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Designing of a Ship Carbon Dioxide Emissions Monitoring Model and Blue Carbon Storage System for Green Shipping in Tanzania: A Case Study of Dar es Salaam Port

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A B S T R A C T

This study aims to design a ship carbon dioxide (CO_2) emissions monitoring model to estimate the amount of CO_2 emissions based on activities at Dar es Salaam port and incorporate with mangroves sequestration as a part of blue carbon storage to help mitigate air pollution. The assessment of the emissions considers three port activities: anchorage, maneuvering, and berthing. The bottomed-up model is the estimating technique employed by taking into consideration engine power, load factor, and fuel emission factor. Following that, the model was developed utilising machine learning techniques, particularly the linear regression method. The model was trained with Scikit Learn, and the data was stored in a PostgreSQL database through Django Python framework. A ship CO_2 emissions monitoring system and the blue carbon storage (SCEMS) are the outcomes of the project. The results in CO_2 emissions showed that there is a consistent relationship between the type of ship and the total CO_2 emission. Ships that spent longer time at port exhibited higher CO_2 emissions, accounting for 72% of the total estimated CO_2 emissions compared to ships that spent shorter time. Tanker ships exhibited the highest rate of total CO_2 emissions, contributing to 72% of the total emissions compared to other types of ships at Dar es Salaam Port. It was determined that 726,975 hectares of mangroves could trap the 610.4475 Mt of CO_2 emissions that were predicted to occur yearly. This designed model presents a compressive solution to maritime CO_2 emissions by not only quantifying emissions but also proposing a natural method for sequestration. Mangroves as part of blue carbon ecosystems are incredibly effective at absorbing CO_2, making them a crucial ally in combating climate change. Furthermore, this discovery opens the possibility for ships or shipping companies to earn carbon credits through mangrove restoration projects. Each ton of CO_2 sequestered can be converted into carbon credits which can be sold or traded on carbon markets, providing an economic incentive for emission reduction.

1. Introduction

The shipping industry has long played an important role in global trade, connecting nations and enabling the movement of products and commodities, transporting over 90% of the world's goods (TPA 2023). However, it is also a significant contributor to greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2), which accounts for a substantial portion of the sector's environmental impact. The shipping industry contributes 3.9% of the world's CO_2 output equivalent to 1260 million tons of CO_2 and this is one of the largest sources of anthropogenic carbon emitters (Budiyanto et al., 2022). According to the report of Fourth Worldwide (IMO) Greenhouse Gases Study, maritime transport activities are expected to rise by over 40% for seaborne trade by 2050. As a result, greenhouse gas release will grow to 90-150% in 2050 (Budiyanto et al.,2022). The growing concern over climate change and environmental sustainability has prompted international calls for greener shipping practices.

In this context, the concept of green shipping which refers to sustainable maritime practices aimed at reducing environmental impacts has gained global attention (Pricillia et al., 2021). Core components of green shipping include emissions monitoring, energy efficiency measures, adoption of cleaner fuels, and integration of nature-based solutions. While many

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developed countries have already initiated regulatory frameworks and technological interventions to monitor and mitigate maritime emissions, developing nations, particularly in Africa, lag in the adoption of such practices (Wan et al., 2021). Tanzania, with its strategic location along the Indian Ocean and a growing maritime industry, is uniquely positioned to lead regional efforts in green shipping. The Port of Dar es Salaam, which is the country's principal seaport, serves as a gateway to several landlocked countries and handles the bulk of Tanzania's import and export activities. The increasing vessel traffic at the port, coupled with the absence of a robust emissions monitoring system, underscores the need for targeted interventions to quantify and manage ship-related CO_2 emissions.

