Development of a Kriging Assessment Framework and Impact Pathway for Researching Contamination With Potentially Toxic Elements in Urban Landfill Soil

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Research Article

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Posted Date: December 8th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1053828/v1

Development of a kriging assessment framework and impact pathway for researching contamination with potentially toxic elements in urban landfill soil

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Abstract

Landfill post-closure with contaminant concentration in soil below permissible limit assessed at limited spot does not represent the contamination issue. Assessment limit to professionals also does not gives a potential of change to practice constant assessment to a wider context of assessor – citizen living nearby – as a collaborative effort to sustain a safe environment. Therefore sizeable, qualitative, and cost-effective analysis of the concentrations of contaminants is needed and this work recommends kriging assessment and the logical impact pathway framework as factors of change in landfill aftercare management. The kriging framework is developed utilising lead (Pb) and chromium (Cr) data from inductively coupled plasma mass spectrometry (ICP-MS) analysis. The development of the kriging framework is conducted based on the observation of censored data from ICP-MS analysis. The estimation analysis involves the analysis of ordinary kriging with regression analysis, showing the interpolation of spatial correlation and regression error. Hence, ordinary kriging with regression of the variable of interest, i.e., Pb, using the data of the explanatory variable, i.e., Cr, is inappropriate. Further investigation with the utilisation of guess-field kriging analysis hypothetically exposed a potential contaminated area using an existing but limited number of explanatory variables; although, guess-field kriging may possibly result immense uncertainty at the area where the explanatory variable does not exist. Besides, this work anticipated outcomes in societal impact and sustainability practices from the proposed kriging framework by recommending a logical impact pathway. The development of the kriging framework and impact pathway reassure the necessary actions to be executed by responsible parties and act as the stimulus of a wider spectrum of improvement initiatives to oversee real issues, such as the time of occurrence, and to prevent negative impacts on the environment and humans.

Keywords: environmental risk assessment; guess-field kriging; heavy metal; impact pathway; landfill aftercare

1. Introduction

A closed landfill is known for its potential risks to ecosystems, and other than its detrimental impact on the environment, particularly at the adjacent polluted area (Vaccari et al., 2018), the contaminants present in the landfill has the potential to affect human health (Hussein et al., 2021). It has been reported that the waste materials buried in landfills may potentially be the cause of birth abnormalities and genetic problems and could increase the risk of cancerous diseases other than that, results in high mortality risk particularly for people residing at close proximity or near landfill areas (Chervona, 2012; Rushton, 2003). Exposure to potentially toxic elements poisons the human body via different pathways, resulting in no known benefits and the deterioration of individual health (Li et al., 2014; Mombo et al., 2015; Zhang et al., 2012). Moreover, the risk of potentially toxic element contamination can potentially be more severe as a result of heterogeneous waste dumped in a non-sanitary landfill. There have been various studies in Malaysia that have discovered the effects of potentially toxic elements in the soil of an operating landfill, but few works have reported this information for closed landfill sites (Agamuthu and Fauziah, 2010; Hussein et al., 2021; Mohd Adnan et al., 2013; Sakawi et al., 2013; Syahirah et al., 2013; Taha et al., 2011; Yusoff et al., 2013).

The analysis of a potential contamination area in a closed landfill is necessary to prevent contamination and pollution. Geostatistics analysis by applying kriging is helpful in identifying the possible contamination area by estimation and a decision-making process. The geostatistics methodology can be applied to allow us to ascertain the dependent variable set at any location in an area and the uncertainty of the statistical interpolation as an instrument to judge the most appropriate and possible interpolation (Gamez et al., 2019). Kriging interpolation, as part of geostatistics, known as a best linear unbiased interpolator technique for examined data for unvisited area, and it performs variogram or spatial modelling by utilising original values on structural characteristics and partition variables (Zhao et al., 2021). Author keywords analysis of co-occurrence using VOSviewer (version 1.6.16) network visualisation for the Web of Science (WoS) core collection by Thompson Reuters Corporation (USA), on April 5, 2021 showed that keyword of “kriging” is closely related to keyword of “soil” in database of publication collection year within the time frame of 1970–2020. The result from the analysis shows a representation of the keywords with large bubble, label and interconnected with links on selected keywords, i.e., “area”, “spatial-distribution”, “contamination”, “pollution” and "risk assessment" (**Fig. 1a**). In addition, from the overlay visualisation (**Fig. 1b**) shown that there is connection for keywords of "urban soils", "agricultural soils", "spatial distribution", and "risk assessment" from the year of 2016 and beyond (indicated by yellow bubbles). This analysis is crucial to understanding the development of research related to the keywords and to identifying core areas or acknowledged hotspots in the kriging research setting by presenting a fundamental connection among keywords in related research papers (An and Wu, 2011).

Other than the research development and hotspots of the utilisation of the kriging analysis, this work aimed to initiate better management initiatives of landfill aftercare by developing a framework for assessing contamination of potentially toxic element in landfill topsoil and recommend it to be outfitted as a decision-making procedure. As a consequence of the development of the framework, drawing a logical scheme of planning, i.e., pathway to impact from the kriging analysis is developed in order to plan for desirable impact.

