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The Capability of Artificial Neural Networks as a Model for Predicting Total Electron Content (TEC): A Review

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Abstract
The results of investigations from a complete analysis of ANN application on Total Electron Content (TEC) prediction are presented in this paper. TEC is important in defining the ionosphere and has many everyday applications, for example, satellite navigation, time delay and range error corrections for single frequency Global Positioning System (GPS) satellite signal receivers. The total electron content (TEC) in the ionosphere has been measured using GPS. GPS are not installed in every point on the earth to make global TEC measurements possible. As a result, it is crucial to have certain models that can aid to get data from places where there is not any in order to comprehend the global behavior of TEC. Neural Network (NN) models have been shown to accurately anticipate data patterns, including TEC. The capacity of neural networks to represent both linear and nonlinear relationships directly from the data being modeled is what makes them so powerful. The survey from literature reveals that, Levenberg-Marquardt algorithm is preferred and used mostly because of its speed and efficiency during learning process, and that ANN showed a good prediction of TEC compared to the IRI model. As a result, NNs are suitable for forecasting GPS TEC values at various locations if the model's input parameters are well specified.

Keywords: *Artificial neural network; Global positioning system; Total electron content*

INTRODUCTION

The sun, which provides energy for life on Earth but also causes space weather, has an impact on the Earth's atmosphere (Chauhan *et al*., 2011; Leong *et al*., 2011; Oron *et al*., 2013; Okoh *et al*., 2019). Space weather refers to any and all states and events caused by the Sun in near-Earth space and the upper atmosphere, which can disrupt space-borne and ground-based technological systems (Kataoka and Pulkkinen, 2008; Wik *et al*., 2009; Shenvi and Virani, 2023; Li and Wu, 2023), and which can have an impact on human existence (Hanslmeier, 2002). Users of equipment such as televisions, radios, and computers, as well as anyone who uses Global Positioning System (GPS) in any manner, are affected by space weather (Sulungu *et al*., 2018b). In addition, space weather has an impact on all passengers flying in jet aircraft in high-latitude zones in both hemispheres (Hanslmeier, 2002). Induced electrical currents in long undersea communications cables, long-haul telecommunication lines, and certain fiber-optic systems are among the other disruptions caused by space weather phenomena (Wik *et al*., 2009).

Disturbances in the systems indicated above are due to changes in the concentrations of charged particles at different ionospheric heights induced by solar influences (Hanslmeier, 2002; Adolfs and Hoque, 2021; Ozkan, 2022), which alter the reflection, absorption, or transmission of electromagnetic waves through it. The ionosphere is the part of the atmosphere that is ionized, containing free electrons and positive ions (Kelley, 2009; Smirnov *et al*., 2023). The quantity of positively charged ions and negatively charged electrons is normally equal, resulting in an electrically neutral medium (Memarzadeh, 2009). During the ionization process, free electrons and ions are produced by the interaction of Extreme Ultraviolet (EUV) and X-ray radiations with the upper atmospheric neutral gas. The number of electrons and ions in the ionosphere is maintained by a continuous process of gaining and losing between their rate of production, which is controlled by the intensity of solar radiation and incident particles, and the rate at which newly freed electrons and ions recombine to produce reconstructed neutral particles (Eddy, 2009). Because of the free electrons, the ionosphere is an inhomogeneous propagation medium for electromagnetic waves, altering satellite signal transmission by modifying their velocity and direction of travel. The impact of the ionosphere, according to Norsuzila *et al*., (2010a) is that it can generate range-rate inaccuracies for GPS satellite users that require high accuracy data. The severity of ionospheric impacts is determined by a variety of factors, including the user's location, the time of day, the season, the status of the earth's geomagnetic field, and the level of solar activity (Leong *et al*., 2011).

A variety of instruments, including the GPS, have been used in studies to better understand the physical and chemical processes that occur in the ionosphere and plasmasphere (GPS) (Chen *et al*., 2022). The GPS's main purpose is to provide users with global navigation, positioning, and time information (Norsuzila, 2010a; Sulungu *et* *al*., 2018b). However, the GPS is currently being used to provide data on the Total Electron Content (TEC) of the ionosphere (Liu *et al*., 2013). TEC is important for defining the ionosphere and has a variety of practical uses, including satellite navigation, delay time, and range error corrections for single frequency GPS (Bhuyan and Borah, 2007; Guoyan *et al*., 2021; Sulungu *et al*., 218b; Xiong *et al*., 2021).

The TEC is the total number of electrons integrated along the path from a terrestrial or spacecraft receiver to each GPS satellite and is measured in TECUs, where 1TECU = 1 x 10^{16} electrons/m^2 (Chauhan *et al*., 2011; Guoyan *et al*., 2021; Lee *et al*., 2021; Norsuzila *et al*., 2010b; Tang *et al*., 2022). It serves as a measure of ionospheric variability. The TEC is given by;

$$TEC = \int_{S_1}^{S_2} N_e dS \tag{1}$$

where N_e denotes the ionospheric electron density and S the signal propagation path length between satellite and receiver positions S_2 and S_1, respectively.

The ionosphere causes a transmission time delay in electromagnetic waves that pass through it. The TEC and the frequency of electromagnetic waves are connected to the magnitude of this effect (Gao and Liu, 2002). According to Hunt *et al*. (2000), the temporal delay generated on a radio frequency signal travelling between S_1 and S_2 can be calculated as follows:

$$\Delta t = \frac{e^2}{8\pi c m_e \varepsilon f^2} \int_{S_1}^{S_2} N_e dS = \frac{40.3}{cf^2} TEC \tag{2}$$

where c represents the speed of light in vacuum, m_e represents the electron mass, e represents the charge of an electron, f represents the transmitted frequency, and ε is the permittivity constant. In meters, the ionospheric range delay (phase advance) is given as:

$$\Delta R = c\Delta t \tag{3}$$

where ΔR is the amount that would be added to the range if the range was calculated under the assumption that the radio signal travels at the speed of light. From (2) and (3) we get the following:

$$\Delta R = \frac{40.3}{f^2} TEC \tag{4}$$

A dual-frequency GPS receiver measures the difference in ionospheric delay between the two signals, L1 and L2 with frequencies f_1 *and* f_2, which are obtained from the fundamental frequency, f_o = 10.23 MHz, so that:

$f_1 = 154f_o$ = 1575.42 MHz and

$f_2 = 120f_o$= 1227.60 MHz

For a dual-frequency GPS receiver, the group delay is given as:

$$P_2 - P_1 = 40.3TEC\left(\frac{1}{f_2^2} - \frac{1}{f_1^2}\right) \tag{5}$$

P_1 and P_2 are pseudo ranges visible on L1 and L2 transmissions, respectively, and f_1 and f_2 are the corresponding high and low GPS frequencies.

To get the TEC, equation (5) can be written as follows (Sulungu *et al*., 2018b; Sulungu and Uiso, 2019):

$$TEC = \frac{1}{40.3}\left(\frac{f_1^2 f_2^2}{f_1^2 - f_2^2}\right)(P_2 - P_1) \tag{6}$$

TEC is divided into two types: slant TEC (TECs) and vertical TEC (TECv). Because different GPS satellites are viewed at arbitrary elevation angles, TECs is a measure of the total electron content of the ionosphere along the ray path from the satellite to the receiver measured at differing elevation angles. To compare the electron contents of pathways with various elevation angles, the TECs are converted into comparable TECv by assuming that the ionosphere is compressed into a thin shell with a shell height h, as shown in Figure 1.

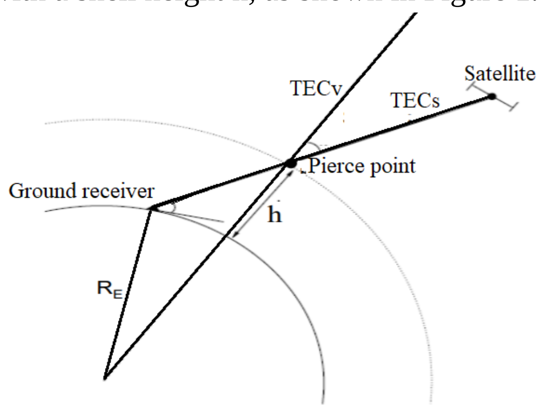

Figure 1: Ionospheric thin shell (Shim, 2009)

At altitude h, the TECv are allocated to an ionospheric pierce point (IPP), which is the intersection of the line-of-sight ray and the thin shell. TECv is frequently calculated from TECs using the following mapping function (Shim, 2009):

$$TECv = M(e) \times TECs, \quad (7)$$

where $$M(e) = \left[1 - \left(\frac{\cos(e)}{1 + h/R_E}\right)^2\right]^{\frac{1}{2}} \quad (8)$$

Here, e represents a satellite's elevation angle, h represents the height of the ionospheric shell, and R_E represents the Earth's mean radius.