Alongside emissions mitigation, blue carbon sequestration ecosystems such as mangroves, seagrasses, and salt marshes offer an additional pathway to enhance maritime sustainability (Pricillia et al., 2021). These ecosystems capture and store significant amounts of carbon, acting as natural carbon sinks. Coastal Tanzania, particularly areas around Dar es Salaam, is home to extensive mangrove forests that, if protected and restored, could play a pivotal role in offsetting maritime emissions (Ricart et al., 2020). However, various factors can impact the effectiveness of blue carbon sequestration. Xiao et al. (2020) conducted field measurements and flow modelling in an intertidal marsh to investigate how crab burrows influence carbon exchange, and these burrows modify blue carbon sequestration in salt marshes. Mariani et al., (2020) highlighted the detrimental impact of fisheries on blue carbon sequestration, with historical catches contributing to additional atmospheric CO2 emissions. Additionally, Liu et al., (2020) found that macroalgal blooms can trigger the breakdown of seagrass blue carbon, reducing seagrass decomposition and carbon sequestration. Similarly, Alsaleh et al., (2023), unveiled the impact of the fishery industry on blue carbon sequestration, emphasizing the need for marine sustainability practices. Overall, understanding various factors influencing blue carbon sequestration is crucial for developing effective strategies to enhance carbon capture and storage in coastal ecosystems. Efforts to protect and restore blue carbon ecosystems, mitigate the impact of human activities such as fishing, and promote sustainable marine practices are essential for maximizing the potential of blue carbon sequestration in combating climate change.

The monitoring and estimation of CO_2 emissions have become crucial in the context of environmental sustainability and climate change mitigation efforts. Various studies have been conducted to develop models and methods for monitoring and estimating CO_2 emissions from different sources. Mentese et al., (2020) conducted a comprehensive assessment of ambient air quality in Canakkale City, Turkey, including the measurement of CO_2 levels, among other pollutants, and their impact on respiratory health. This study highlights the importance of monitoring CO_2 emissions for public health concerns. In addition, Shi et al., (2020) proposed an inversion method using differential absorption Lidar to estimate point source carbon emissions. This novel framework aims to improve the monitoring, reporting, and verification of anthropogenic carbon emissions, emphasizing the need for accurate emission estimation models. Furthermore, Hayashida et al., (2020) developed a spatially explicit fossil fuel CO_2 emissions model for Osaka, Japan, to optimize a CO_2 monitoring network. This study demonstrates the importance of building detailed emission models and monitoring networks to effectively track and reduce CO2 emissions in urban areas. Mei et al., (2020) focused on analyzing the impact of climate change on the energy-economy-carbon nexus system in China, using simulation and optimization approaches. This study highlights the complexity of the factors influencing CO_2 emissions and the need for integrated models to address uncertainties in emission projections. In the same vein, Yu et al., (2020) proposed a carbon emission measurement method for individual travel based on transportation big data, specifically focusing on the Nanjing metro system. This research emphasizes the importance of developing models to track emissions from transportation systems to promote sustainable urban mobility. Overall, the literature review indicates a growing interest in developing models and methods for monitoring and estimating CO_2 emissions from various sources, highlighting the importance of accurate emission data for environmental and public health concerns.

Despite the growing global emphasis on sustainable maritime practices, there is a significant lack of localized research and implementation frameworks in many developing countries, including Tanzania. While international mechanisms such as the IMO Data Collection System (DCS) and the EU Monitoring, Reporting and Verification (MRV) framework have laid the foundation for tracking ship emissions, these tools are primarily designed for global or regional applications and often require advanced infrastructure, technical capacity, and regulatory enforcement factors that remain underdeveloped in the Tanzanian maritime context.

Currently, there is no established CO_2 emissions monitoring model specifically tailored for ports in Tanzania, particularly for Dar es Salaam Port, which is the country's busiest and most strategic maritime hub. The absence of baseline data on ship-related CO_2 emissions makes it difficult to assess environmental impacts or formulate effective policies for emissions reduction. Furthermore, existing port operations and environmental management frameworks do not integrate carbon accounting or emissions reduction as core objectives. Additionally, blue carbon ecosystems, such as mangroves and seagrasses along Tanzania's coast, are recognized for their carbon sequestration potential, yet their role in offsetting maritime emissions remains largely unexplored in national climate strategies and port sustainability planning. While several studies highlight the ecological importance of mangroves in Tanzania, very few assess their quantitative carbon storage potential in relation to maritime emissions or consider their use in a formal offset mechanism.

This project seeks to address these challenges by designing a comprehensive Ship CO_2 Emissions Monitoring System and developing a complementary Blue Carbon Storage Model. The proposed system aims to provide real-time data collection, reporting, and analysis of CO_2 emissions from ships, while the blue carbon model seeks to quantify and integrate the benefits of carbon sequestration by coastal and marine ecosystems into the industry's carbon management framework. Together, these solutions aim to promote greener shipping practices, support regulatory compliance, and contribute to global efforts to mitigate climate change.

