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Estimation of Mg, Cd, and Ni levels in urban waterfront using one-dimensional transport model

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Accurate quantification of heavy metals is essential for optimizing remedial efforts at polluted waterfronts. Although surface water quality models can be helpful tools for rapid quantification of heavy metals in streams, they cannot be extrapolated to other water bodies. This study estimated Mg, Cd, and Ni levels in one of the polluted urban waterfronts in the Niger Delta Province, Nigeria (5.317°N, 6.467°E) using one-dimensional transport model. To do this, water samples were collected along the waterfront in both dry and rainy seasons and analyzed for the selected heavy metals using a SHIMADZU® AA6800 Atomic Absorption Spectrophotometer according to international standards. Model parameters were determined by simple linear regression using the experimental dataset. Results showed that the average concentrations of Mg (5.964 mg/L), Cd (0.088 mg/L), and Ni (0.071 mg/L) in the waterfront in both dry and rainy seasons exceeded both local and international regulatory values. The seasonal variation of the heavy metals in the waterfront showed that the concentrations of Mg and Cd were higher during the dry season. Model validation of experimental data showed reasonable prediction precision with root mean square error (RMSE) of 0.0016-0.2254 mg/L in the dry season, RMSE of 0.0026-0.3259 mg/L in the rainy season, and corresponding average validation r^2 of 0.985 in both seasons. These results suggest that the waterfront is laden with heavy metals and the one-dimensional transport model is a useful tool to rapidly estimate the levels of Mg, Cd, and Ni in the waterfront for pollution control.

Key words: Environmental monitoring, heavy metals, water pollution, water quality modelling.

INTRODUCTION

Water is an important commodity for human beings and it covers over 70% of the earth's surface. Surface water includes creek, river, stream, pond, lake, and sea (Donald, 1997). Water is required in almost every life process including biochemical reaction, digestion, absorption, dissolution of substances, and thermoregulation, as well as other activities such as transportation and sports (Kleiner, 1999). Although because of anthropogenic activities, water quality has significantly been impaired. Additionally, the degradation of water environment has posed serious challenges in the management of water resources. In most waterfronts

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(coastal areas), a lot of human activities including tourism, shipping, transportation, agriculture, and oil and gas processing activities are carried out; and wastes from these activities have had damaging effects on aquatic organisms (Dublin-Green et al., 1999).

Waterfronts in Nigeria Niger Delta Basin have suffered prolonged environmental pollution and degradation from human activities, leading to deposition of heavy metals and all sorts of environmental contaminants (Abu and Egenonu, 2008; Abbasi, 2012; Onojake et al., 2017; Okparanma et al., 2016). Most water pollutants are detrimental to humans and organisms. For instance, the effects of oil spillage on water bodies could leave many organisms still affected years after the spill (Fingas, 2010). This is even worse when polycyclic aromatic hydrocarbon (PAH)-carrying compounds such as soot is released into the water as in most cases from local oil refining operations (Vincent-Akpu and Nwachukwu, 2016; Osuagwu and Olaifa, 2018).

Water quality is a term used to describe the chemical, physical, and biological characteristics of water in relation to its suitability for a particular purpose (Gupta et al., 2009). Since the mid twentieth century, there has been growing concern on the effects of inorganic and organic pollutants such as heavy metals and hydrocarbons respectively on water quality. Consequently, past studies have been dedicated to the assessment and management of water quality involving water quality modelling and water quality index evaluation (Moez et al., 2019; Sutadian et al., 2016). In recent times, several studies have formulated various water quality indexes and their application has been strongly advocated by agencies responsible for water supply and control of water pollution (Lumb et al., 2003; Patterson et al., 2003; Darren et al., 2005; Kannel et al., 2007).

Surface water quality models can be helpful tools in simulating and predicting contaminant levels, distribution, and risks in a water body. This is because results from the models under different pollution scenarios are very important components of environmental impact assessment and they can give a basis and decision support for environmental management. For instance, the rates of biological oxygen demand caused by sediment release and surface runoff, as well as the changing rate of dissolved oxygen in rivers have been studied through water quality models (Wang et al., 2013). Similarly, Vincent-Akpu and Nwachukwu (2016) studied the pollution of Nembe/Bonny/Iwofe Rivers in Rivers State, Nigeria due to waste discharged into the Rivers; and reported that lead, chromium, cadmium, copper, and zinc concentrations were high. Moreover, Xia et al. (2017) have also shown that pollution from urban runoff was heavier in the rainy season, which increased the level of contaminants in rivers.

Despite the benefits of surface water quality models, no study has as yet given attention to the application of this important decision-support tool in evaluating the concentration of heavy metals such as Mg, Cd, and Ni along the polluted Marine-Base waterfront of Amadiama creek in Port Harcourt metropolis, Nigeria. The objective of this study was to investigate the application of one-dimensional transport model in the estimation of Mg, Cd and Ni levels along the polluted Marine-Base waterfront of Amadiama creek in Port Harcourt metropolis, Nigeria for pollution control.

MATERIALS AND METHODS

Study area

Marine-Base waterfront of Amadiama Creek in Port Harcourt City Local Government Area of Rivers State in the Niger Delta Province of Nigeria (Figure 1) is subject to human induced pressures resulting from industrialization, urbanization, and heavy navigation. The waterfront lies on the north of Bonny River in Rivers State between longitude 5°60′-6°60′N and 6°06′-6°07′ E. The creek is brackish water, which flows and ebbs daily and links Okirika Island and other neighbouring communities. The waterfront also has a jetty where local boats and other vessels used for navigation anchor. People living close to the waterfront and marine companies operating nearby now use the waterfront for illicit dumping of all kinds of wastes including water from slaughter houses and domestic wastes, as well as wrecked vessels. There are also local crude oil refining activities around the waterfront resulting in oil bunkering and the emission of soot. Both the soot and spilled petroleum products eventually end up in the river, contributing to the increasing level of pollution in the waterfront and making fishing and trading almost impossible. Therefore, it is expedient to regularly monitor the waste load of the waterfront.