However, GPS receivers are not installed at every location on the earth to allow global TEC measurements. As a result, it is essential to have some models that can help gather data from regions with no receiver in order to comprehend the TEC's global behavior (Sulungu and Uiso, 2019). The International Reference Ionosphere (IRI) is a globally utilized empirical ionospheric model for TEC forecasting. However, in places where data is poor, the IRI model does not provide accurate forecasts (Akir *et al*., 2015; Watthanasangmechai *et al*., 2012). As a result, models based on Neural Networks (NN) are used to forecast TEC (Sivavaraprasad *et al*., 2020). Neural Networks (NNs) are commonly employed in predictive modeling because of their learning and pattern recognition capabilities. They have been shown to be powerful tools that can learn trends and patterns in specific data and, as a result, accurately predict future trends and patterns for that data (Adolfs and Hoque, 2021). It has also been demonstrated that by altering the weights, a neural network may be trained to execute a certain purpose (Demuth and Beale, 2002; Okoh *et al*., 2016). The capacity of neural networks to capture both linear and nonlinear relationships directly from the data being modeled is one of its most powerful features (Okoh *et al*., 2016).

Therefore, the results from a comprehensive application of Artificial Neural Network (ANN) on TEC prediction are presented in this study. In comparison to other models such as the International Reference Ionosphere, the applicability of ANN in predicting TEC is discussed. The study also highlighted a number of authors' perspectives on the use of ANN in TEC prediction.

Ionospheric Modeling

Several models have been created over the last several decades to better understand the physics that affects the dynamics of the ionosphere. Empirical models are one of the sorts of models that have been developed; they provide an average ionosphere behavior based on observable data. However, the amount of data and the spatial and temporal coverage of the data that are employed in their construction limit these models (Shim, 2009). Despite these limitations, empirical models are extensively utilized due to their simplicity (Sulungu *et al*., 2018a). The NeQuick model (Nigussie *et al*., 2012) and the International Reference Ionosphere (IRI) model (Bilitza, 1986) are two examples of such models.

The IRI model

The International Reference Ionosphere (IRI) was established by the Committee on Space Research (COSPAR) and the International Union of Radio Science (URSI) in an effort to create an international standard for the specification of ionospheric parameters based on all available data from both ground-based and satellite observations from around the world (Kenpankho *et al*., 2011). The model is based on experimental evidence gathered from all available ground and space data (Bilitza *et al*., 2014). As new data and modeling methodologies become available, the IRI model is regularly upgraded (Sulungu *et al*., 2018a), resulting in many major editions of IRI.

There are three topside options that the IRI model employs to predict TEC, these are the NeQuick option, the IRI-2001-corrected option, and the IRI-2001 option. The NeQuick option is the default option for the IRI model in its standard form (Leitinger *et al*., 2001; Rathore *et al*., 2015). The inputs of the IRI model are latitude and longitude, date and time in UT, and altitudes ranging from 60 to 2000 km. The IRI model, on the other hand, has a lot of outputs, such as electron density, electron temperature, ion composition, ion temperature, F2-layer peak height, density, and TEC (Kumar *et al*., 2015). The IRI model's accuracy in a specific location is determined by the availability of trustworthy and plentiful data in that area (Adewale *et al*., 2011). For example, because of the vast number of stations in the northern mid-latitude region, the model could make accurate predictions there (Bilitza and Reinisch, 2008).

Artificial Neural Network (ANN)

ANN is made up of several simple processing units (layers) that communicate with each other by transmitting signals via a large number of weighted connections (Unnikrishnan *et al.,* 2018). Each layer takes input from its neighbors or external sources and uses it to create an output signal that is transferred to the next layer. The neural system is made up of three layers: an input layer that receives data from outside the neural network, a hidden layer that keeps the input and output signals within the neural network, and an output layer that sends data out of the neural network (Anderson, 1997; Galushkin, 2007; Kröse and van der Smagt, 1996).

Topologies of Neural Networks

Feed-forward networks and recurrent networks are two types of neural networks that differ in their layer connections and data propagation patterns.

Layers in feed-forward networks are connected in one direction to allow data to flow from the input to the output layer and do not allow closed paths inside the network connections; examples include Perceptron and Adaline (Haykin, 2001). In a feed-back connection, some or all layers have connections that allow them to move backwards to the preceding layer (Habarulema, 2010; Kröse and van der Smagt, 1996) (Figure 2).

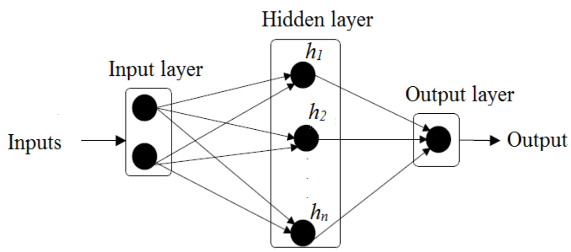

Figure 2: Three layers of a feed forward network (Habarulema, 2010)

On the other hand, in recurrent networks, there are no feedback connections. The network's dynamical features are crucial in this type of network. In some circumstances, the activation values of the units go through a relaxation process, resulting in the network reaching a stable state where the activation values do not vary. In some applications, the change in the activation values of the output neurons is significant enough that the network's output is determined by its dynamical behavior (Kröse and van der Smagt, 1996; Pearlmutter, 1990). These include the Elman network (Figure 3) which feeds some of the hidden unit activation values back to the input layer, to a group of extra neurons known as the context units, and the Jordan network that feeds output values back to the input layer, to a set of extra neurons known as the state units (Figure 4).

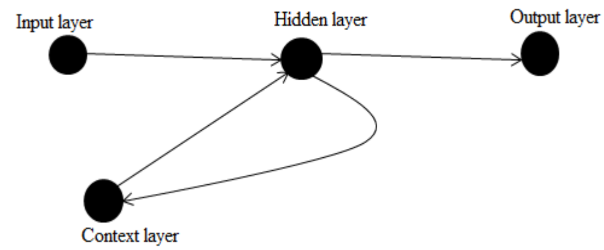

Figure 2: The Elman network (Kröse and van der Smagt, 1996)

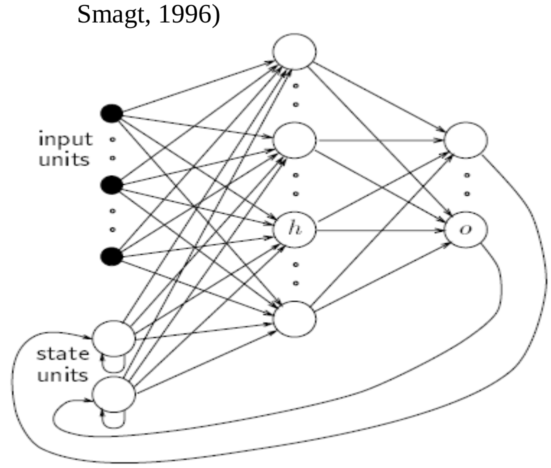

Figure 3: The Jordan network (Kröse and van der Smagt, 1996)

However, many real-world problems are solved when feed forward network topologies are used instead of recurrent networks, which are more difficult to employ (Pearlmutter, 1990).

Artificial neural networks training

The construction of a neural network should be done in such a way that when a set of inputs is applied, the desired set of outputs is produced. This is accomplished by either clearly setting the weights based on a priori knowledge, or by training the machine by feeding it teaching configurations and allowing it to adjust its weights based on some learning instructions.

There are two types of learning in neural networks: supervised (associative) learning and unsupervised learning (self-organization).

Supervised (associative) learning is a sort of learning in which the network is changed based on output and target comparisons until the network output matches the target. An external trainer or the system containing the network (self-supervised) can offer these input-output pairings (Demuth and Beale, 2002; Kröse and van der Smagt, 1996).

Unsupervised (self-organization) learning, on the other hand, is a sort of learning in which an output is trained to respond to collections of patterns within the input by identifying statistically significant aspects of the population. The system creates its own representation of the incoming stimuli in this sort of learning, and there is no predetermined set of categories into which the patterns should be classified (Demuth and Beale, 2002; Haykin, 2001).

Multi-layer feed-forward networks

A neural network connection can be either a single-layer connection with significant constraints on the types of activities that can be done, or a multi-layer connection with more flexibility (Graupe, 2007; Hu and Hwang, 2002).

