general, Port Sudan was and still remains the target of a series of roads and trade routes that serve transportation with the country and the harbour, which forms an economic triangle that links the coast, inland city areas and the various regions of the country. These important roles of the road network greatly contributed to Port Sudan's urban growth.

Constraints to the urban expansion of Port Sudan

Urban expansion is governed by some natural and/or artificial constraints, which compel the physical form of the city. Natural constraints of Port Sudan include the Red Sea shoreline, which restricts the city to eastward expansion as well as the RSH, which restricts

the city to westward expansion. All the khors must be left clean to avoid the environmental and health hazards caused by solid waste. Also, the northeast coastal areas are shown as a major driving force for tourism development; therefore, they have to be free from logistical restrictions.

Conclusion

In this study, the used post-classification comparison and ratio, masking and overlay approaches were very effective in determining the status, highlighting the problems of Port Sudan on different dates and assuring descriptive and quantified information about the city and coast changes during the studied period. Approximately 2.37 km² and 0.35 km² of coral reefs and coastal habitats have been buried by landfill and dredging activities in constructing the harbour extensions and the crossing highway in the north lagoons of Kilo Tamanya, respectively. Furthermore, an area of about 0.01 km² south of el-Khair port has been mostly formed by sediment accretion during the recent constructions of the harbour. Producing very good accuracy multirate (1999, 2008 and 2018) LULC maps of medium-resolution Landsat images using SVM provided useful references for future studies of the study area. Furthermore, monitoring the changes between the consecutive dates provided the basis for understanding the effect of developing the main economic base of the coastal city (the harbour in the current study) on urban growth, urban population growth, loss of agricultural and mangrove areas as well as the burial of coral reefs and coastal habitat. The increased urban areas (+200%), the decreased agricultural lands (−40%), and mangrove (−40%) during the study period were largely due to socio-economic and environmental factors, which are expected to have their adverse impacts on the city, inhabitants and coastal and marine environments and their resources unless proper management plans are considered. The natural increase of mesquite forests (> 74%) represents an advantage for combating desertification and providing energy for domestic household use. The natural environment, the oil economic activities, harbour development, population growth, road networks and transportation, areas of gentle slopes and availability of construction raw materials positively affected the urban growth of the study area during the study period. Further research is needed to

monitor mesquite forests (green carbon) and sources of blue carbon as well as coastal sabkha in the coasts of the Red Sea at the local and regional levels. Also, there is a need to conduct an in-depth study to assess the impacts of the coastal structures on the shoreline and the natural longshore sedimentation and along-shore processes in a suitable study period.

Data availability All data generated or analysed during this study are included in this article.

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