2. Methodology

A combination of methods of research design was used in this study to examine the best ship emissions monitoring system to be used and how the CO_2 emissions were to be sequestered through blue carbon storage. As a result, it combined qualitative and quantitative methods for gathering, analyzing, and presenting data. Primary data collection for this study was done at Dar es Salaam port at Tanzania Ports Authority (TPA). The primary data collected was the time of the ship in port (ie. Turnaround time) this was since in the secondary data obtained from the Dar es Salaam port control logbooks lacked the departure time which was very important in determining the shipping time at port and the Allowed

Speed (AS) of ships when entering the port. This primary data was obtained through structured interviews with the Harbor Master and Port Control officers. The secondary data for this study were Gross Tonnage, Emission Factor for the Main Engine (ME) and Auxiliary Engine (AE), Maximum Speed (MS) and Mangrove Sequestration Capacity for the part of blue carbon storage. The Gross Tonnage was obtained from the dataset in the Dar es Salaam Port Control Logbooks, Maximum Speeds (MS) for different types of ships used as samples were obtained from Fleetmon.com and Mangrove Sequestration Capacity which was found to be 13.53 Gt year-1 (Alongi, 2014). A mixed methodologies approach, on the other hand, combines the advantages of the two approaches into one study (Shekhar et al., 2019).

2.1 Area of Study

This study was conducted at the Dar es Salaam Port. This area was selected as it is the busiest port in Tanzania with a rated capacity of 14.1 million tons of dry cargo and 6.0 million tons of bulk liquid cargo and it accommodates many ships compared to other ports in Tanzania. The port serves the landlocked countries of Zambia, the Democratic Republic of Congo, Burundi, Rwanda, Malawi, Uganda and Zimbabwe. The port is strategically located not only to serve East and Central Africa but also the middle and far East, Europe, Australia and America.

2.2 Description of the Development of the Model

The ship's carbon dioxide emission monitoring system and blue carbon storage (SCEMS) model were programmed in Python programming language using Django Framework. Supervised Machine learning techniques were used; Linear Regression was used based on the set of statistical data obtained. Along with the selection of the supervised machine learning technique the ship's carbon dioxide emission estimate was evaluated and integrated with the quantity of mangrove biomass required to sequester it (Alam & Chowdhury, 2020). The following steps provide a summary of the processes used to construct the model:

STEP 01: Since the nature of the goal of this study was to produce a predictive output, it was determined that a model had to be designed to be able to predict the emissions by ship using machine learning techniques.
STEP 02: Relevant data were gathered on ship characteristics and activities in Dar es Salaam port. Due to the nature of the dataset, it was determined that linear regression was the best machine-learning technique to be used for this model.
STEP 03: Due to its flexibility, it was determined that Python was the best programming language to implement the model.
STEP 04: A Django application was created to host the model.
STEP 05: The dependent and independent variables were identified using feature engineering.
STEP 06: The model was trained using Scikit, ensuring it learned the patterns related to ship emissions and blue carbon storage.
STEP 07: The dataset was divided into two sets the training set used to train the model and the testing set used to measure the performance of the model (Fig 1).
STEP 08: After testing the model, it was then integrated with the ship's carbon dioxide emissions monitoring system and blue carbon storage (SCEMS) (Fig 2).

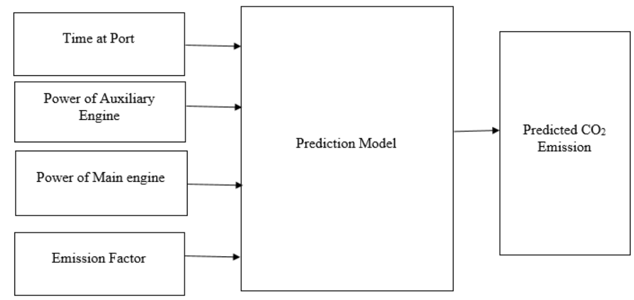

Fig. 1. A Sketch showing how the system was designed.