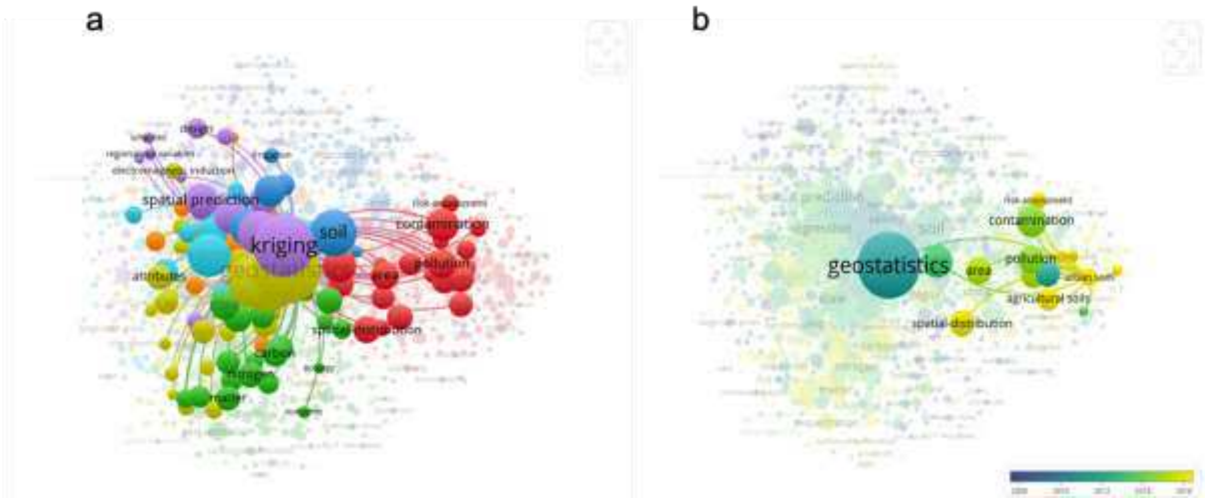

Figure 1 Bibliometrics analysis based on keyword analyses in relation to kriging and soil research by operating Web of Science (WoS) core collection within period of 1970–2020. **a**) Co-occurrence matrix. **b**) Overlay visualisation of the keywords.

2. Materials and methods

2.1. Description of the closed landfill

The largest population state in Malaysia, Selangor, with area of 7,951 km^2 and 6.53 million of population (Department of Statistics Malaysia, 2021). Selangor state is the main municipal solid waste producer for the nation's total waste with 33.3% (Sharifah-Norkhadijah et al., 2009). Furthermore, the state is presently encountering a critical crisis of waste disposal as the state is the receiver of waste from Kuala Lumpur city, due to the city has scarcity of location for landfilling (Sharifah-Norkhadijah et al., 2013). To date, there are twenty-two landfills reported to be present in the Selangor state with eight landfills operating and fourteen are ceased for operation (National Solid Waste Management Department, 2021). A closed urban non-sanitary landfill located in Sepang, Selangor, i.e., Ampar Tenang landfill, was selected for this study. The landfill was served non-segregated refuse from the Federal Territory of Kuala Lumpur, and other cities in Selangor state together with mixed municipal waste from Federal Territory of Putrajaya, the federal Malaysian administrative centre.