Sample collection, preparation, and analysis for heavy metals

The sampling points along the Marine-Base water front in the Amadiama creek in the Niger Delta Province of Nigeria are shown in Figure 1. The waterfront was partitioned into three sections namely SW1, SW2, and SW3; and water samples were collected from each section using a canoe, wading gear, and 1 m long marine rope of 3 mm diameter. From the waste discharge point, water samples were collected at intervals of 10 m up to 100 m away from the discharge point in the direction of water flow on the water surface in both rainy and dry seasons. The samples were collected in triplicates at each sampling point to reduce error that may arise due to non-uniform distribution of the water properties. Sample management was strictly in line with standard procedures (APHA, 1998). The concentrations of heavy metals in the water were determined by flame atomic absorption spectrophotometry using a SHIMADZU® AA6800 Atomic Absorption Spectrophotometer according to APHA (1998) method.

Measurement of the river velocity

The velocity of the river was measured to enable the application of the model. To do this, two stainless steel rods were planted in the river at a distance of 1 m apart in the direction of water flow. Afterwards, a floating material was dropped on the water surface (using the upstream rod as starting point) and allowed to move with the river current towards the second rod downstream. The time taken for the floating material to move from the upstream rod to the downstream rod was recorded. This was repeated three times and the average velocity of the river was deduced by dividing the

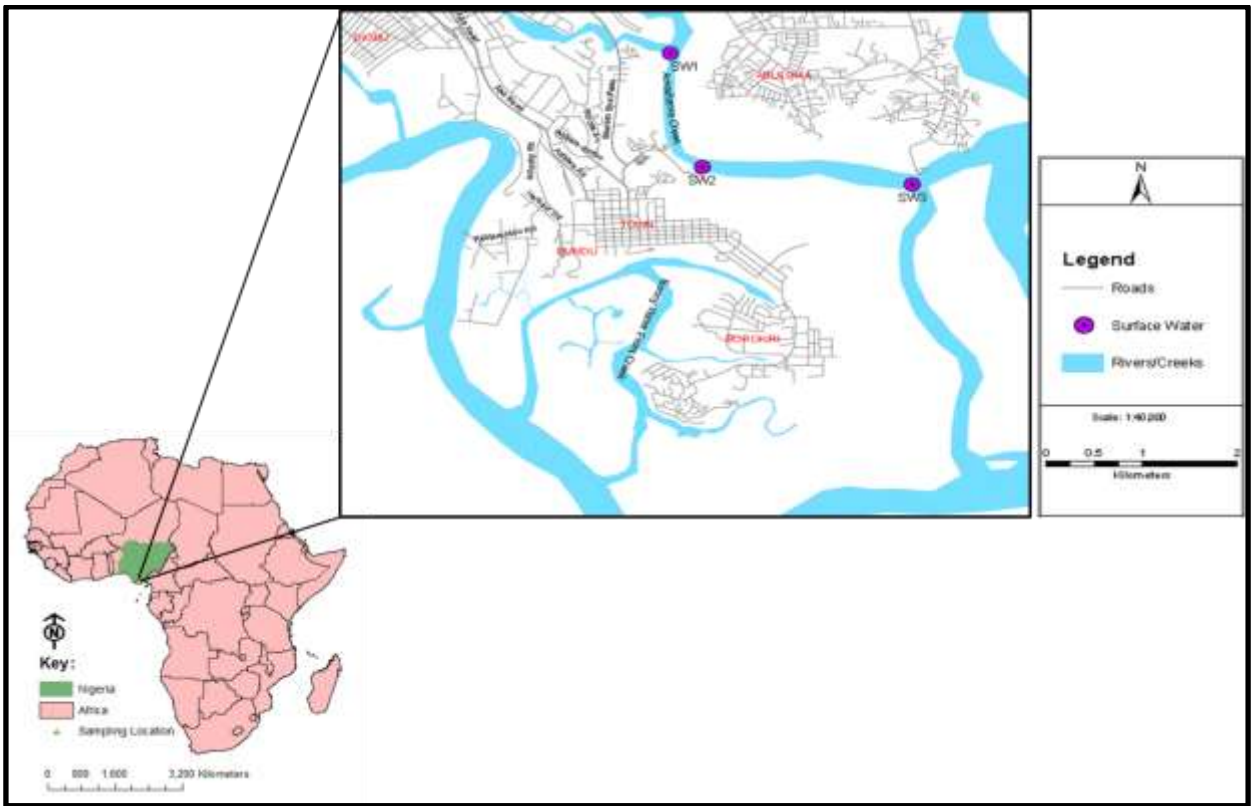

Figure 1. The sampling locations (SW1, SW2, and SW3) along Marine-Base Waterfront of the Amadiama Creek, Port Harcourt in the Niger Delta province, Nigeria (Projection: GCS/WGS/1984; Datum: D/WGS/1984; Prime Meridian: Greenwich; Angular Unit: Degrees; Africa Shape File Source: ESRI™, CA, USA).

distance covered by the floating material by the average time recorded.

Modelling procedure

In order to study the transport of the selected heavy metals in the contaminated waterfront, the simplified one-dimensional expression describing the processes in the movement of contaminants in water was applied. The simplified one-dimensional transport model for contaminants in water (Chawla and Singh, 2014; Patil and Chore, 2014) is stated in Equation 1.

$$\frac{\partial C}{\partial t} = \frac{k}{\rho C_p}\frac{\partial^2 C}{\partial x^2} - v\frac{\partial C}{\partial x} \quad (1)$$

Where: $C =$ Concentration of heavy metal (mg/l); $k =$ Conductivity of contaminated water (J/s.m.K); $C_p =$ Specific heat capacity of contaminated water (J/kg.K); $\rho =$ Density of contaminated water (g/l); $v =$ Velocity of contaminated water (m/s); $t =$ Time of contaminant transport (s); and $x =$ Distance along the direction of transport (m).