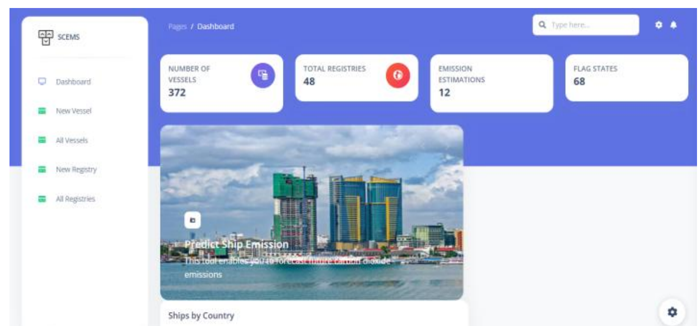

Fig. 2. Screenshot of the Ship CO_2 emission monitoring system and blue carbon storage (SCEMS).

2.3 Population of the study and sampling techniques

The population of this study was container ships, RORO ships, tanker ships, dry bulk carriers, general cargo carriers and all other types of ships entering Dar es Salaam port. The Dar es Salaam Port receives about two hundred (200) ships shifting from one port terminal to another, and about one hundred (100) ships without counting shifting from different terminals every month and four (4) Tanker ships every month summing up to a total of two hundred and four ships (204) a month. Therefore, the number of people entering Dar es Salaam Port per year by shifting to different terminals is 2448. According to Creswell (2014) and Krejcie & Morgan (1970), the formula for calculating the sample size for the finite population is;

$$n = \frac{N \times Z^2 \times p \times (1-p)}{(\mathrm{N}-1) \times \mathrm{E}^2 + Z^2 \times p \times (1-p)} \quad (1)$$

Where:
n = Required Sample Size
N = Population Size (2448 in this case)
Z = Z-Score (typically 1.96 for a 95% confidence level)
p = Estimated Proportion of Population with a particular characteristic (if unknown, 0.5 can be used for maximum variability)
E = Margin of error (typically expressed as a decimal fraction)
To determine the appropriate sample size, a 95% confidence level (Z = 1.96) was used and a margin of error of 5% (E = 0.05).

$$n = \frac{2448 \times (1.96)^2 \times 0.5 \times (1-0.5)}{(2448-1) \times (0.05)^2 + (1.96)^2 \times 0.5 \times (1-0.5)}$$

$$n \approx 332$$

The sample size that was used was 332 ships, this was the ideal number of ships to be used as a sample based on the calculations made in Equation (1).

The researcher used both probability and non-probability sampling in this investigation. Purposive sampling was utilized for non-probability sampling techniques to pick the sample such as Tanker ships, whilst a simple random sampling approach was used for probability sampling to select the sample such as ships of any type entering the port. Using these methods, the researcher was able to choose the study sample size from the study population at all levels (Table 1).

Table 1. Sample Size and Sampling Techniques

S/n	*Target Group*	*Target Population*	*Sample Size*	*Sampling Techniques*
1	*Any type of ship entering the port*	*2400*	*306*	*Randomly from all the ships*
2	*Tanker ships*	*48*	*26*	*Purposive sampling*

2.4 Data collection methods

Primary data collection for this study was done at Dar es Salaam Port at TPA and/or available filed data from relevant works. The primary data collected was the time of the ship in port (ie. Turnaround time). This was because the secondary data collected from the Dar es Salaam port control logbooks missed the departure time, which was critical in estimating the shipping time at the port as well as the Allowed Speed (AS) of ships entering the port. The primary data was obtained through structured interviews with the Harbor Master and Port Control officers. It was discovered that for Container Ships the time the ships spent at port was 72 hours (3 days), Car Carriers had a turnaround time of 22 hours and Tanker Ships had a turnaround time of an average of 192 hours (8 days). The Allowed Speed of ships entering the port was found to be 6-8 knots, this was according to the recommendations of the pilot onboard.

Moreover, the secondary data for this study were Gross Tonnage, Emission Factor for the Main Engine (ME) and Auxiliary Engine (AE), Maximum Speed (MS) and Mangrove Sequestration Capacity for the part of blue carbon storage. The Gross Tonnage was obtained from the dataset in the Dar es Salaam Port Control Logbooks, Maximum Speeds (MS) for different types of ships used as samples were obtained from Fleetmon and Mangrove Sequestration Capacity which was found to be 13.53 Gt year (Alongi, 2014).