To determine the network parameters, a variety of algorithms are used. In the field of neural networks, the algorithms are known as learning or teaching algorithms (Poulton, 2001). Back-propagation and Levenberg-Marquardt algorithms are two of the most well-known algorithms. Back-propagation learning rule was first proposed by Rumelhart, Hinton, and Williams in 1986 (Rumelhart *et al.*, 1986), where the errors for the hidden layer units are determined by back-propagating the errors of the output layer units. This is a gradient-based algorithm with a lot of variations. The Levenberg-Marquardt approach, on the other hand, is more efficient than back propagation since it saves time (Bishop, 1995; Haykin, 2001; Poulton, 2001).

Artificial Neuron's Major Components

This section describes the major components of the artificial neuron using information from a variety of sources, including (Anderson and McNeill, 1992; Anderson, 1997; Demuth and Beale, 2002; Galushkin, 2007; Haykin, 2001).

The weighting factors are the first component. Weights are network adaptable coefficients that control the strength of the input signal as perceived by the artificial neuron. They are numerical elements that connect the output value of a neuron to the next neuron to which it is connected. They are also a measure of an input's connection strength, which might change in response to different training sets, as well as a network's structure and learning rules.

Summation function is the second component in which, if the inputs and weights are vectors that can be represented as $X = [x_1, x_2... x_n]^T$ and $W = (w_1, w_2... w_n)$, then, the summing function is calculated by multiplying each component of the X vector by the corresponding component of the W vector and then adding up all the products. Thus:

$$X^T.W = x_1w_1 + x_2w_2 + ... + x_nw_n = \sum_{i=1}^{n} x_iw_i \quad . \qquad (9)$$

This summation must be passed on to the transfer or activation function for the summation result to vary with time.

In the third component, when the product of the inputs and weights is obtained, the result is turned into the output via an algorithmic process known as the transfer function, which is often non-linear. The hyberbolic tangent (tanh) and a sigmoid function are the most widely employed activation functions.
Scaling and limiting make up the fourth component. This is a procedure in which the outcome of the transfer function of the processing element passes through. It simply adds an offset after multiplying a scaling factor by the transfer value. Its core function is to make sure the scaled result doesn't go beyond a certain limit. This limiting is also in addition to any limitations imposed by the initial transfer function.

In the fifth component, output function (competition), one output signal from each processing unit passes to hundreds of additional neurons. In most cases, the network's output is identical to the transfer function's output. During the process, some network topologies' transfer outcomes may be adjusted to accommodate competition among neighboring processing nodes. Neurons can compete against one another in this process. The competition's goal is to figure out which artificial neuron will be active in generating an output or which processing unit will be involved in the learning or adaption process.

The error function and back-propagated value make up the sixth component. The obtained output always differs from the targeted output during the process of determining the output, and the difference is calculated. The error function then adjusts the error between these two outputs to reflect the network design. Most basic neural network topologies employ this error directly; however, some of them square the error while keeping its sign, while others adjust the raw error to serve their special needs. The error of the generated artificial neuron is then propagated backwards to a previous layer by being sent through the learning function of another processing element. After the learning function has scaled this back-propagated value, it is multiplied against each of the incoming connection weights in order to change them before the next learning cycle.

The learning function is the final component, and it is used to adjust the weights of the input connections in order to obtain certain outputs. This function is also known as the adaption function or the learning mode, and it is used to change the variable connection weights on the inputs of each processing unit using a neural-based algorithm.

Single-node multilayer perceptron

Figure 5 depicts a multilayer perceptron (MLP) network.

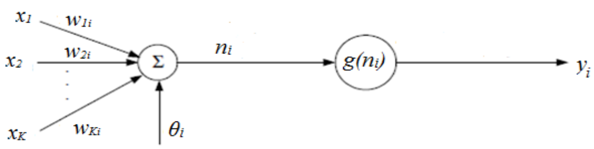

Figure 4: An example of a single node in a MLP network (Demuth and Beale, 2002)

To obtain the output $y = n_i$, the inputs $x_k, k = 1,2,.......K$ to the neuron are multiplied by weights and added together with the constant bias factor θ_i.

$$y = n_i = \sum_{j=1}^{K} w_{ji} x_j + \theta_i \qquad (10)$$

The resulting n_i is used as an input to the activation function $g_i = g(n_i)$, and the final output is as follows:

$$y_i = g_i = g(\sum_{j=1}^{K} w_{ji} x_j + \theta_i) \qquad (11)$$

Multilayer Perceptron with more than one node

Figure 6 depicts an MLP network generated when many nodes are joined in parallel and series. The activation function g has been employed in both layers, as shown in the Figure 6, and the superscripts in θ, n, or w specifies the network layer. The equation for the final output in Figure 6 can be determined by considering the expression for the output value given in equation (11).

The first inputs and weights produce the following output:

$$g_i = g(n_j^1) = g\left(\sum_{k=1}^{K} w_{kj}^1 x_k + \theta_j^1\right) \qquad (12)$$

The final output y_i, i = 1, 2, can now be given as;

$$y_i = g\left(\sum_{j=1}^{3} w_{ji}^2 g(n_j^i) + \theta_j^2\right) = g\left(\sum_{j=1}^{3} w_{ji}^2 g\left(\sum_{k=1}^{K} w_{kj}^1 x_k + \theta_j^1\right) + \theta_j^2\right)$$

. (13)

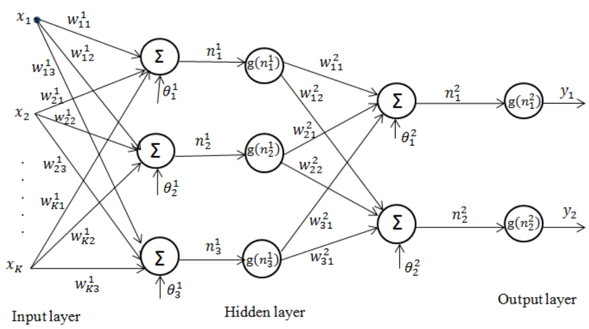

Figure 5: A multilayer perceptron network with one hidden layer

When using a set of training samples that include input values x^p and desired (or target) output values d^p, where p is the number of iterations, the network's output is always different from the target value. If y^p is the network's actual output, then $d^p - y^p$ is the difference between it and its target output. The weights are changed based on these differences in order to achieve the best output values (Kröse and van der Smagt, 1996).

The error function (least mean square error) is calculated using the summed squared error E given as;

$$E = \sum_p E^p = \frac{1}{2}\sum_p \left(d^p - y^p\right)^2 \qquad (14)$$

where the index p ranges over the set of input patterns and E^p represents the error on pattern p.

The Least-Mean-Square (LMS) approach is used to find the values of all the weights using a method called gradient descent in order to minimize the error function. A weight change is proportional to the negative of the derivative of the error measured on the current pattern with respect to each weight (Kröse and van der Smagt, 1996).

$$\Delta_p w_j = -\gamma \frac{\partial E^p}{\partial w_j} \tag{15}$$

Where γ is the learning-rate parameter, which is a proportionality constant. To reduce the value of E^p, the minus sign in equation (15) accounts for gradient descent in weight space. Equation (15) can be rearranged to give the following result:

$$\frac{\partial E^p}{\partial w_j} = \frac{\partial E^p}{\partial y^p}\frac{\partial y^p}{\partial w_j} \tag{16}$$

From equation (10),

$$\frac{\partial y^p}{\partial w^p} = x_j \tag{17}$$

and from (14),

$$\frac{\partial E^p}{\partial y^p} = -\left(d^p - y^p\right) \tag{18}$$

Thus,

$$\Delta_p w_j = \gamma \delta^p x_j \, . \tag{19}$$

where $\delta^p = d^p - y^p$

Based on this relationship, the weight can be adjusted suitably for target and actual outputs of either polarity for input and output units of the network.

Early stopping training approach

The mean square error diminishes as the number of epochs increases in the back-propagation process. This is due to the fact that, the multilayer perceptron learns in phases, ranging from simple to more complicated functions throughout the training session. If the training session is not interrupted at the proper point, the network may end up overfitting the training data. To circumvent this, the training data is divided into two parts: estimation (training) and validation (validation). The network is trained using the estimation part of the data and paused every now and then, and the validation part of the data is utilized to test the data after each training session. The estimation session is restarted for another period when the validation procedure is completed; the process is repeated until the optimal value is achieved (Demuth and Beale, 2002; Haykin, 2001).

Studies based on Neural Networks approach

Neural networks (NNs) are powerful predictive modeling tools that combine machine learning and pattern recognition capabilities. They can recognize patterns and trends in specific data and, as a result, correctly anticipate future trends and patterns in the data. Demuth and Beale (2002) and Okoh *et al*. (2016) demonstrated that a neural network may be trained to execute a certain purpose by altering the weights. The capacity of neural networks to capture both linear and nonlinear relationships directly from the data being modeled is one of its most powerful features (Okoh *et al*., 2016).