Letting $\frac{k}{\rho C_p} = D$ (longitudinal dispersion coefficient of contaminant in the river (m^2/s)), then Equation 1 reduces to Equation 2.

$$\frac{\partial C}{\partial t} = D\frac{\partial^2 C}{\partial x^2} - v\frac{\partial C}{\partial x} \quad (2)$$

Assuming steady state transport, where change in concentration with time is constant, Equation 2 reduces further to Equation 3.

$$D\frac{d^2 C}{dx^2} - v\frac{dC}{dx} = 0 \quad (3)$$

Since concentration of contaminants was decreasing as distance away from the discharge point increases, concentration gradient $\frac{dC}{dx}$ would be negative; thus, equation 3 can be re-written as in Equation 4.

$$D\frac{d^2 C}{dx^2} + v\frac{dC}{dx} = 0 \quad (4)$$

The solutions to equation 4 can be obtained by solving for *m* in the auxiliary Equation 5.

$$Dm^2 + vm = 0 \quad (5)$$

For which,

$$m = \frac{-v \pm \sqrt{v^2}}{2D} \quad (6)$$

$$m = \frac{-v + v}{2D} = 0 \quad (7)$$

$$m = \frac{-v - v}{2D} = -\frac{v}{D} \quad (8)$$

But for real and different roots, the solution of Equation 4 is as shown in Equation 10:

$$C = A\exp(0)x + B\exp\left(-\frac{v}{D}x\right) \quad (9)$$

$$C = A + B\exp\left(-\frac{v}{D}x\right) \quad (10)$$

To obtain values for the constants, A and B, the following boundary conditions were applied:

At $x = 0$; $C = C_o$, and at $x = \infty$; $C = 0$

Therefore, $A = 0$ (11)

And $B = C_o$ (12)

Substituting Equations 11 and 12 into Equation 10 gives Equation 13.

$$C(x) = C_0 exp\left(-\frac{v}{D}x\right) \quad (13)$$

Where, C_0 is the concentration of the heavy metal at source of pollution. In the waterfront, the heavy metal is assumed to be a non-conservative contaminant, whose concentration follows a simple exponential function of the form shown in Equation 13. Therefore, Equation 13 becomes the model for predicting the concentration of the heavy metal at any distance in the range 0 to 100 m in the contaminated waterfront. The ratio $\frac{v}{D}$ and C_0 were determined by linearizing Equation 13 as shown in Equation 14.

$$\mathrm{In}C = \mathrm{In}C_0 - \frac{v}{D}x \quad (14)$$

By regression, Equation 14 was fitted to the experimental dataset by plotting $\mathrm{In}C$ against x and estimating the constant coefficient (α) and regression coefficient (β) in the estimated regression line of the form shown in Equation 15.

$$\mathrm{y} = \alpha + \beta x \quad (15)$$

Where, α is equivalent to $\mathrm{In}C_0$ and β is equivalent to $-\frac{v}{D}$; comparing Equations 14 and 15. The values of α and β were then substituted into equation 13 and D was calculated for each of the selected heavy metals in both dry and rainy seasons using the values of v measured during the dry and rainy seasons, respectively.

Testing the significance of β

The significance of β was also tested to determine whether there is association between y and x in the manner assumed in Equation 15. The β was considered to be significantly different from zero if the calculated Student-t value (t_{cal}) is greater than the tabular Student-t value (t_{tab}) with n–2 degrees of freedom at 5% level of significance; and not significantly different from zero if otherwise. If β is significantly different from zero, then there is association between y and x in the manner assumed; otherwise, there is no association. The t_{cal} was deduced using Equation 16.

$$t_{cal} = \frac{b}{\sqrt{\frac{s^2_{y.x}}{\sum x^2}}} \quad (16)$$

With $$s^2_{y.x} = \frac{\sum y^2 - \frac{(\sum xy)^2}{\sum x^2}}{n-2} \quad (17)$$

And $$b = \frac{\sum xy}{\sum x^2} \quad (18)$$

Where, $s^2_{y.x}$ is the residual sum of squares, b is the estimate of β, and n is the number of samples in the dataset (or number of pairs of x and y).

Statistical evaluation of model quality

Model validation was carried out by predicting the concentrations of the selected heavy metals using the developed model and comparing the experimental data with the model results. The prediction ability of the model developed was evaluated on the bases of the root-mean-square error (RMSE) (Equation 19) and corresponding coefficient of determination (r^2) (Equation 20).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \quad (19)$$

$$r^2 = \left[\frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}\right]^2 \quad (20)$$

Where, y_i and x_i are the predicted and measured ith values respectively; and $\bar{x}$ and $\bar{y}$ are the predicted and measured mean values respectively.