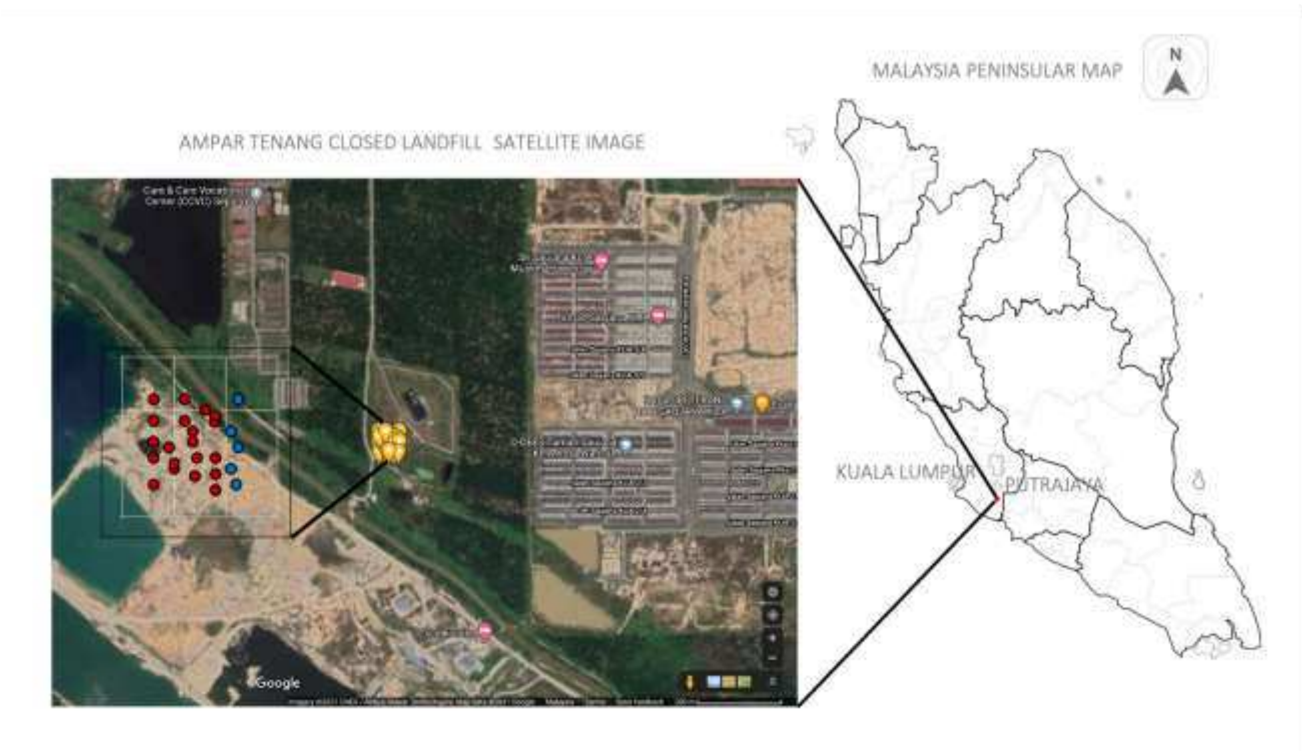

Figure 2 Map of the location of the Ampar Tenang non-sanitary closed landfill tagged with sampling points in Sepang, Selangor, and the sampling grid in a 5 m × 5 m diagram (insert). The bubbles in the grid denote the location of soil samples (tagged in map) where the blue bubbles refer to the missing data from inductively coupled plasma spectrometry analysis of Pb (Imagery ©2021 by Google Maps, 2021).

The closed urban landfill of Ampar Tenang situated in the suburban district of Sepang, south of the principal cities of Klang Valley or Greater Kuala Lumpur region, i.e., Kuala Lumpur city centre and Putrajaya (**Fig. 2**). The landfill geographical zone is skirt around with a palm oil plantation, and at eastern bank of Labu River (a tributary of Langat River) with latitude 2°49'06.9"N and longitude 101°40'47.8"E. Active real estate development is being constructed and existing residential zone surrounding adjacent areas of the plantation. The landfill initially an open dump area or closed open-tipping site categorised as Level 0 (L0) and then upgraded to a controlled waste disposal site with Level 1 (L1) status (Ministry of Housing and Local Government, 2004; Mohd Adnan et al., 2013). The landfill started operation in the year 2000 and it is reported to schedule closing in 2006, however it was operating till it was obstructed and authoritatively ended operation in 2010 (Krishnan, 2008; Mohd Adnan et al., 2013). During the ten years of operation period, the site accumulated approximately 100 tonnes of municipal solid waste per day (waste thickness range: 4.5 – 9.0 m) uncovered with no engineered linear material system (Elwali et al., 2010; Taha et al., 2011). The landfill was initially managed by Sepang local authority and was then assigned to a private limited company for cessation of operation and maintenance.

2.2. Soil sampling

Sampling of the closed landfill surface soil (mixture of topsoil and subsoil at depth 30 cm from surface of the closed landfill) utilising stainless-steel shovel were conducted in November 2016 to March 2017 (during northeast monsoon in a tropical climate). Square grid (5 m × 5 m) (insert in **Fig. 2**) was used as sampling design. One sample at approximately the centre of the grid for each grid was taken for analysis.

2.3. Laboratory analysis

Collected soil samples were prepared by fifteen minutes of sterilisation in autoclave at 121°C prior air drying under room temperature. Samples were then powdered in an agate mortar and sieved after constant weight of air-dried soil samples were achieved. Approximately 0.5 g of homogenised soil samples were partially digested for matrix opening with 10 mL of HNO_3 in a microwave digestion system. Dilution with Milli-Q® water and filtered with cellulose membrane filter of 0.45 μm prior to potentially toxic element analysis utilising an inductively coupled plasma mass spectrometry (ICP-MS). Samples were analysed in triplicate and following standard operating procedures to obtain precision in data analysis.

2.4. Geostatistics

Procedures to execute geostatistical analysis were conducted as follow (**Fig. 3**):

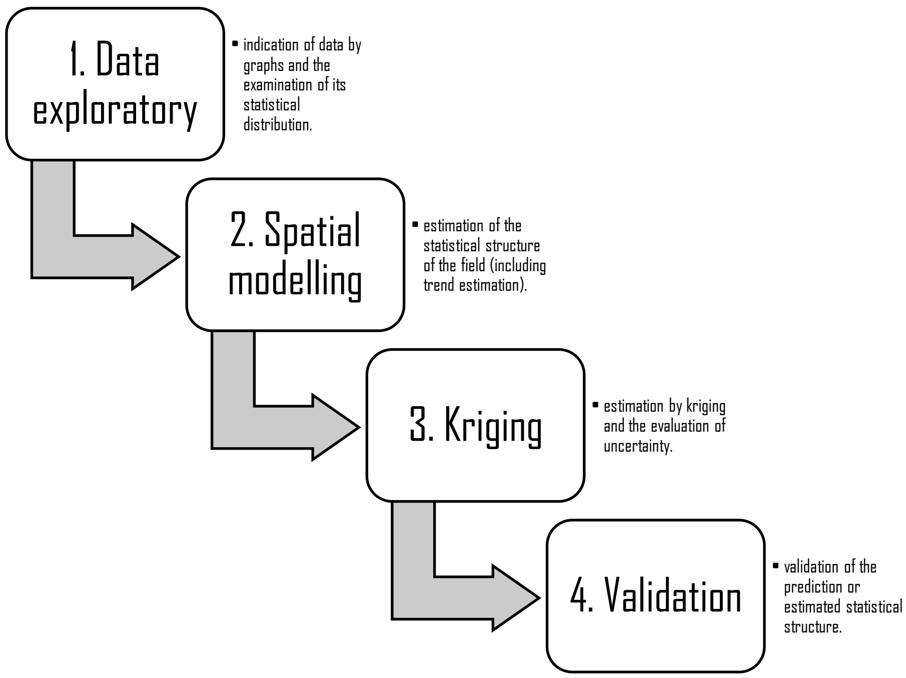

Figure 3 Fundamental geostatistical analysis procedures applied in this work.