The capability of neural networks in ionospheric modeling has been proved in a number of researches conducted in various locations. According to Okoh *et al*., (2016) in their study on a regional GNSS-TECv model over Nigeria utilizing neural networks, DST, SSN, and IRI-foF2 as input layer neurons on the networks are effective in boosting the network performances. They implemented Levenberge-Marquardt backpropagation algorithm because of its speed and efficiency in learning. When comparing TEC predictions from the NN with the IRI model, Okoh et al. (2016) observed that, the developed model makes better predictions than the IRI model. Habarulema *et al*. (2007) used a feed forward network with back propagation algorithm and found that NNs are suitable for forecasting GPS TEC values at places inside South Africa, and that their results were able to predict the TEC values more correctly than IRI-2001. They also demonstrated that the NN model accurately forecasts the trend of GPS TEC diurnally and seasonally, while the created model overestimates or underestimates the TEC in some cases. The same study indicated that correlation coefficients between the NN modeled TEC and GPS TEC were more consistent as compared to those from the IRI-2001 model over South African region. When the verification data set used is within the training data set range, the NN based model's prediction accuracy is more apparent (Habarulema *et al*., 2011).

Homam (2014) discovered that a network configuration that uses TEC values during lower solar activity had a lower Root-Mean Square Error (RMSE), as well as absolute and relative error, than a network configuration that uses TEC values during higher solar activity. Homan chose to use Levenberg-Marquardt back propagation algorithm due to its fast processing, although it needs more memory when compared with other algorithms. Leandro and Santos (2007) used the Levenberg-Marquardt back-propagation algorithm to train the neural network model for regional vertical total electron content simulation utilizing the Brazilian network data. The findings revealed that the neural network model gave TEC value approximations with an average absolute error of 3.7 TECU and a standard deviation of 2.7 TECU.

Sulungu and Uiso (2019) established a model for GPS TEC prediction across Eastern Africa using a neural network (NN) approach. They used the multi-layer perceptron neural network because of its speed and efficiency during learning process. According to their findings, the more input layer neurons that were added to the networks, the better the networks learned and produced the improved results. They also found that when sunspot numbers (SSN) and the IRI-NmF2 were incorporated as input neurons, correlation coefficients indicated that, the created NN model could accurately predict GPS TEC. Sulungu and Uiso (2019) also found that the generated NN model well predicted the diurnal variational pattern of the TEC parameter, and that the model closely matched the GPS TEC in most cases when compared to the IRI-2012 model. This result was also obtained by Sahu *et al*. (2021) on their study on prediction of TEC using NN, utilizing the Levenberg-Marquardt algorithm, over anomaly crest region Bhopal.

Okoh *et al*. (2020) used a neural network approach to create a storm-time total electron content (TEC) model over the

African sector. They trained the network using Bayesian regularization backpropagation algorithm. In comparison to low and equatorial latitude regions, the model performed better in mid-latitude. Sivavaraprasad *et al*. (2020) studied the performance of TEC forecasting models based on Neural Networks (NN) across equatorial low latitude Bengaluru, India. They used Levenberg-Marquardt algorithm as the training technique due to its speed and efficiency in learning and found that the NN model was more accurate than IRI-2016 model. Y By using Bayesian Regularization process according to Levenberg-Marquardt optimization, Cesaroni *et al*. (2020) forecasted Total Electron Content (TEC) 24 hours ahead of time at a global scale. They obtained a very satisfactory result in terms of RMSE, ranging between 3 and 5 TECU.

Tulunay *et al*. (2004) utilized the Levenberg-Marquardt backpropagation algorithm in training the Middle East Technical University Neural Network based models, to estimate 10-minute TEC variations during the high solar activity of 2000-2001, and the NN model's sensitivity and accuracy were found to be good. They concluded that the methodologies they developed can be utilized to characterize the electromagnetic wave propagation medium for the purposes of planning and operation of radio systems. Watthanasangmechai *et al*. (2012) applied the Levenberg-Marquardt algorithm as the training function in their investigations on TEC prediction with neural networks for equatorial latitude stations in Thailand. Their results showed a good prediction of TEC by the NN model compared to the IRI-2007 model. Their findings also demonstrated that, large variations in TEC made it hard for the NN to learn during specific periods, and they linked this problem to the formation of an equatorial plasma bubble as well as day-to-day TEC variations in the equatorial area. When Uwamahoro and Habarulema (2015) were modeling total electron content during geomagnetic storm conditions in South Africa, they trained the network using the Leverberg-Marquardt back propagation algorithm because of its time saving advantage during training and found that the choice of hidden node number could alter the NN prediction capability.

Li and Wu (2023) developed an Ionospheric TEC Model with a storm option over Japan based on a multi-layer perceptron (MLP) neural network. The maximum RMSE was lower than 2TECU, while the corresponding RMSEs for the IRI exceeded 5TECU. Shenvi and Virani (2023) forecasted the ionospheric TEC using a multivariate deep long short-term memory (LSTM) model for different latitudes and solar activity. Their results showed that, LSTM predicted TEC with more accuracy than MLP. MLPs fail to predict accurately in cases where the data is noisy or turbulent, particularly during solar active years and during the occurrence of geomagnetic. Smirnov et al (2023) developed a neural network-based model of electron density in the topside ionosphere, and shows outstanding agreement with the observations, beating the IRI model, especially at 100-200 km above the F2-layer peak. An artificial neural network model developed by Ozkan (2022), based on

Levenberg-Marquardt backpropagation algorithm, for predicting VTEC over central Anatolia in Turkey, showed better performance than the global IRI-2016 model. Adolfs and Hoque (2021) established a neural network-based TEC model capable of reproducing nighttime winter anomaly. NN model results were compared with the Neustrelitz TEC Model (NTCM), and the results showed that, the neural network model outperformed the NTCM by approximately 1 TECU. Okoh et al. (2019) developed a neural network-based ionospheric model over Africa from constellation observing system by training the networks using the Bayesian regularization back-propagation algorithm. After testing the usefulness of three solar activity indices (sunspot number, solar radio flux at 10.7-cm wavelength [F10.7], and solar ultraviolet [UV] flux at 1 AU), the F10.7 and UV were more operative, and the F10.7 was chosen since it produced the smallest errors on the validation data set used.

Several studies (Conway *et al*., 1998; Habarulema *et al*., 2007; Maruyama, 2009; Okoh *et al*., 2016; Watthanasangmechai *et al*., 2012) shown that, the NN model performs well when data is collected over a long period of time, at least one solar cycle (11 years). However, investigations by Leandro and Santos (2007) and Homam (2014) found that, the NN model can accurately predict GPS TEC even with data from shorter time periods. Therefore, from this survey of literature, it shows that, Levenberg-Marquardt algorithm is preferred and used mostly because of its speed and efficiency during learning process. It is also found that NN is able to forecast TEC values more correctly than the IRI model.

CONCLUSION

According to the literature survey, building a neural network should be done in such a way that, applying a set of inputs results in the desired set of outputs. This is accomplished by either clearly setting the weights based on a priori knowledge, or by training the machine by feeding it teaching configurations and allowing it to adjust its weights based on some learning instructions. The survey from literature reveals that, Levenberg-Marquardt algorithm is preferred and used mostly because of its speed and efficiency during learning process. It is also found that NN is able to forecast TEC values more correctly than the IRI model, as well as the trend of GPS TEC diurnally and seasonally, although the model over or underestimates the TEC in some cases. It is also clear that the number of hidden nodes chosen can have an impact on the NN's capacity to forecast. The research also has shown that, the NN model performs well when data is collected over lengthy periods of time, at least one solar cycle (11 years), while some investigations revealed that the NN model can predict GPS TEC even with data collected over shorter time periods.

Therefore, the Levenberg-Marquardt algorithm is a popular optimization technique used for training artificial neural networks. It is an efficient method for minimizing non-linear least squares problems and is often employed for training neural networks due to its fast convergence properties.

However, after going through different literature on application of NN in predicting TEC, the following recommendations are made for future research:

Investigation on the incorporation of temporal and spatial features to capture the dynamic nature of the Earth's ionosphere should be done. ANNs capable of processing spatiotemporal data might yield more accurate predictions.

Exploring the potential of transfer of learning is essential, where knowledge learned from one region or dataset is transferred to improve predictions in another region with limited data.

Investigation of techniques to adapt ANNs trained on data from one geographical location to be effective in different but related regions.