RESULTS AND DISCUSSION

Concentrations of studied heavy metals in the urban waterfront

Figure 2 shows the concentrations and seasonal

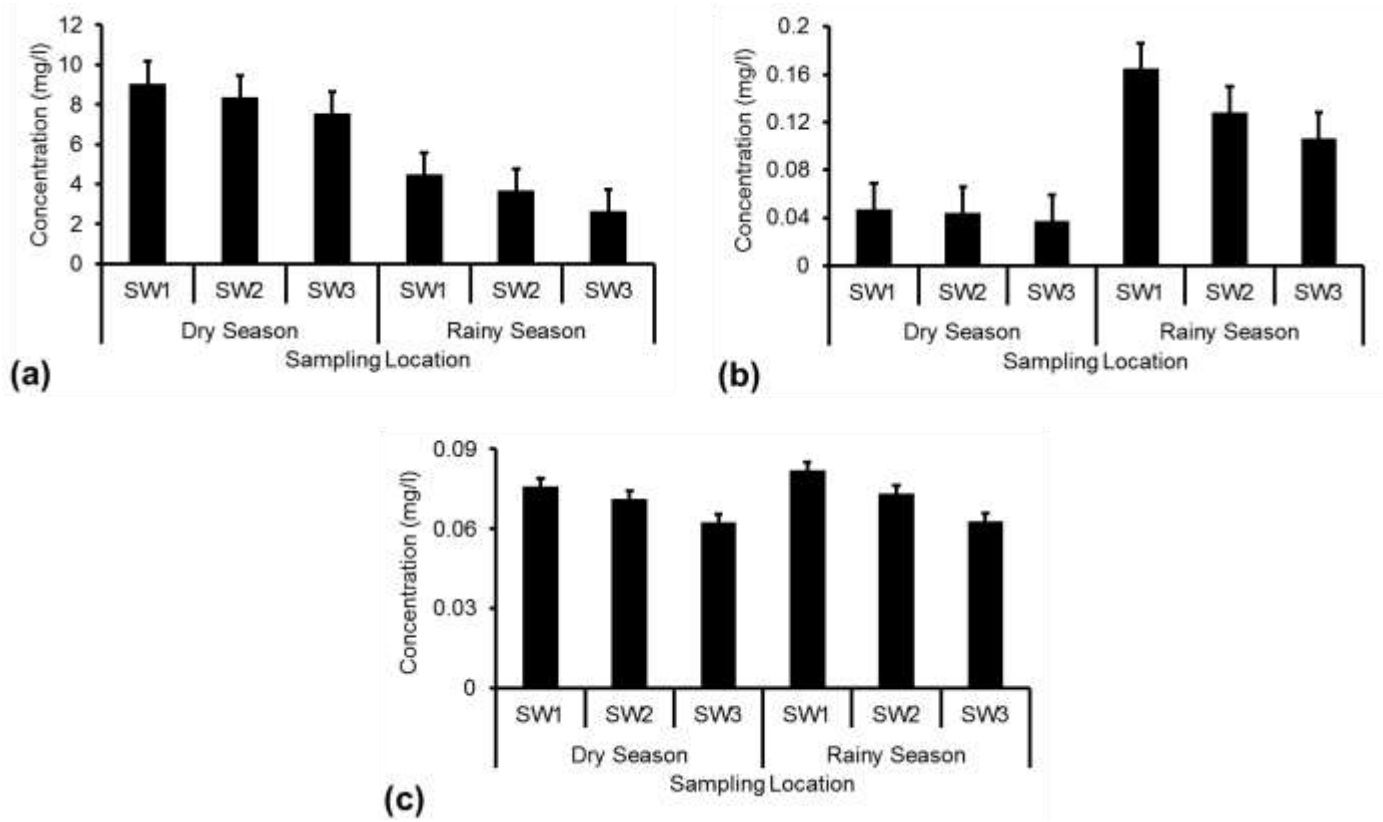

Figure 2. Seasonal variations in concentrations of (a) Mg, (b) Cd, and (c) Ni in the urban waterfront (Charts show error bars with standard error).

variations of Mg, Cd, and Ni in the urban waterfront. The results showed that the concentrations of the heavy metals under study varied distinctly among sampling points and also between seasons. It can be observed in Figures 2a and 2b that the average concentrations of Mg (5.964 mg/L) and Cd (0.088 mg/L) were far too high compared with the World Health Organization (WHO, 2008) permissible limits of 0.2 and 0.003 mg/L for Mg and Cd respectively. On the other hand, the average concentration of Ni (0.071 mg/L) (Figure 2c) was slightly higher than the WHO (2008) permissible limit of 0.07 mg/L. The high Mg, Cd, and Ni levels observed in this study underscore the need for this study; and are a clarion call for researchers to start focusing on the prevalence of these heavy metals in waterfronts much the same way it is currently done for Cr and Pb. Moreover, consumption of contaminated sea food from the waterfront could lead to trophic transfer and bio-magnification of these heavy metals in the food web, which could have ramifications for ecological health.

The concentrations of Mg were higher in the dry season than in the rainy season at the three sampling points (Figure 2a) while the opposite trend was observed with Cd (Figure 2b). For Ni, its concentration was slightly higher in the rainy season at sampling point SW1, but at sampling points SW2 and SW3 there were no appreciable changes in its concentrations in both seasons. This seasonal variation in heavy metal levels may be as a result of the differences in the types of activities at the different sections of the waterfront. This variability in concentration of studied heavy metals due to season in the waterfront could also be attributed to mass action of the bulk fluid. The trends exhibited by the heavy metals in this study are corroborated by reports in previous studies that seasons have effect on pollutant variability in creeks (Onojake et al., 2017).

Transport of studied heavy metals in the urban waterfront

In Figure 3, the variations in concentrations of studied heavy metals with distance in the urban waterfront are presented. As it can be observed in Figure 3, the concentrations of the heavy metals generally decreased with distance across both seasons. It was also observed that the heavy metals (except Cd during the dry season (Figure 3b)) dispersed at a faster rate in the first 60 m than they did in the last 40 m in both seasons (Figure 3). This decay pattern exhibited by the studied heavy metals