2.4.1 Data exploratory

In this procedure the potentially toxic element data were analysed using SPSS 24.0 (IBM, Chicago, Illinois, USA) for multivariate and descriptive statistical analyses, i.e., one-sample *t* test, parametric test and one-way analysis of variance with significant differences when $P < 0.05$. Prior construction of spatial modelling, i.e., variogram, data were transformed for convenient of certain types of analyses which if it is back-transform, the data will return to their original state (Yarus and Chambers, 2006).

2.4.2 Spatial modelling

An exponential model was used in this study for the spatial modelling, as follows:

$$\gamma_2(h) = c_0\left[1 - e\left(-\frac{h}{a_0}\right)\right]$$

here c denotes sill, h denotes lag distance and nugget = 0 were utilised for kriging.

2.4.3 Kriging

Kriging is a best linear unbiased interpolator which possess minimal probable estimation variance and the structural information is optimally estimated by using a regionalised sample data. Furthermore, the sample points estimated in kriging have mutual spatial positional relationship (Cui, 2016; Zhen et al., 2019). In this work, interpolation in 2D developed from a programming language, i.e., macros utilising Visual Basic for Applications (VBA) in a Microsoft® Office software was conducted for kriging analysis. Types of kriging tested to obtain the best estimate for the potentially toxic element contamination in the topsoil of the closed landfill were ordinary kriging (OK), regression kriging (RK), and guess-filed kriging (GFK).

- *Ordinary kriging (OK)*

The most unexceptional method used for kriging is ordinary kriging due to its function based on assumption that mean is unknown and interpolate data to primary levels at unsampled locations (Webster and Oliver, 2007), the ordinary kriging explains as follows:

Ordinary kriging: $\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2$

here γ(h) is magnitude of lag distance between location of two samples; h represents the lag distance which disconnects points that pairing; N(h) denotes the number of pairs disconnected by the lag distance, h; $Z(x_i)$ is a arbitrary variable at location x_i; and Z(x + h) and Z(x) represent the existent values at locations x + h and x, respectively (Bhunia, Shit, and Chattopadhyay, 2018; Lin et al., 2008). The value of Z at location X_0 estimates by ordinary kriging utilising linear combination of n data, as follows:

$Z_0^{\wedge} = \sum_{i=1}^{n} \lambda_i Z(X_i)$

- *Regression kriging (RK)*

Regression kriging is commonly employed in regard to its low error of estimation. It also named as simple kriging with changeable local means (Pei et al., 2010). This is effective by improving predictions of regression models with kriging interpolation (Pouladi et al., 2019; Yigini and Panagos, 2016). The method is executed by employing regression on supplementary information follow with simple kriging using a known mean to estimate residuals from the regression model (Zhen et al., 2019). Nevertheless, regression kriging has no error of self-correlation but exception to estimation of same variable with a different methodology applied although this case is rare. So, regression is assumed from a response variable and the explanatory variable as in an equation below:

Regression kriging: $Z_1(X) = g[Z_2(X)] - \varepsilon(X)$

here $g[Z_2(X)]$ indicates regression equation and $\varepsilon(X)$ is an error term of an expectation value.

- *Guess-field kriging (GFK)*

Guess-field kriging is valid to the following regression equation:

Guess-field kriging: $Z_1(X) = g\big(Z_2(X)\big) + \varepsilon(X)$

here $g(Z_2(X))$ indicates regression equation and $\varepsilon(X)$ is an error term of an expectation value. In case of $Z_1(X)$ and $Z_2(X)$ are assessed at similar location, the estimation error $\eta(X)$ can be determined as the following:

$$\eta(X) = Z_1(X) - g\big(Z_2(X)\big)$$

Assume that $\eta(X)$ and $g(Z_2(X))$ have by no means of correlation. Kriging estimates $\hat{Z_0}$ and kriging variance σ_{k0^2} at X_0, with the guess-field kriging of the response variable being acquired as the following:

$$\hat{Z_0} = g\big(\hat{Z_0}\big)_0 + \hat{\eta_0} \qquad \sigma_{k0^2} = \sigma_{kg0^2} + \sigma_{k\eta 0^2}$$

where $g(\hat{Z_0})_0$ is the kriging interpolate of Z_1 by applying m transformed data; $g(Z_2(X_i))$ (i = 1, 2, …); σ_{k0^2} is the kriging variance; $\hat{\eta_0}$ is the kriging interpolate of the residual error utilising n residual error; $\sigma_{k\eta 0^2}$ is variance of kriging; and n is the sampling points number where Z_1 and Z_2 are both studied.

2.4.4. Validation

Estimation from kriging analysis necessitate validation to predict the statistical formation for agreeing the calculation. Validation was directed utilising programming languages in Microsoft® Office, i.e., VBA. Macros utilised for the VBA program presented in **Supporting Information**.

2.5. Visual basic for applications (VBA)

Kriging analysis was assessed in this study by operating the transformed data, prior administered into VBA programs in Microsoft® Excel to obtain the concluding estimation. The VBA program principally implement two types of kriging procedures with functional macros in this analysis, i.e., ordinary kriging (OK) and advanced kriging (RK and GFK). Macros utilised for the VBA program presented in **Supporting Infromation**.

2.6. Development of impact pathway

A logic model of impact pathway is developed as a research tool to facilitate data from kriging assessment to outline categories of payback from research or impact that is beyond academic. The model was adapted from the concept of Payback Framework by Donovan and Hanney (2011), with an adjustment that was appropriate to the kriging assessment circumstances.