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The Usage of social media in Creating Land Degradation Awareness in Rombo District, Kilimanjaro Region - Tanzania

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Abstract
The environment is the fundamental for all living things, and land conservation is of greater apprehension for the sustainable economic development. To attain higher level of land conservation there should be greater effort in creating awareness to people on land degradation conservation. The study aimed to find out the usage of social media in creating land degradation awareness. Specifically, the study intended to: find out the causes of land degradation, identify the status on the usage of social media for land degradation awareness, likely determine the type of social media frequently used for land degradation awareness. The field work covered Rombo district in the Kilimanjaro region Tanzania, where five administrative wards were scrutinized, to mention: Tarakea, Motamburu, Olele, Mahida, and Ngoyoni. Data was collected employing household survey and interview and analyzed using descriptive and thematic analysis techniques. The results show that the usage of social media that can be used in creating land degradation awareness includes providing education through media for peoples to understand relationship between human activities and land quality, providing user-friendly tools for knowledge sharing, enabling users to create, edit and add online contents, engaging discussions through social media on environmental issues as well as reporting on land degradation. Further, social media can be used to create land degradation awareness to peoples in Rombo district by 59%. It was concluded that, public campaign program to enhance awareness on land degradation should be strengthened through the usage of social media for sustainable land usage.

Keywords: *Land degradation, Land degradation awareness, social media, Rombo district, Kilimanjaro region-Tanzania.*

INTRODUCTION

It is well recognized that environment is fundamental for all living things because every resource necessary for them is interrelated to the environment (Anderson, 2017). Unless the environment is protected, the existence of life on earth would eventually be impossible. That is why environmental protection specifically land degradation safety have become so sensitive and globally important (Ashe, & Poberezhskaya, 2021). According to Schuberth, (2020) land degradation has global aspects that require action at the global level due to serious land degradation results from developments taking place in developed as well as developing countries (Abdul-Razak & Kruse, 2017). Therefore, all people need to have a common understanding of the role that have to be played by human beings to reduce the worsening of land (Anderson, 2017).

There are various ways that has been introduced to lessen the worsening of land involving, the use of energy more efficiently, the use of electricity and natural gas as like as the use of social media to create awareness (Nyahunda and Tirivangasi, 2021). The use of social media has a big role to play in making people aware of land degradation issues and taking actions to protect the environment (Saikia, 2017). Zhang *et al., (*2018) point out that over 2600 global media channels operate with the support of about 3000 satellites, reaching nearly 1.5 billion people across the globe. It can be argued that the majority of global Citizens learn about Environmental issues, beyond their immediate Surroundings, through the global Media and technology (Abdullah, and Ward, 2016).

The spread of land degradation awareness to alert and inform the entire public has been successful in developed Countries. One of the techniques used is social media. The use of social Media has big role to play in making people aware of land degradation and taking actions to protect the land. For example, Dumpit, and Fernandez, (2017) used social media to outline land policies, campaigns and agendas on land degradation management, Abdullah, and Ward, (2016) stated that architecture students Used social media platforms (Facebook, Twitter, and WhatsApp) to create land usage consciousness that involved the built of land to the site context, creating spaces for the community and using building materials for new Ways of sustainable living, also Roma, (2016) successful used Instagram social media platform to enable awareness to people on local and global Land degradation issues.

Tanzania as one of the developing countries land degradation awareness is increasingly a challenge due to the increase in human activities (Mohamed and Dominic, (2021). The utilization of the environment in an unfriendly manner has been increasing as a result of lack Of information and knowledge about the conservation strategy (ibid). Several initiatives have been taken by the government to increase citizen's land degradation awareness (Antwi-agyei *et al.*, 2017). For example, the country has enacted the Environmental Policy of 1992, which aimed to prevent land degradation and informing stakeholders to protect land beauty (Kilagwa *et al.*,2020). Furthermore, different strategies have been undertaken by the government and civil societies to address the land degradation to the public by provision of knowledge through newspapers, radio, and using bylaws in every district and town to protect and conserve the land, sadly the initiatives have not been successful (Antwi-agyei *et al.*, 2017).

Mohamed and Dominic, (2021), argue that in Tanzania there are lack of new emerging technologies of sharing information and instructional materials. Also, Kilagwa *et al.*,(2020) added that, the social media is increasingly recognized as accessible technology fostering public participation and effectiveness to spread Land. information to the entire social spectrum. The challenges are still overwhelming in the developing countries including Tanzania, specifically in Rombo district. The use of social media to raise land degradation awareness to the entire public (Kilagwa *et al.,* 2020). In order to address the gap, this study aimed to find out the utilization of social media in providing environmental awareness to reduce degradation of the land.

METHODOLOGY

This study employed a cross sectional survey research design of which the target respondents were studied at a single point in time for the researcher to find out the utilization of social media to provide land awareness in reducing degradation. Davis & Newstrom, (2015) affirms that the design provides a snapshot of the outcome and associated characteristics at a specified point in time also it save time during the data collection process.

Further, a qualitative research approach was involved. The approach concerned with valuation of traits, opinions and actions which help to analyze, explain, and build arguments to understanding content of the study (Bickman *et al.,* 2014). The approach was used in this study as it enables to get necessary information for the study, also the nature of objective in this study requires qualitative data.

The study was conducted in Rombo district in the Kilimanjaro region – Tanzania. Five administrative wards in the district were selected including Tarakea, Motamburu, Olele, Mahida and Ngoyoni. The area offers an ideal geographic location for the research as the area precisely represents a population of 260,963 within the area of 1,471 Km^2 where land tensions are played out. Also, the other factors motivated to select the area under study include: the district is faced with land threats including adjacent land use, high temperature causing fire, and climate change along Kilimanjaro Mountain which play a crucial role in livelihood and national income (Munishi *et al.,*, 2019).

The study used simple and purposive sampling techniques. First, the list of sampling frame or target population (household heads) was identified and prepared in the proper list manner with a totality of all household available in the Rombo district which is about 1200. Yamane (1967) formula was used to identify sample size which was 92. Thereafter, each household of 1200 were assigned numbers then, 92 households were selected using simple random sampling and head of households were assigned as focal persons for responding the questions. The technique was used since it gives equal chance of each member in a population to be selected also avoid bias in sample selection (Coughlan *et al.,* 2017).

Using purposive sampling technique 16 respondents were selected proportionally for further studies; involving, one (1) IT staff, one (1) planning officer, one (1) District Director, four (4) Ward executive officer (WEO), four (4) village executive officer (VEO), two (2) Tanzania Forest Services Agency (TFS) Staff, one (1) Kilimanjaro National Park (KINAPA) staff, and two (2) National Environment Management Council (NEMC) staff. The mentioned respondents were selected basing on their official positions since they have notable access of information regarding the usage of social media in creating land degradation awareness. Purposive sampling technique method allows to include respondents with required features therefore get valuable information and data (Davis, & Newstrom, (2015).

The methods of data collection were categorized regarding the sources of data. Primary data was collected by using a questionnaire and interview while secondary data was collected by the use of the documentary review method.

In line with data analysis, data collected was analyzed by the use of descriptive analysis, such as frequency and percentage; also, thematic analysis were employed where unit of analysis was defined, categories developed, consistency of categories on relevance to the themes was assessed then the results were generalized and presented. Further, some of respondents' arguments were presented through direct verbatim quotations.

RESULTS

The study aimed to identify the usage of social media in creating land degradation. Awareness in Rombo district council. In identifying the usage of social media in creating environmental awareness, 14 questions items from household survey were asked to respondents for valuation and the results are given in Table 1.