2.5 Data analysis

The top-down method and the bottom-up method are the two generally employed methods for developing ship exhaust emissions estimations. Using a bottom-up approach, this study was conducted. The top-down approach is activity-based and depends on both static and dynamic data on a ship. The key issue in using this method is uncertainty in the calculation of emissions due to the absence of some data that can be used with activity-based approaches. The bottom-up method was employed because the estimations are based on ship dynamics and some information like engine load factor, fuel type, ship speed, position, and duration. This method also has a higher spatial and temporal resolution. As a result, the bottom-up method produces more accurate estimation results than the top-down method (Budiyanto et al., 2022).

The primary data and secondary data collected by the researcher were used in the calculation of the ship's carbon dioxide emissions, important parameters including Power of the Main Engine (ME) which was obtained from previous research literature studies comparing ships' Gross Tonnage and ship processes through non-linear regression in Equation 2 (Chen et al.,2016), Power of the Auxiliary Engine (AE) obtained from the power ratio auxiliary engine AE to ME for container ships is used 0.22 in Equation 3 (Wang et al., 2020), Load Factor (LF) in Equation 4 (Styhre & Wines, 2018), Main Engine Emission in Equation 5 (Budiyanto et al.,2022), Auxiliary Engine Emission in Equation 6 (Budiyanto et al., 2022), Total Emissions in Equation 7 (Budiyanto et al., 2022).

$$P_{ME} = 2.22 \times GT^{0.889} \quad (2)$$

Where:

P_{ME} = Power of the Main Engine.

GT = Gross Tonnage.

$$\frac{AE}{ME} = 0.22 \quad (3)$$

Where:

AE = Auxiliary Engine Power.

ME = Main Engine Power.

$$LF = \left(\frac{AS}{MS}\right)^3 \quad (4)$$

Where:

LF = Load Factor.

AS = Actual Speed.

MS = Maximum Speed.

$$E_{ME} = T \times P_{ME} \times P_{ME} \times LF \times EF_{ME} \quad (5)$$

Where:

T = Time (Hours).

E_{ME} = Emission from the Main Engine.

P_{ME} = Power of the Main Engine.

LF = Load Factor.

EF_{ME} = Emission factor of the Main Engine.

$$E_{ME} = T \times P_{AE} \times P_{AE} \times LF \times EF_{ME} \quad (6)$$

Where:

T = Time (Hours).

E_{AE} = Emission from the Main Engine.

P_{AE} = Power of the Main Engine.

LF = Load Factor.

EF_{AE} = Emission factor of the Main Engine.

$$E_T = E_{ME} + E_{AE} \quad (7)$$

Where:

E_T = Total Emissions

E_{ME} = Emissions from the Main Engine.

E_{AE} = Emissions from the Auxiliary Engine.

The total emissions produced in (gram), T is the time of the ship at port

(Hours), ME is the power of the main engine in (kW), AE is the power of the auxiliary engine or generator in (kW), LF is the Load Factor in (%) the percentage use of ship engine in port and EF is emission factor in (g/kWh).

3. Results and Discussion

The shipping activity at Dar es Salaam port was calculated based on berthing time, which is divided into three main activities, namely Anchorage, Shipping and Berthing process. These activities are the same for all types of ships except for the Tanker ships which have a special anchorage and berthing area at Dar es Salaam port. The Tanker ships have a special anchorage area (anchorage number 7) while the berthing area is called a Single Bouy Mooring (SBM).

Depending on the berthing location, the ship waits for the berthing schedule from Dar es Salaam Port control while anchoring in the anchorage area. During this time the ship's main engine remains on as there is no order to be allowed to berth. Next is the shipping process which is the process of assistance of the vessel from the pilot boarding area to its designated berthing place under the assistance of the tug and the pilot. The ship uses power from the main engine and auxiliary engine to maneuver the ship. Then the berthing process is the process of leaning the ship to the berth place. Usually, the auxiliary engine is used for the loading and unloading process. If the movement of the ship affects the time taken in each process, also it affects the fuel consumption so eventually, it affects the emission produced. Shipping activity at Dar es Salaam port is shown in Fig.3. In addition, for tanker ships, the shipping activity is shown in Fig. 4. Several time variables were needed to calculate the ship's CO_2 emissions depending on the three activities being performed at Dar es Salaam Port, but due to the nature of the data that was obtained at Dar es Salaam Port the actual time that was used in the model for calculation was the entire time spent by the ship at the port.