3. Results and discussion

3.1. Kriging assessment

3.1.1. Ordinary kriging (OK)

Regression combined with kriging analysis were assessed for ICP-MS analysis data of Cr and Pb in the topsoil of the studied landfill. This involved interpolating Pb content by utilising the Cr analysis result for kriging with regression analysis. In this study, Pb was the response variable, and Cr was the explanatory variable. Ordinary kriging framework processed in this work presented in **Fig. 4**. In this work, analysis is developed to support interpolation of the considered missing of Pb data as response variable by utilising Cr data as explanatory variable. The prime reason of using Pb and Cr data as response and explanatory variable respectively due to both data had correlation from the same instrument tested i.e., ICP-MS. Ordinary kriging show no clear outline flow of distribution due to the small, estimated correlation (results are not shown).

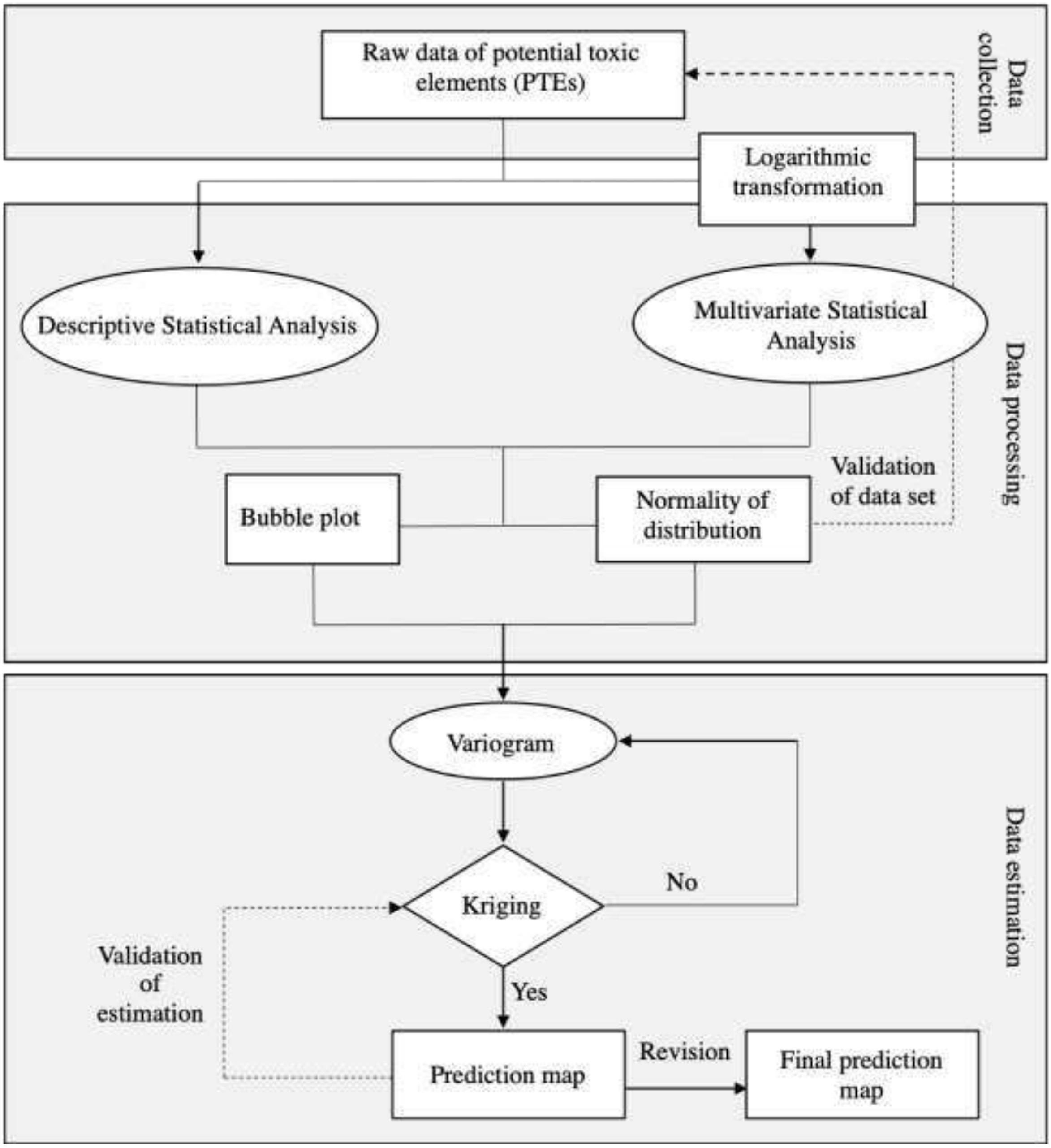

Figure 4 Diagram of the ordinary kriging framework applied in this study via the application of Visual Basic for Applications (VBA)

Semivariogram of explanatory and response variable estimated as follows:

Cr: $\gamma_{Cr}(h) = 0.13 \times \{1 - \exp(-h/1.5)\}$

Pb: $\gamma_{Pb}(h) = 0.062 \times \{1 - \exp(-h/0.8)\}$

Distribution results from ordinary kriging showed large difference due to the assumed missing data is greater than standard deviation. This is reflecting large uncertainty in the distribution of ordinary kriging and the 95th percentile estimate.