Table 1: Usage of social media in Creating Land Degradation Awareness

Household survey items	**Strongly disagree**		**Disagree**		**Cumulative %**	**Neutral**		**Agree**		**Strongly agree**		**Cumulative %**
	F	%	F	%		F	%	F	%	F	%	
1. Creating conversation through social media on air, water, and waste deprivation as like as ozone layer depletion and protection	4	4.3	8	8.7	13	8	8.7	66	71.7	6	6.5	78.2
2. Sharing materials with peers related to land degradation and conservation	10	10.9	32	34.8	45.7	0	0	41	44.6	9	9.8	54.4
3. Posting or introducing various campaign regarding Urban Sprawl and economic/trade related activities	5	5.4	15	16.3	21.7	2	2.2	54	58.7	16	17.4	76.1
4. Allotment of problem-solving skills on land harms	1	1.1	6	6.5	7.6	3	3.3	46	50	36	39.1	89.1
5. Advertise ways to keep the land sustainable for years to come	14	15.2	16	17.4	32.6	11	11.9	41	44.5	10	10.9	55.4
6. Sharing land humiliation problems and solutions	8	8.7	12	13.0	21.7	8	8.7	42	45.6	22	23.9	69.5
7. Making people aware about the economic importance of the plants in the form of ethno botanical and ethno medicinal importance	1	1.1	8	8.7	9.8	2	2.2	58	63.0	21	22.8	85.8
8. Telling story through social media about intensive farming activities and management	12	13	21	22.8	35.8	12	13	38	41.3	10	10.9	52.2
9. Development of platform providing information about natural disasters, destruction of biodiversity and land protection	2	2.2	25	27.2	29.4	15	16.3	30	32.6	20	21.7	54.3
10. Leverage peoples' lifestyles and waste related problems on trends and breaking news	0	0	2	2.2	2.2	0	0	71	77.2	19	20.6	97.8
11. Encourage audiences to share environment contents on agriculture chemical contamination, global warming, and government land protection policy	22	23.9	31	33.7	57.6	10	10.9	20	21.7	9	9.8	31.5
12. Use social media to post hash tags for environmental education	3	3.3	9	9.8	13.1	28	30.4	30	32.6	22	23.9	56.5
13. Sending message to keep people aware on water humiliation and shortages, loss of biodiversity and waste management	4	4.3	15	16.3	20.6	13	14.1	42	45.7	18	19.6	65.3
14. Publicize knowledge on greenhouse gas prevention measure, genetic modification of crops and hydrology	4	4.3	32	34.8	39.1	5	5.4	41	44.6	10	10.9	55.5

Source: Researcher, (2021)

Table 1 above shows that on item, creating conversation through social media on air, water, and waste disposal as like as ozone layer depletion and protection 13% of respondents disagreed and strongly disagreed, 8.7% were neutral and 78.2% agreed and strongly agreed; as regards to item sharing materials with peers related to land degradation and conservation 45.7% disagreed and strongly disagreed, 0% were neutral and 54.4% agreed and strongly agreed; for item posting or introducing various campaign regarding Urban Sprawl and economic/trade related activities 21.7% disagreed and strongly disagreed, 2.2% were neutral and 76.1% agreed and strongly agreed; allotment of problem-solving skills on land harms was another variable involved in this study the results show that 7.6% disagreed and strongly disagreed, 3.3% were neutral and 89.1% agreed and strongly agreed; and for item advertise ways to keep the land sustainable for years to come32.6% disagreed and strongly disagreed, 11.9% were neutral and 55.4% agreed and strongly agreed; on item sharing land deprivation problems and solutions 21.7% disagreed and strongly disagreed, 8.7% were neutral and 69.5% agreed and strongly agreed; and under item making people aware about the economic importance of the plants in the form of ethno botanical and ethno medicinal importance 9.8% disagreed and strongly disagreed, 2.2% were neutral and 85.8% agreed and strongly agreed.

In parallel with the findings for item, telling story through social media about intensive farming activities and management35.8% disagreed and strongly disagreed, 13% were neutral and 52.2% agreed and strongly agreed; the findings on item development of platform providing information about natural disasters, destruction of biodiversity and land protection29.4% disagreed and strongly disagreed, 16.3% were neutral and 54.3% agreed and strongly agreed and on item leverage peoples' lifestyles and waste related problems on trends and breaking news 2.2% of respondents disagreed and strongly disagreed, 0% were neutral and 97.8% agreed and strongly agree; on item encourage audiences to share environment contents on agriculture chemical contamination, global warming, and government environmental protection policy57.6% disagreed and strongly disagreed, 10.9% were neutral and 31.5% agreed and strongly agreed; for item using social media to post hash tags for land degradation education 13.1% disagreed and strongly disagreed, 30.4% were neutral and56.5% agreed and strongly agreed; the findings on item sending message to keep people aware on water dilapidation and shortages, loss of biodiversity and waste management show that 20.6% disagreed and strongly disagreed, 14.1% were neutral and65.3%agreed and strongly agreed and finally on item publicize knowledge on greenhouse gas prevention measure, genetic modification of crops and hydrology 39.1% disagreed and strongly disagreed, 5.4% were neutral, and 55.5% agreed and strongly agreed.

To summarize the findings, the following are the usage of social media in creating land degradation awareness at Rombo district council identified by respondents since more than 50% of respondents agreed and strongly agreed on the items, to mention: creating conversation through social media on air, water, and waste litters as like as ozone layer depletion and protection, sharing materials with peers related to land degradation and conservation, posting or introducing various campaign regarding Urban Sprawl and economic/trade related activities, allotment of problem-solving skills on land harms, advertise ways to keep the land sustainable for years to come, sharing land dilapidation problems and solutions, making people aware about the economic importance of the plants in the form of ethno botanical and ethno medicinal importance, telling story through social media about, intensive farming activities and management, development of platform providing information about natural disasters, destruction of biodiversity and land protection, leverage peoples' lifestyles and waste related problems on trends and breaking news, use social media to post hash tags for environmental education, sending message to keep people aware on water disposal and shortages, loss of biodiversity and waste management as like as publicize knowledge on greenhouse gas prevention measure, genetic modification of crops and hydrology.

Out of that, the results from open ended questions show that, the other usage of social media that can be used in Rombo district to create land degradation awareness involves: capacity building on use of social media in creating land degradation awareness, environmental stake holders should infer size on use of social media for environmental sustainability, government should establish rules on use of social media to enhance land degradation awareness and community education should be provided on social media to keep citizens more informed on the need to conserve their environment. Also, the type of social media frequently used to acquire environmental education is Instagram for about 59.4% followed by Whats App media 22.3%, 12% by YouTube, 4.1% by Twitter while 2.2% by Facebook. To add, the time that social media used mostly is night where 48% of the respondents agreed, followed by 25% during the evening, then 16% during the morning and 11% during the afternoon.

The results from interview show that, 59% of respondents said that social media can be used to create land degradation awareness to peoples in Rombo district. In addition, the usage of social media that can be used to create sustainable development include: community involvement through social media in solving land dilapidation effects such as global warming, bunning fossils and deforestation, providing education through media for peoples to understand relationship between human activities and land quality, providing user-friendly tools for knowledge sharing, enabling users to create, edit and add online contents without any professional training, engaging discussions through social media on environmental issues as well as reporting on land dilapidation.

The results also show that the ways that can be used to enhance people usage on social media include reducing tax on social media usage, providing education to promote effective use of social media, improve internet accessibility, providing bonuses to mostly using social media to access various matters, providing important governmental and nongovernmental services through social media, seek relationships on social media usage and not only followers, also internet should be active all the time. Not only that, when respondents were asked on the current usage of social media for land degradation awareness in the district the following were the outputs, 51% of respondents said its good, 28% said its poor, 15% its fair, and 6% said it's excellent.

Moreover, the extent to which land deprivation affect healthy of people was among the variable observed important to this study, the results show 64% of respondents said deprivation affect healthy of people Greatly, 22% said Considerably, 13% Not much and 1% Not at all. To add, respondent's views on the people's altitude with regard to environmental conservation show that: 48% are Considerably, 27% are Greatly, 15% Not much and 10% Not at all. Finally, respondents' suggestions on the social media pace to avoid environmental damage are well described under.

Respondent 1 said that: "*Rules and regulation concerning land protection should be made more effective to avoid people spoiling the land by burning and throwing plastics to protect our environment"* (Interview, 2021).

Respondent 3 said that*: "Using renewable energy systems, such as solar and wind, reduce impact on the land significantly while lowering energy bill. Further, a variety of local incentives are available to make installing renewable energy more affordable"* (Interview, 2021).

Respondent 4 said that: "*Energy is used (and emissions generated) to heat the water used in facility and process wastewater, reduce water heater temperatures and repair leaks. Also, install low-flow showerheads and aerated faucets to reduce the amount of water used; this can be especially effective in lodging and multi-family facilities*" (Interview, 2021).

Respondent 6 said that: "*All of the materials and equipment produced should not be disposed to the environment rather than being reused and recycled whenever Possible or brought to the company for recycling*" (Interview, 2021).

Respondent 7 said that: "*Peoples driving to and from work produce a substantial amount of air. They should be encouraged (or subsidize) to use public transportation or smog organize carpools and allow employees to work from home whenever possible*" (Interview, 2021).

Respondent 11 said that: "*Use energy more efficiently such as producing electricity and Natural gas and delivering it to door generates greenhouse gas emissions. Also, installing energy-efficient building systems and equipment can save energy and reduce land footprint"* (Interview, 2021).