3.1. Estimated Total Carbon Dioxide Emissions

The estimated total emissions during the ship activities at Dar es Salaam Port were calculated from the operational data of ships at the port combining all three activities at port, which are anchorage, shipping process and berth to obtain the time spent by each type of ship at port. Container ships spent an average of 72 hours at Dar es Salaam Port, Car carriers, Vehicle carriers, General cargo and RORO ships spent an average of 22 hours and Tanker ships spent an average of 192 hours which was the longest time of all the types of ships involved in this study. Navy ships were not included in this study since the data of important parameters are confidential due to security matters. The allowed speed when entering the port was according to the pilot's recommendation which should be within the Dar es Salaam port set range of 6 to 8 knots.

The emission factor for the main engine was according to the type of engine, slow speed diesel engines had an emission factor of 62000 g/KWh, medium-speed diesel engines had an emission factor of 68300 g/KWh and high-speed diesel engines had an emission factor of 68600 g/KWh. The emission factor represents the amount of emissions produced per unit of energy generated by an engine. Slow-speed Diesel engines generate emissions of 62,000 grams per kilowatt-hour of energy produced. Medium speed Diesel engines generate 68,300 grams per kilowatt-hour and finally High-Speed Diesel engines generate 68,600 grams per kilowatt-hour. The emission factor for the auxiliary engine was 68300 g/KWh. Fig. 5 shows the relationship between the types of ships and the resulting estimated emissions.

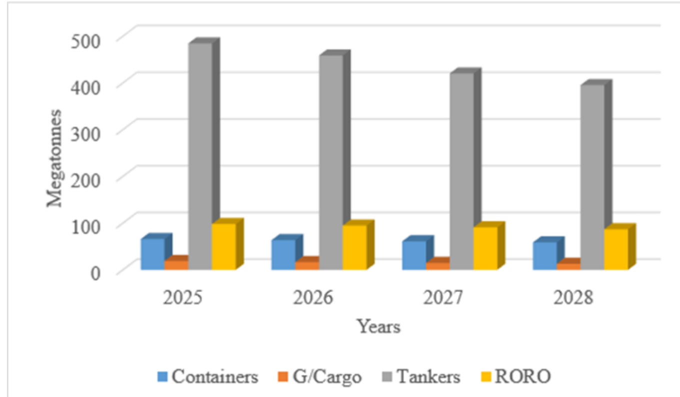

Fig. 5. Chart showing estimated ship emissions in megatonnes.

The average estimated carbon dioxide emissions per year is 610.4475 megatonnes. Tanker ships have very high CO_2 emissions rates because they spend longer time at the port. They have an average emission of 439.6775 megatonnes per year. This contributes to 72.0% of the total CO_2 emission at Dar es Salaam port. Container ships have an average of 62.3 megatonnes of CO_2 emissions per year, which contributes 10.2% of the total emission. On the other hand, General Cargo ships have an average of 15.7975 megatonnes of CO_2 emission per year, which contributes to 2.6% of the total emission at the port. RORO ships have an average of 92.6725 megatonnes of CO_2 emission per year, which contributes to 15.2% of the total emission at the port.

3.2. Assessment of Carbon Dioxide Sequestration Capacity of Mangroves

The global CO_2 sequestration rate is 13.53 Gt/year (Alongi, 2014). A hectare of mature mangrove forests absorbs 840 tonnes of carbon dioxide, this means that one mangrove tree removes 308 kg (0.3 tonnes) of CO2 from the atmosphere which is 12.3 kg per year (IEA,2021). The average total annual CO_2 emission estimation obtained from the model was 610.4475 Mt which is equivalent to mangrove restoration of about 726,975 hectares per year. According to Global Mangroves Watch, the area of Mangrove habitat in the world was 147,358.99 km2 in 2020, this represents a linear coverage of 14.93% of the 2,139,308.93 km of the coastline. Except for the Zanzibar and Mafia channels, which reach a width of approximately 62 km, Tanzania's coastline is roughly 1,424 km (including the coastline of the major islands and islets). The width of the continental shelf is 5.8 km, and it drops off to waters with depths greater than 500 meters quite close to the coastline (Mangora et al., 2016). The annual recommended mangrove restoration of about 726,975 hectares per year will contribute to increasing the world Mangrove coverage by 4.93% per year.