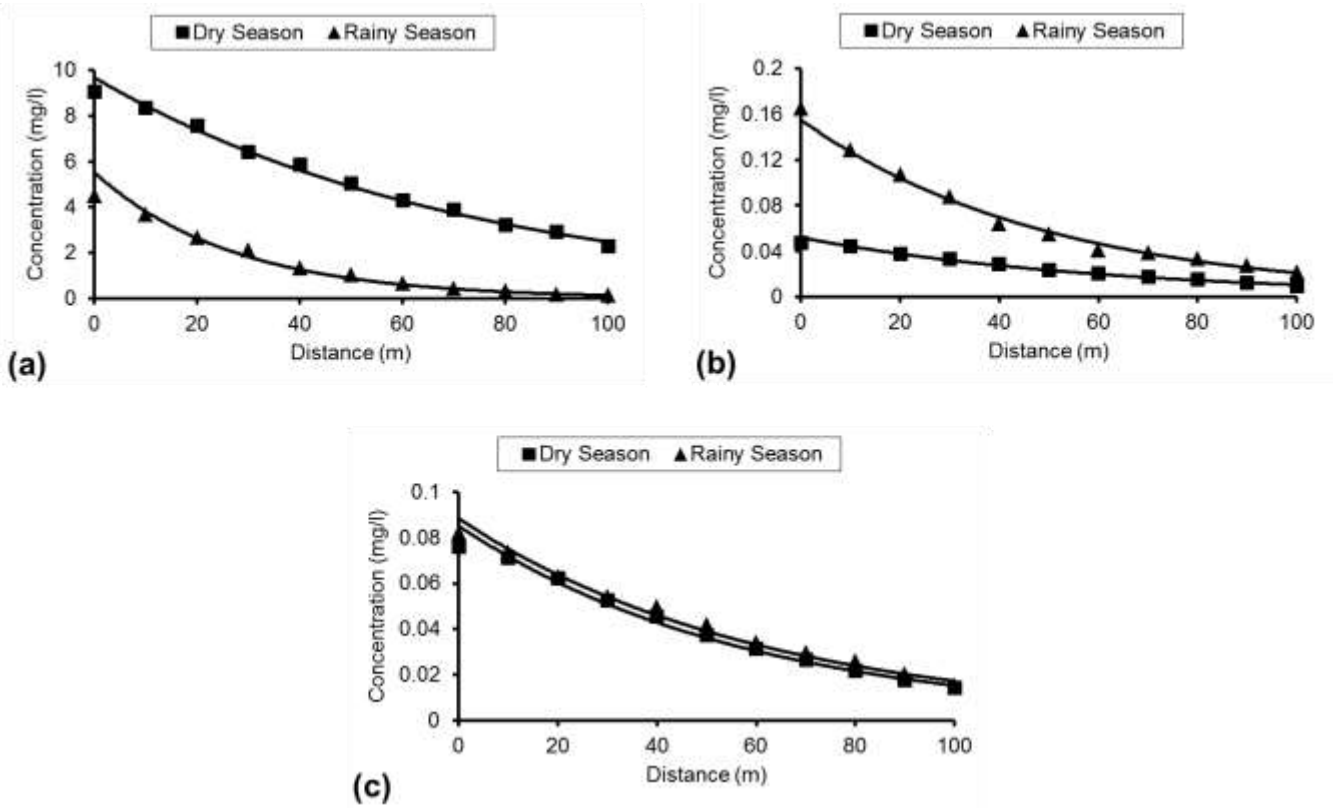

Figure 3. Change in concentration with longitudinal distance for (a) Mg, (b) Cd, and (c) Ni in the urban waterfront.

is typical of non-conservative contaminants (Kashefipour et al., 2006).

Although the concentration of Mg decreased with distance (Figure 3a), the dry season residual concentration of 2.296 mg/L at 100 m from the source of pollution was still higher than the permissible WHO (2008) limit of 0.2 mg/L. However, the rainy season residual concentration of Mg (0.119 mg/L) at 100 m from the source of pollution (Figure 3a) was less than the WHO (2008) permissible value. This suggested that in the dry season Mg in the waterfront dispersed farther than 100 m from the origin; and Mg poisoning can still occur more than 100 m from the source of pollution. Similar trends in the seasonal variations of river contaminants have been reported by Edwin and Murtala (2013).

Similarly, the concentrations of Cd decreased as the distance from the origin increased (Figure 3b). However, both the dry and rainy season residual concentrations of 0.0095 and 0.021 mg/L respectively at 100 m from the pollution source were higher than the permissible WHO (2008) limit of 0.0.003 mg/L. This suggested that Cd in the waterfront dispersed farther than 100 m from the origin regardless of the season. As stated, unlike Mg, Cd concentrations measured during the rainy season were higher than those measured during the dry season. However, like Mg in the dry season, Cd poisoning beyond 100 m from the source of pollution is inevitable all season. A similar observation has also been reported in previous studies including Onojake et al. (2017) and Amic and Tadic (2018).

Furthermore, like the other heavy metals, the concentration of Ni decreased with distance in the waterfront (Figure 3c). However, as can be observed in Figure 3c, Ni concentrations measured during the rainy season were only slightly higher than those measured during the dry season. The average concentrations of Ni remaining 100 m away from the source of pollution in both dry and rainy seasons were about 8-folds less than the permissible WHO (2008) limit of 0.07 mg/L. In both reasons, it is clear that Ni concentrations dropped to non-lethal concentrations of about 0.06 mg/L at 20 m distance from the pollution source (Figure 3c). Even then, up to 100 m from the origin, Ni did not decay completely; suggesting that other smaller organisms in the waterfront 100 m away from the pollution source might still be at risk of Ni poisoning.

Heavy metal–regression models and longitudinal dispersion coefficients

Figure 4 shows the plots of natural logarithm of metal concentration against longitudinal distance from origin