DISCUSSION

The study describes that, the explosion of social media usage such as Instagram, WhatsApp, and YouTube among peoples in Rombo district is deemed to have great potential in widely disseminating land sustainability awareness. Usage of social media plays an active role in creating land sustainability among peoples such that, any development on the land degradation and its attributed activities is minimized. Furthermore, social media has become a part and parcel of present-day lifestyle with the advancement in industrialization, science, technology, and globalization, various environmental issues are taking place locally and globally. People are using social media now days to support land degradation campaigns and to connect people locally and globally on minor to major environmental issues. It also provides ordinary people with the ability to track the quality of the air, water, climate around them, and then discuss likewise share data with others. Thus, social media can be utilized in Rombo district as a tool to promote awareness regarding various current environmental issues in a much faster way and to a large mass within a very short span of time.

The findings were found similar to: Omar, Nyahunda, and Tirivangasi, (2021); Rahim and Adeen (2016) and Kichatov, (2010) who stated that social media is a powerful technological tool that allows users to create content, share ideas, express opinions, disseminate information, share knowledge and exchange user-generated content regarding land degradation and conservation. Notably, (Chan *et al*, 2017) specified that prevailing lifestyles, technological advancement, land degradation and educational changes can be credited to unprecedented growth in the use of the internet and its allied social networking tools and platforms of interest to improve awareness. Also, Zhang and Skoric (2018) provide user-friendly social media tools for knowledge sharing, enabling users to create, edit and add online contents on land humiliation problems and solutions without any professional training. It is now possible to create, edit, add and share multimedia content through videos, photos and other formats through instantaneous posts. Likewise, Tobey and Manore, 2014; (Munishi *et al*, 2019) argued that social media is used to activate and build up a rally for community support in advocating or fighting for various causes of land degradation around the world.

CONCLUSION

Land degradation is due mainly to non-sustainable human activities, such as over cultivation, overgrazing, deforestation and poor irrigation practices. The status on the usage of social media for land degradation awareness is at 59% and is mainly through Instagram followed by Whats App media.

Thus, enhancing land degradation awareness through the use of social media has been proposed as a roadmap in tackling the complexity of this phenomenon. Therefore, public campaign program to enhance awareness on land degradation should be strengthened through the usage of social media for sustainable land usage/economic production considering the social media usages identified.

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Designing PostGIS Database System with Fuzzy Theory to Support Accessibility Tools for Urban Pedestrians

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Abstract

The combination of fuzzy logic and crowdsourcing can be a powerful tool for generating geospatial data for pedestrians with mobility challenges in urban areas. Although potentially useful, information about the accessibility of paths that is generated through crowdsourcing is susceptible to a high degree of imprecision. Spatial data management is required for such systems, which supports the management of uncertain data. Fuzzy theory allows us to model ambiguous information. To fill this gap, an improved method based on a fuzzy relational PostGIS database (FPostGIS) is proposed. The method includes extensions to represent imprecise data within an entity-relationship (ER) data model specifically tailored for path accessibility, and a set of steps for the derivation of FPostGIS from this extended ER model. According to the case study, this methodology has been applied in the design and development of decision support application within the Maps for Easy Paths (MEP) project. This application stores and retrieves accessibility information about a particular path and allows performing spatial operations and analysis inside the database.

Keywords*: Ambiguous information, database design, FuzzyMEP, Imprecise and uncertain information, PostGIS, rule modeling.*

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INTRODUCTION

Numerous real-world systems and applications, like those that use crowdsourcing, must deal with ambiguous and contradictory information, vagueness, uncertainty, and imprecision in data. The application of fuzzy theory in combination with crowdsourcing finds its application in various contexts. It aids in selecting the most suitable bank for arranging a mortgage, evaluating of client credibility, choosing an insurance company, purchasing a property, selecting a car, ajob, etc. These are the first large groups of applications for decision support. The second group of applications concerns control systems. For example, fuzzy regulators could be used for checking a valve in mechanical engineering and for releasing only the right amount of steam, which is necessary for the correct operation of the device. Fuzzy regulators are used in much smaller devices such as digital cameras, washing machines, controlling mechanism of cars, and the like for controlling many variables, ranging from the correct photographic exposure to the setting of the time needed to wash properly specific clothes in a washing machine (Bezdek, 2011). There are many examples of successful application of fuzzy theory (Bojadziev, 2007).

The applications of database technology involving fuzzy theory in filtering information and assisting in decision-making include manipulating uncertain and imprecise information to support navigation (Chen et al., 2012). Navigation systems provide spatial data which can be retrieved by users in order to make decisions regarding the best path to follow in a given moment and under given circumstances. Such databases require information that is created dynamically. For such database systems, information management components that support managing this ambiguous data are necessary. Fuzzy theory allows us to model ambiguous information. Fuzziness has garnered a lot of attention in relational database systems (RDBs), but little has been done to model fuzziness in conceptual data models for PostGIS Database Systems. To fill this gap, the researchers have proposed a design methodology for developing fuzzy RDBs (Chaudhry et al., 1999). This methodology, based on the Entity-Relationship (ER) design methodology of De Sousa et al., 2018, describes a sequence of steps to implement a fuzzy RDB. However, there seems to be no previous work in developing the ER design methodology FPostGIS for the accessibility of a path for people with mobility challenges. Then, the authors propose a generic data model that employs the ER data model to describe fuzzy rules. The syntax chosen for the fuzzy rules allows expression of explicit data against a consequent in addition to the traditional data for a consequent. This implies that the fired rules can have conflicting data. New techniques are proposed for making decisions on these rules so as to allow decision making on contradictory information.

In Section 2 of this paper, we review the state of the art in fuzzy theory and fuzzy database modeling. Section 3discusses the fuzzy association rule ER design methodology. Section 4 contains a description of the decision-making process and the fuzzy rule firing mechanism utilized by MEP in the PostGIS Database System. This study is concluded in Section 5 with a summary of the findings and an outline of future research.

State of the Art of Fuzzy Theory

Fuzzy logic is a convenient tool for handling imprecise and uncertain data in automatic decision-making systems, asreported by Edward et al., 2009. For example, Zadeh, Lotfi A. (2015) describes many applications in the areas of information sciences and control systems. According to Purian et al., 2013 using fuzzy logic is shown to be a very promising methodology for modeling traffic and path planning; mobile robots are finding a free way without encountering barriers in different environments targeting to reach to the destination. Whilst these and others, such studies have shown a greater consensus has grown around the peculiar idea of using Fuzzy theory to handle imprecise information of exemplary article by Medina et al., (1994) and hence to bring models closer to the real application. Modeling the real world using fuzzy logic is an interesting approach for the quality and condition of the accessibility of a path.

In a review work of Nguyen et al., (2012), Fuzzy theory has been used for control applications, but to our knowledge fuzzy databases have not been previously utilizedfor predicting the condition and the quality of the accessibility of a path.

Maps for Easy Paths (MEP)

The MEP (Maps for Easy Paths) (http://mep5x1000.wix.com/mepapp) is an ongoing project, proposing a set of tools and mobile apps for the enrichment of geographical maps with information about the accessibility of urban pedestrian pathways for people with mobility challenges. They range from users with manual or electric wheelchair, to the elderly with/without mechanical support, to people in temporary situations of reduced mobility by providing with information about accessible routes. It collects motion data from sensors commonly available in mobile devices and reconstructs the travelled path (Comai et al., 2017). The underlying idea is that a path that can be travelled by a person with motor disabilities can be considered accessible also for other persons having the some (or a lower) type of disability.