4. Conclusion

The estimation of ship CO_2 at Dar es Salaam Port was carried out using the bottom-up method involving parameters such as engine power, load factor, emission factor and operation time. The data used is based on annual historical data taken from Dar es Salaam Port Control.

- Three types of ship activity at the port were evaluated and combined to obtain the time at port namely anchorage, shipping process and berthing. From the data 2448 ships operating at Dar es Salaam Port were used. The results show a consistent relation between the total emissions and the time the vessel spent at the port.
- The emission contributions of Tanker ships, Container ships, General Cargo and RORO were 439.6775Mt which is equivalent to 72.0% of the total emissions, 62.3Mt which was equivalent to 10.2% of the total emissions, 15.7975Mt which was equivalent to 2.6% and 92.6725Mt which was equivalent to 15.2% of the total emissions respectively.
- In pursuing the Greenport concept which minimizes the effect of emissions on the environment and meets the IMO 2050 regulation by reducing emissions up to 50% the model can be a very powerful tool in predicting the CO_2 emissions at the Dar es Salaam port and this can be easy to plan mangrove plantation and restoration to sequester the emissions produced which is a natural way of mitigating atmospheric pollution by the greenhouse gases.
- Furthermore, it is recommended that TPA enhances its data collection methodology, particularly regarding time. Currently, TPA simply records the overall amount of time each ship stayed, but it would be very important to record the amount of time spent on each port operation, such as berthing, shipping, and anchoring. These values are very useful in determining accurate predictions of ship CO_2 emissions.

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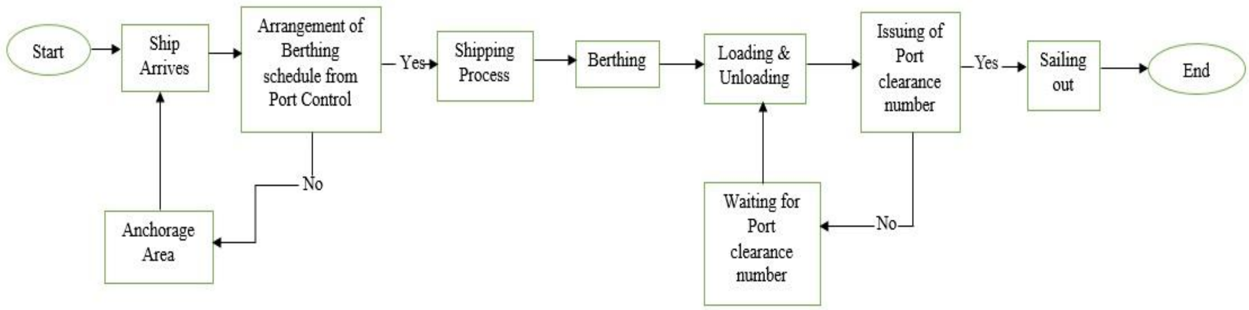

Fig. 3. Ship Activities in Dar es Salaam Port.

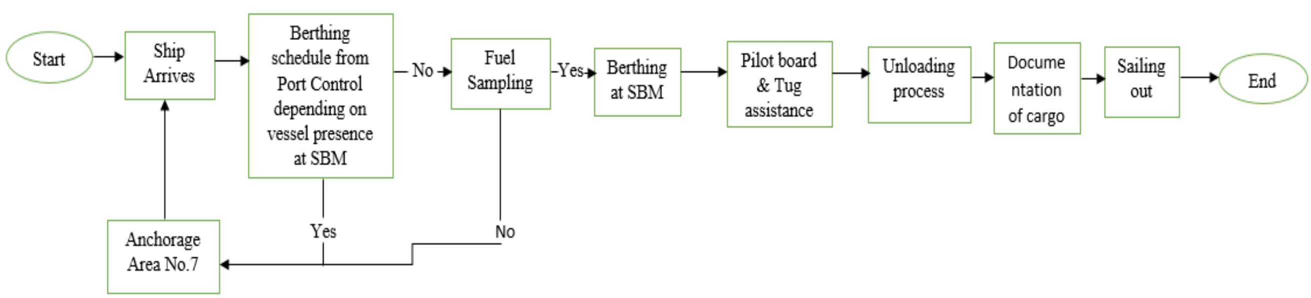

Fig. 4. Tanker Ship Activity at SBM.