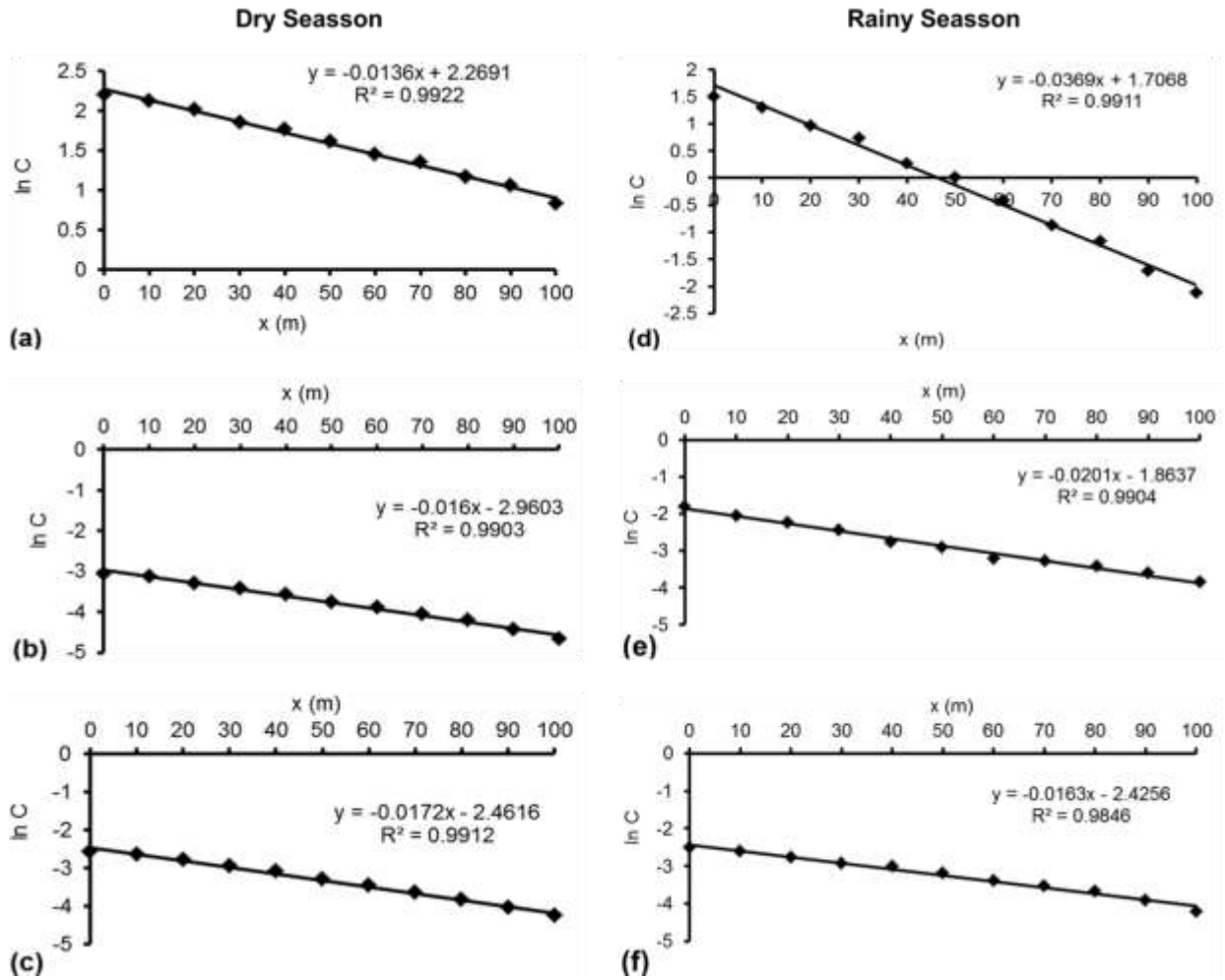

Figure 4. Plots of InC vs. x for (a) Mg, (b) Cd, (c) Ni in the dry season and (d) Mg, (e) Cd, and (f) Ni in the rainy season.

(for $0 \leq \times \leq 100$ m). The plots were used to determine the model parameters, α and β for the estimation of C_0 and D (discussed shortly). As can be observed in Figure 4, the plots yielded non-zero negative β for all the studied heavy metals across the two seasons. By extension, this implies that the natural logarithm of the metal concentration is negatively linearly correlated with the longitudinal distance of travel from the origin. Thus, a positive change in the longitudinal distance is associated with a negative change in the natural logarithm of the metal concentration. Table 1 summarizes the calculation to test the significance of β. As shown in Table 1, for all the studied heavy metals in both seasons, there was no significant difference ($t_{cal} < t_{tab}$) between β and 0 at the 5% significance level. This suggests that the relationship between concentration of the heavy metal and longitudinal distance from the origin in the polluted waterfront is not linear, which is in agreement with Figure 3. The models developed for prediction of Mg, Cd, and Ni in the studied waterfront in both dry and rainy seasons are shown in Table 2, which confirms an exponential instead of a linear relationship between concentration of the heavy metal and longitudinal distance. As stated, this agrees with the decay pattern of non-conservative contaminants in water bodies (Kashefipour et al., 2006).

Furthermore, Table 2 shows the estimated longitudinal dispersion coefficients of the studied heavy metals across the two seasons. It is evident in Table 2 that Mg had the highest longitudinal dispersion coefficient during the dry season despite the higher mean velocity of the water body in the rainy season. It is well known that apart from mean velocity, other mixing characteristics of the water body can affect dispersion coefficient. The longitudinal dispersion coefficients shown in Table 2 indicate that Mg dispersed farthest in the waterfront during the dry season and least during the rainy season. This explains why in the dry season, relics of Mg as far as 100 m from the pollution source were extremely high compared with NESREA (2009) permissible limit; and during the rainy season, the remaining concentration at the same

Table 1. Summary of calculation to test the significance of β.

Heavy metal	$t_{(cal)}$		$t_{(tab)}$
	Dry season	Rainy season	5%
Mg	2.15 ^{ns}	0.86 ^{ns}	2.26
Cd	1.92 ^{ns}	1.47 ^{ns}	2.26
Ni	1.83 ^{ns}	1.91 ^{ns}	2.26

$t_{(cal)}$ = Calculated Student-*t* values, $t_{(tab)}$ = Tabular Student-*t* value, ^{ns}, not significant at 5% significance level.

Table 2. Heavy metal–regression models and corresponding dispersion coefficients of studied heavy metals in the urban waterfront as estimated in this study.

Heavy metal	Season	v (m/s)	D (m^2/s)	Model
Magnesium	Dry	0.71	52.21	$C(x) = 9.6707e^{-0.0136x}$
	Rainy	0.77	20.87	$C(x) = 5.5113e^{-0.0369x}$
Cadmium	Dry	0.71	44.38	$C(x) = 0.0518e^{-0.0160x}$
	Rainy	0.77	38.31	$C(x) = 0.1551e^{-0.0201x}$
Nickel	Dry	0.71	41.28	$C(x) = 0.0853e^{-0.0172x}$
	Rainy	0.77	47.24	$C(x) = 0.0884e^{-0.0163x}$

distance of 100 m was way less than the permissible limit (Figure 4). On the other hand, Ni had very close longitudinal dispersion coefficients in both seasons, which indicates that seasonal variation in the waterfront did not have much effect on the dispersion of Ni as it did for Mg and Cd. This also supports the close similarity observed in the decay curves for Ni in both seasons (Figure 4).

Quality of heavy metal–regression models

Figure 5 shows the scatter plots of measured vs. predicted values of Mg, Cd, and Ni in the waterfront in both dry and rainy seasons. Typically, the plots show how the experimental and the model results are comparable. The error in model prediction, as indicated by the RMSE value, was highest for Mg in the rainy season (Figure 5d). For Cd and Ni, the prediction errors were very low in both seasons (Figure 5b, c, e, and f). Overall, it was observed that the RMSE values were higher during the rainy season than during dry season (Figure 5). This trend might be attributed more to the magnitude than frequency of the difference between the laboratory-measured and model-predicted concentrations of the heavy metal due to high model predictions. For instance, for Mg, there were five high model predictions in the dry season at 0, 10, 30, 80, and 100 m respectively (Figure 5a), but only four were recorded in the rainy season at 0, 10, 90, and 100 m respectively (Figure 5d). Regardless, the rainy season RMSE value for Mg prediction was almost one-and-half times higher than the dry season's (Figure 5d and a, respectively). This is due largely to the relatively large difference (1.0233 mg/L) between the model-predicted (5.5113 mg/l) and laboratory-measured (4.488 mg/L) Mg concentrations particularly at the pollution source (that is, at x = 0) (Figure 5d). It is important to state that the error in the prediction of heavy metals in water bodies can be influenced by a number of factors including (but not limited to) the decay process (Kashefipour et al., 2006) and covariates like pH (Wu et al., 2005), electrical conductivity (Turner et al., 2002), and organic carbon (Sakultantimetha et al., 2009). Therefore, in this study, there was no attempt to study the influence of these factors on heavy metal prediction.