3.1.2. Regression Kriging (RK)

The analysis flow developed for the regression kriging analysis is shown in **Fig. 4**. In this study, there was a correlation between Cr and Pb with equation:

$$\text{Pb (ICP-MS)} = 0.5343 \times \text{Cr (ICP-MS)} + 0.3877$$

where $R^2 = 0.5467$, and the variance of the estimation error is 0.029. Regression kriging estimates has indicated distribution around the missing data area as compared to ordinary kriging. Nevertheless, no clear outlines in the distribution due to the estimates utilises only semivariogram of Pb and the regression kriging contains spatial correlation (result not shown). Hence, the distribution from regression kriging estimates is inappropriate to support interpolation of the missing data.

3.1.3. Guess-field kriging (GFK)

The analysis flow developed for the guess-field kriging analysis is shown in **Fig. 4**. Lead semivariogram for regression estimated as follows:

$$\gamma_{reg}(h) = 0.534322 \times \gamma Cr(h) = 0.534322 \times 0.13 \times \{1 - \exp(-h/1.5)\} =$$
$$0.0371 \times \{1 - \exp(-h/1.5)\}$$

Regression residual for Pb semivariogram estimated as follows:

$$\gamma_{resid}(h) = 0.032 \times \{1 - \exp(-h/1.5)\}$$

Guess-field kriging interpolation as shown in **Fig. 5** able to demonstrate distinct distribution outline at the area of missing data. It can be postulated that in case of minimal number of explanatory data, distribution of response variable in this study, i.e., Pb can be interpolated. Nonetheless, it is acknowledged that guess-field kriging can generate large uncertainty area as compared to ordinary kriging interpolation. The findings in the development of the missing data interpolation by utilising similar explanatory data, in this study, Cr from the ICP-MS analysis, has shown the ability of guess-field kriging in better managing of response variable data or in visualising hotspots in case of limited number of data obtained.

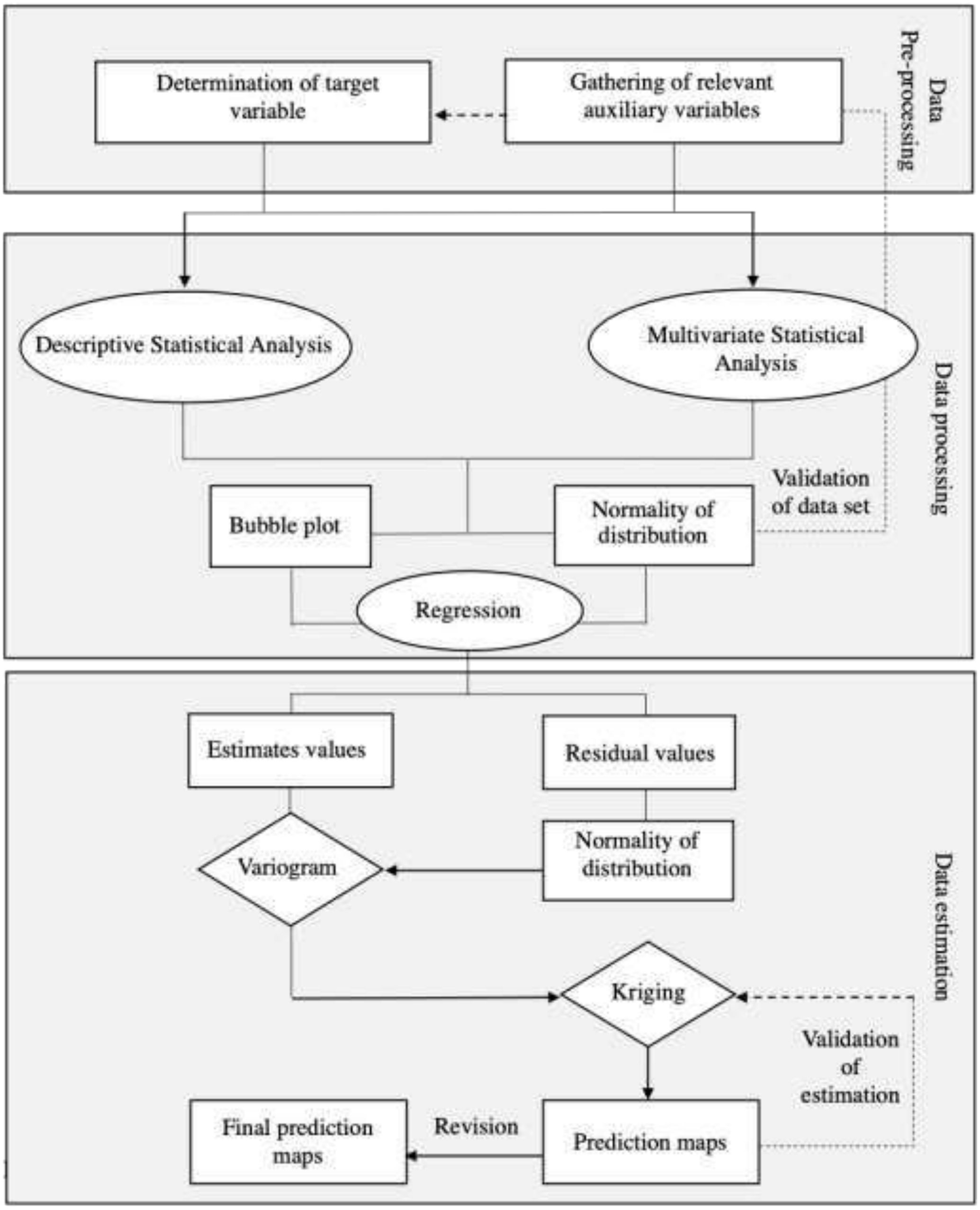

Figure 5 Diagram of the advanced kriging (regression and guess-field) framework applied in this study via the application of VBA. The target variable tested in this study was Pb, and the auxiliary variable was Cr