The r^2 was used to assess the ability of the model to predict the concentrations of the heavy metals in the linear regression system. The validation r^2 obtained for the selected heavy metals in this study ranged from 0.98-0.99 across the two seasons (Figure 5); suggesting that, on the average, 98.5% of the variance in the predicted dataset was explained by the linear regression line. This high validation r^2 indicates that the model is a good fit for the experimental dataset. Previous studies have also reported good fits for measured data for Cd in river water (Wu et al., 2005; Wu, 2008; Kashefipour and Roshanfekr, 2012). In a related study, Torres-Bejarano et al. (2019) reported high prediction of Cd, Pb, and Ni in river water

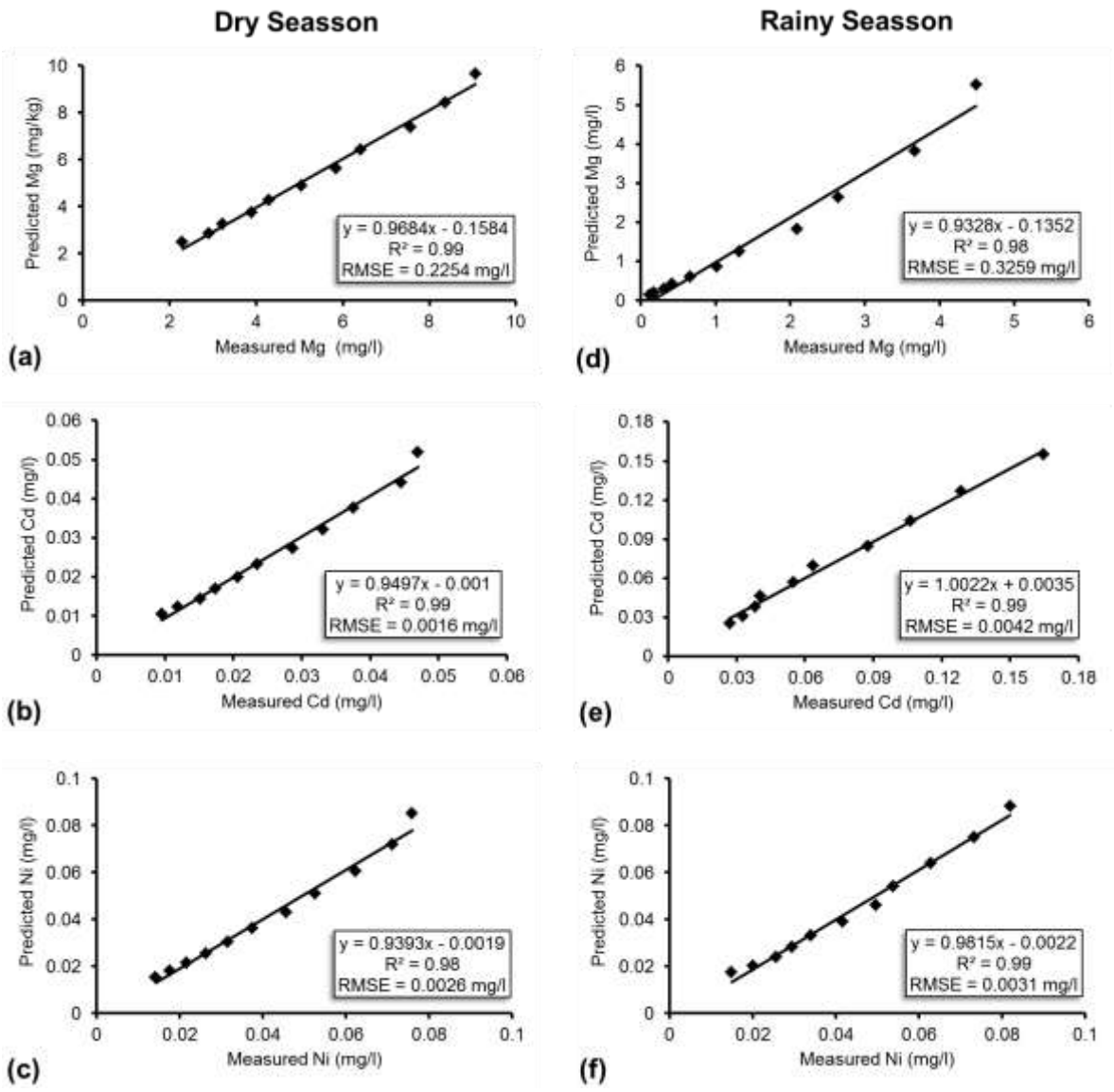

Figure 5. Scatter plots of measured vs. model-predicted values of (a) Mg, (b) Cd, (c) Ni in the dry season; and (d) Mg, (e) Cd, and (f) Ni in the rainy season at the waterfront.

using two-dimensional water quality model they developed numerically.

Conclusions

In this study, the levels of Mg, Cd, and Ni in the polluted Marine-Base waterfront of Amadiama Creek in Port Harcourt Metropolis, Nigeria were estimated using one-dimensional transport model in both dry and rainy seasons. Results obtained support the following conclusions: (1) the average concentrations of Mg (5.964 mg/L), Cd (0.088 mg/L), and Ni (0.071 mg/L) in the waterfront in both dry and rainy seasons exceeded both local and international regulatory values; (2) the concentrations of Mg and Cd in the waterfront were higher during the dry season; (3) magnesium dispersed farthest (longitudinal dispersion coefficient = 52.21 m^2/s) during the dry season with relics of up to 2.296 mg/L and exceeding safe limit were observed 100 m from the pollution source; and (4) model validation showed reasonable prediction precision with RMSE ranging from 0.0016-0.2254 mg/L) in the dry season, 0.0026-0.3259 mg/L in the rainy season, and average validation r^2 of 0.985 in both seasons. These results show that the Marine-Base waterfront of Amadiama Creek in Port Harcourt Metropolis, Nigeria is highly polluted and the one-dimensional transport model is a useful tool to

rapidly estimate the levels of Mg, Cd, and Ni in the waterfront for pollution control. Therefore, it is recommended that urgent remediation of the waterfront be carried to protect ecological health.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Abbasi SA (2012). Water quality indices, state-of-the-art report. National Institute of British Columbia Water Quality Status Report – April. Victoria, BC Canada.