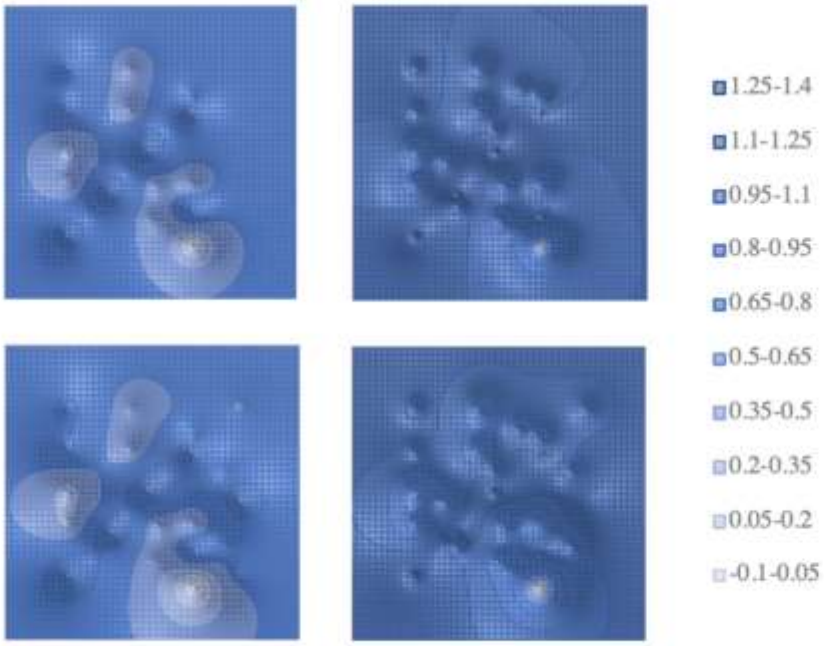

Figure 6 *Above*: Ordinary kriging (OK) interpolation of Pb (left) and 95th percentile value of the OK (right). *Below*: Guess-field kriging (GFK) of Pb (left) and 95th percentile value of the GFK (right)

3.2. Real impact pathway

As part of the kriging analysis framework development, the real impact pathway was developed as a strategy for achieving sustainability of this work's overarching purpose (**Fig. 6**). This is aimed to provide answers to questions to is related to what this research works and make improvements based on research data as well as advocacy to exhibit the paybacks of research, education, and innovation to community, as discussed by Adam et al. (2018) and Morgan et al. (2013) of "Four As" in research impact assessment which are; analysis, advocacy, allocation, and accountability. Even if there is no constructive assessment for research impact in the region particularly in the aspect of scientific area and stakeholder requirement, the prima facie effectiveness of the framework can be developed by mapping out through the logical impact pathway. It is a model on the environment of the research work as a guide to generate outcomes and impact from the research output. Furthermore, it can offer variety of stakeholders or practitioners, a platform to communicate and collaborate to captivate the full spectrum of impact and benefits in the sustainability of the impact derive originally from the research work. Through the visualisation of the impact pathway, it will be able to support decisions to be made as well as providing outlook to enhance mission for achieving impact. This is part of the capacity or precondition for impact orientation to manifest the practise of creating impact (Springer-Heinze et al., 2003). The pathway effectiveness as a guide shall need to be included with self-evaluation for establishing direct benefits of the outputs at the targeted group of concern and the applied system as practise to evaluate the pathway to impact (Douthwaite et al., 2003).

Altogether, the framework development aimed to sustainably improving the livelihood of people residing near the closed landfill area apart from the environmental dimension. In between of the impact pathway subjected to harness benefits as outcome of the research work, process of innovation is to ascertain the dynamic change of environment which this process helps to revisit the program strategies in regular basis by obtaining effective training citizen as a prerequisite for succeeding outcome. The process of innovation is analogous to the bridge of the outcome and the sustainability's pillars of impact (social, economic and environmental impact) vis-à-vis, the process of development (**Fig. 6**). Positive response by stakeholders with active participation of this movement of change will eventually experiencing impact as result. This is important part of learning approach on captivating different perspectives of innovation and development as discussed in-depth by Springer-Heinze et al. (2003) on strengthening impact orientation in an impact pathway analysis of agricultural research, although this work of risk assessment may encounter relatively different angle of the perspectives as a real challenge. Aside from that, frameworks deliver support by addressing key operational encounters and contrasts of research impact ranging from diverse fields, organisations, and countries (Adam et al., 2018).

Despite myriad impact frameworks and assessment methods readily available in literature to be incorporated by innovation to the kriging assessment framework for achieving sustainability in landfill aftercare management, this pathway is presenting a broad-spectrum yet definitive method for hypothesising impact developments, which provides a logical pathway for research preparation and able to map out potential stakeholder's engagement by facilitating communication. Although further analysis on detailing scaling up and scaling out of the projected dimensions as well as aggregated objectives for the pathway is needed to be developed for the intended impact to be achieved. Nevertheless, there is a limitation of the framework developed, which is feedback paths and direct impact paths is not pointed in the pathway as well as wider society categories of stakeholders that can be engaged at different stages of the framework.