Abu GO, Egenonu C (2008). The current pollution status of the New Calabar River in the Niger Delta region of Southern Nigeria: A survey of antibiogram profiles of its bacterial isolates. African Journal of Environmental Science and Technology 2:134-141.

American Public Health Association (APHA) (1998). Standard Methods for Examination of Water and Waste Water. Washington DC.

Amic A, Tadic L (2018). Analysis of basic physical-chemical parameters, nutrients and heavy metals content in surface water of small catchment area of Karašica and Vucica Rivers in Croatia. Environment 5:20-46.

Chawla A, Singh SK (2014). Modelling of Contaminant Transport from Landfills. International Journal of Engineering Science and Innovation Technology 3(5):222-227.

Darren TR, Robert WGC, Carl EO, Paul HP, David DH, Aida MF (2005). Polycylic Aromatic Hydrocarbon in Water, Sediments and Snow from Lakes in Grand Teton National Park, WYOMING. Final Report USGS- CERC- 91344. United States Geological Survey, VA.

Donald KA (1997). Effects of overproduction of the catalytic domain of 3-hydroxy-3 methylgluutaryl coenzyme A reductcase on squalene synthesis in Saccharomyces cerevisiane. Applied Environmental Microbiology 63(9):3341-4.

Dublin-Green CO, Awosika IF, Folorusho R (1999). Climate Variability Research Activities in Nigeria. Nigerian Institute of Oceanography and Marine Research. Victoria Island Lagos, Nigeria.

Edwin AI, Murtala AI (2013). Determination of water quality index of river Asa, Ilorin, Nigeria. Advances in Applied Science Research 4(6):277-284.

Fingas M (2010). Oil Spill Science and Technology.1st Edition. Gulf Professional Publishing, MA, USA.

Gupta A, Ria DK, Pandey RS (2009). Analysis of some heavy metals in the riverine water sediments and fish from River Ganges at Allahabad. Environmental Monitoring and Assessment 157(1-4):499-458.

Kannel PR, Lee S, Lee Y (2007). Application of water quality indices and dissolved oxygen as indicators for river water classification and urban impact assessment. Environmental Monitoring and Assessment 132:93-110.

Kashefipour SM, Roshanfekr A (2012). Numerical modelling of heavy metals transport processes in riverine basins. In: Miidla P (Ed.). Numerical Modelling, InTech. pp. 91-114.

Kashefipour SM, Lin B, Falconer RA (2006). Modelling the Fate of faecal indicators in a coastal basin. Water Research 40:1413-1425.

Kleiner SM (1999). Water: An essential but overlooked nutrient. Journal of the American Dietetic Association 99(2):200-206.

Lumb A, Halliwell D, Sharma T (2003). Canadian water quality index to monitor the changes in the Mackenzie River–Great Bear: In: Proceeding of the 29th Annual Aquatic Toxicity Workshop. Whistler, BC, Canada.

Moez K, Fabienne T, Mohamed K, Sehim J (2019). Water quality indices: Challenges and application limits in literature. Water 11(2):1-26.

National Environmental Standards and Regulations Enforcement Agency (NESREA) (2009). Permissible Limit. NESREA, Abuja, Nigeria.

Okparanma RN, Jumbo RB, Chukwu FN (2016). Combined effects of municipal and industrial wastes on the quality of the New Northern Calabar River, Nigeria. International Journal of Water Resources and Environmental Engineering 8(8):103-112.

Onojake MC, Sikoki FD, Akpiri RU (2017). Surface water characteristics and tarace metal level of the Bonny/New Calabar River estuary, Niger Delta, Nigeria. Applied Water Science 7:945-959.

Osuagwu ES, Olaifa E (2018). Effect of Oil spill on Fish Production in the Niger Delta. PLoS ONE 13(10):e0205114. Available at: https://doi.org/10.1371/journal.pone.0205114.

Patterson RN, Watts KC, Gill TA (2003). Micro-particles in recirculating aquacultural systems: Determination of density gradient centrifugation. Agricultural Engineering 27(2):105-115.

Patil SB, Chore HS (2014). Contaminant transport through porous media: An overview of experimental and numerical studies. Advances in Environmental Research 3(1):45-69.

Sakultantimetha A, Bangkedphol S, Lauhachinda N, Homchan U, Songsasen A (2009). Environmental fate and transportation of cadmium, lead and manganese in a river environment using the EPISUITE Programme. Journal of Natural Science 43(3):620-626.

Sutadian AD, Muttil N, Yilmaz AG, Perera BJC (2016). Development of river water quality indices – A review. Environmental Monitoring and Assessmement 188(58).

Torres-Bejarano F, Couder-Castañeda C, Ram-rez-León H, Hernández-Gómez JJ, Rodr-guez-Cuevas C, Herrera-D-az IE, Barrios-Piña H (2019). Numerical modelling of heavy metal dynamics in a river-lagoon system. Mathematical Problems in Engineering 2019(1):8485031.

Turner A, Martino M, Le roux SM (2002). Trace metal distribution coefficients in the Mersey estuary, UK: Evidence got salting out of metal complexes. Environmental Science and Technology Journal 36(21):4578-4584.

Vincent-Apku IF, Nwachukwu LC (2016). Comparative water quality assessment of Nembe, Bonny, and Iwofe Ferry Terminals in Port Harcourt. IOSR Journal of Environment, Science, Toxicology, and Food Technology 10(7):15-19.

Wang Q, Li S, Jac P (2013). A review of surface water quality models. Scientific World Journal 2013(3):231768.

World Health Organization (WHO) (2008). Guidelines for Drinking-Water Quality*:* Incorporating the First and Second, Addenda, Volume 1 Recommendations (3rd Edition), WHO Press, Geneva, Switzerland.

Wu W (2008). Computational River Dynamics, Taylor & Francis Group, London P 494.

Wu Y, Falconer RA, Lin B (2005). Modelling trace metal concentration distributions in estuarine waters. Estuarine, Coastal and Shelf Science 64(4):699-709.

Xia J, Wang LF, YU JJ (2017). Impact of environmental factors on water quality at multiple spatial scale and its spatial variation in Huai River Basin, China. Science China Earth Sciences 61(1):82-92.