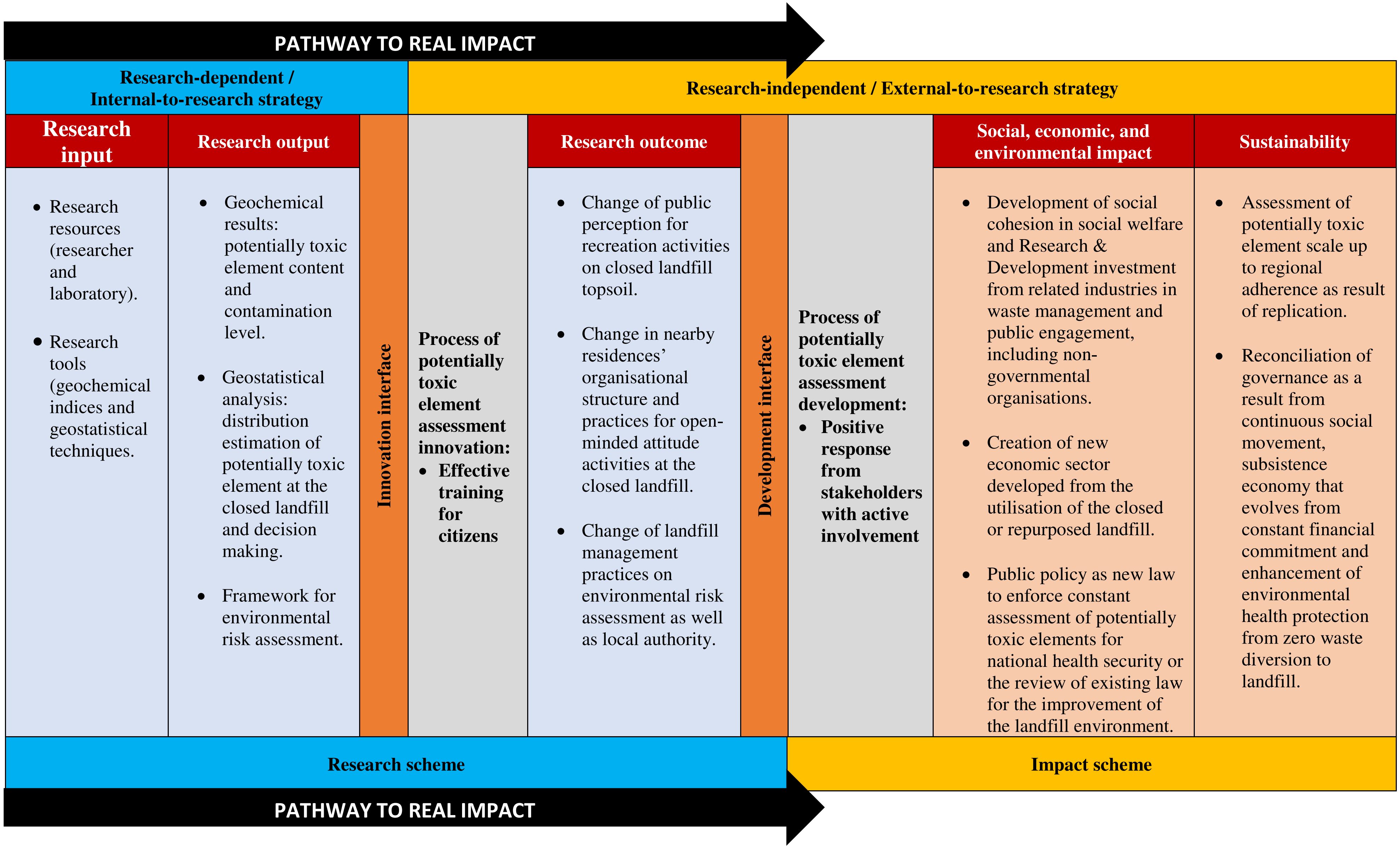

Figure 7 The logical framework of the pathway to real impact for potentially toxic element assessment in a closed landfill

4. Conclusions

The framework on geostatistical analysis by ordinary and advanced kriging in this study was developed as a guide for the analysis of potentially toxic element interpolation at an unmeasured studied site. The framework is meant to deliberately identify the potentially toxic element distribution in a closed landfill with the existence of censored data on appropriate confidence levels. This study framework estimation was conducted via utilisation of VBA application, constructed by programming code, i.e., macros, which is effective to automate the interpolation and incurring a lesser extent of cost as compared to sophisticated software. On another note, the impact pathway developed in this study is the beginning step to map out a more complex environment with characterising direct benefits at different scale. This is described through the outputs of the works, which is expected to project direct benefits by change of socio- environment and wider impact spectrum detailing out from each dimensions of sustainability, i.e., social, economic, and environment. Nevertheless, the impact pathway developed in this work is open for improvement by evolving through the dynamic of unprecedented knowledge expansion and impactful innovation processes as well as different views or perspectives of stakeholders.

Author contribution AAB Conceptualization, Investigation, Methodology, Writing-Original draft preparation; MY Conceptualization, Investigation, Methodology, Writing-Reviewing; NZM Conceptualization before manuscript submission.

Funding Authors are grateful to the research financial support from Japan Society for the Promotion of Science (JSPS) (Scholarship no. R11611) and Universiti Malaya (ROGS no. BR005-2016).

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent to publish All authors have checked the manuscript and have agreed to the publication on Environmental Science and Pollution Research.

Competing interests The authors declare no competing interests.

Supporting information The online version contains supplementary material available at Supporting information.

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