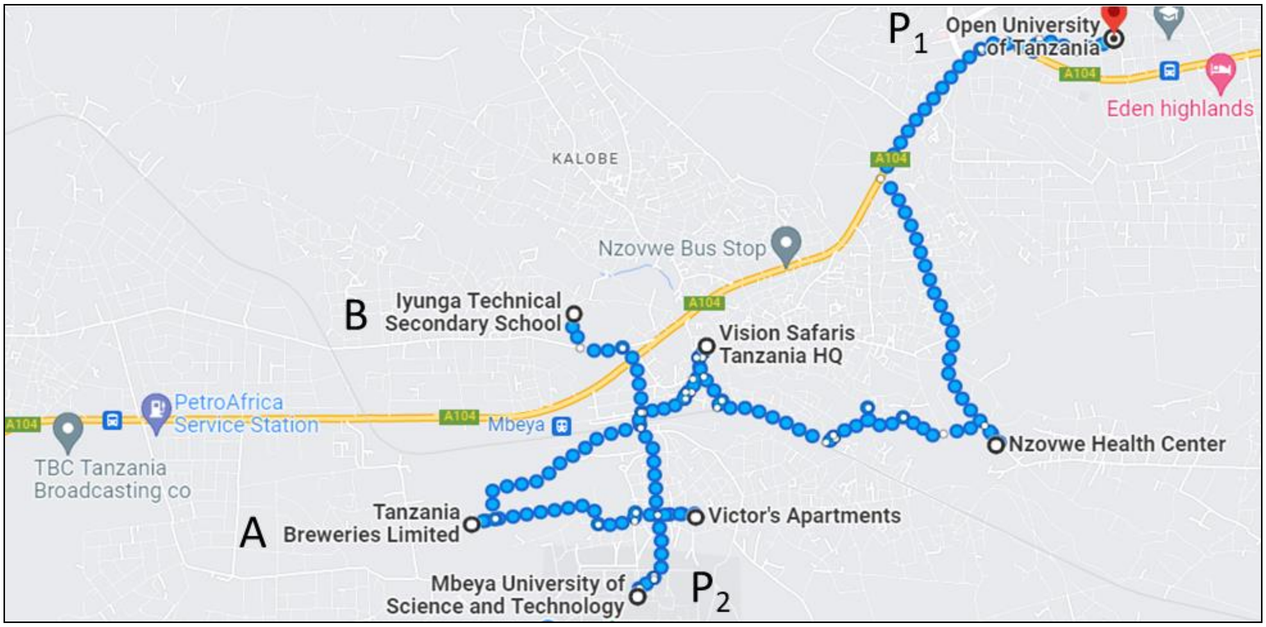


Figure 6. Describing the part of the accessibility of the path which has been travelled by a user and the other part not
Source: Own processing

Introduction to the problem

Fig. 1, shows some paths connecting some points of interest (POIs): points *A* (Tanzania Breweries Limited), *B* (Iyunga Technical Secondary School), P_1(Open University of Tanzania) and P_2(Mbeya University of Science and Technology). The paths in the figure have been travelled and mapped by users with some mobility problems. In particular, Paul follows a routine where he traverses the pathAP_1 to reach his university office every workday. Using his smartphone, he can easily map this path.

Imagine now that Peter has a smartphone with our MEP application as in Figure 1 and does not know anything about the accessibility of the streets of this AP_2 . The data collected implicitly are uploaded on the MEP server for further processing, which will end up in the construction of the path taken by the user. Once Paul reaches the endingpoint of the path AP_1, he can rate his path, for example as a "medium" accessible path. Path AP_1 is therefore associated with metadata 'L = Level of accessibility = 2′ on the MEP server. In the same way, the other paths in the map will be associated with the profile of the users who collected the data and with their ratings. Imagine now that Peter, a second person with similar mobility problems as Paul, wants to reach the target place P_2 in Fig. 1, starting from point *A*. He can connect to MEP app and query for the path.Since Paul has partially passed that path and the information is being stored, and he rated the path as medium (or L = 2), the MEP app can retrieve the available information for all the pathsand predict the condition of the accessibility of the path AP_2 for Peter using a fuzzy logic model approach.

In this case, the path AP_1 is a route frequently taken by Paul (having similar mobility problems), the path AP_2 has been partially taken by him, while the other part of the route has never been taken before by any user or has been taken by users with different (possibly lower) mobility problems. Considering only the two paths of Paul and Peter, we have:a sequence of coordinates forAP_1 and a sequence of coordinates for AP_2. We can define the partial intersection of the two paths with the following definitions.

Subset: Path AP_2 is said to be a subset of path AP_1 if and only if $\exists x, x \in AP_2 \Rightarrow x \in AP_1$.

Proper Subset: Path AP_2 is said to be a proper subset of path AP_1 if and only if $\forall x, x \in AP_2 \Rightarrow x \in AP_1$. In this case, we write $AP_2 \subset AP_1$. The empty set that contains no members is denoted by Ø. Two paths are disjoint if they do not have any elements in common, that means, if

$$AP_1 \cap AP_2 = \emptyset \quad (1)$$

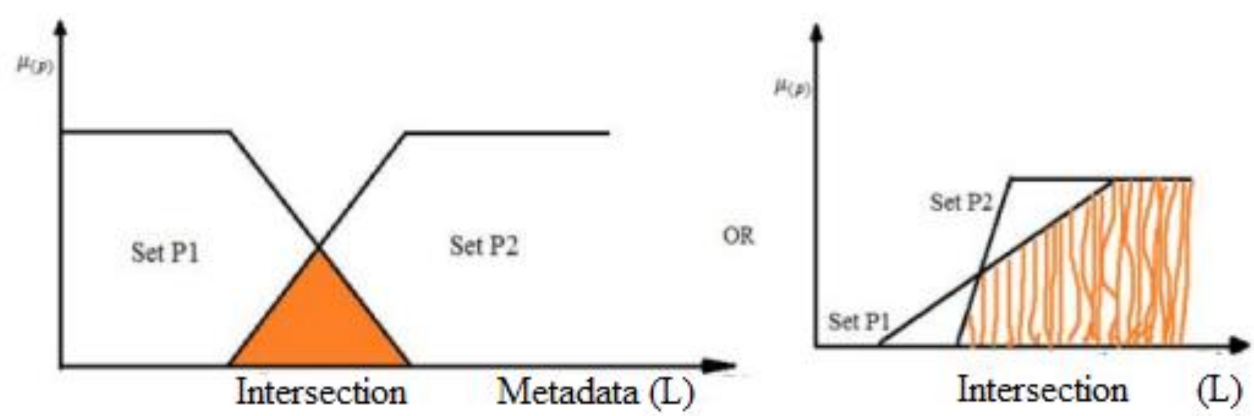
In traditional set theory, a set is defined as a collection of distinct elements. For each element, it either belongs to the set (membership degree = 1) or doesn't belong to the set (membership degree = 0). This is known as a crisp set, where membership is sharply defined.

Fuzzy set theory generalizes this concept by allowing membership degrees to be any value between 0 and 1. This means that elements can belong to a set with varying degrees of membership. In the context of fuzzy sets, an element's membership in a fuzzy set is described using a membership function. For the fuzzy set P_1, the degree to which an element A belongs to P_1 is denoted as $\mu_{P_1}(A)$. This value is a real number in the interval (0, 1). When $\mu_{p1}(A) = 0$, A does not belong to P_1 at all, and when $\mu_{p1}(A) = 1$, A fully belongs to P_1. Therefore, the fuzzy set $P1$ consists of ordered pairs [A, $\mu_{p1}(A)$] for all elements A that belong to the fuzzy set P_1

$$P_1 = [A, \mu_{P_1}(A)] : A \in P_1 \quad (2)$$

One approach to define fuzzy subsets of the intersection set is shown in the following figure:

Figure 7. Fuzzy Intersection



(***Source** : Sinkonde, et al, p.4. 2017*)

To compute membership values with fuzzy intersection, the minimum is used:

$$\mu P_1(L) \cap \mu P_2(L) = Min\,[\mu P_1(L), \mu P_2(L)] \qquad (3)$$

Table 1A. Fuzzy linguistic variables

Linguistic Variables Label	*Barriers*	*Comment*	*Pavement*
Linguistic Values	-Low -Medium -High	-Low -Medium -High	-Narrow -Dark no light -Wide
Metadata		1- 4	
Membership Function	-µLow -µMedium -µHigh	-µLow -µMedium -µHigh	-µLow -µMedium -µHigh

Table 1B. Frequency of Special Characters Membership Values for Barriers

Linguistic labels	Criticality rate (L)			
Variables	1	2	3	4
High (H)	0	0	0	1
Medium (M)	0	0	0.7	0.4
Low (L)	0	0.4	0.3	0
Very Low (VL)	0.3	0.2	0	0

***Source**: Own processing*

Fuzzy PostGIS Relational database

The Fuzzy Relational Database Model (called FPostGIS) extends a relational model by incorporating concepts from fuzzy set theory, thus addressing the lack of precision in quantitative data. There are five examples of unreliable information generated through crowdsourcing: contradictory information regarding one issue, imprecise information, vague information, uncertain information, and ambiguous information. Then, first, there is the imprecision in the degree of membership of a tuple in a relation, and second, there is the imprecision in a data value [18]. The use of dynamic database for the control of MEP is relatively new [9] and has made it widely applicable, flexible, and portable.

Fuzzy Relation: Let Pbe the intersection of n discourses $P_1, P_2, \ldots, P_n$, and its Cartesian product. Then, an $n-ary$ fuzzy relation$r$ in P is a relation which is characterized by an –variety membership function ranging over$P$, so that $\mu_r \rightarrow [0,1]$. The fuzzy relation$r$ tuple can be stated as follows:

$$t_j = \langle P_{j_1}, P_{j_2}, \ldots, P_{j_n}, \mu_r(P_{j_1}, P_{j_2}, \ldots. P_{j_n}) \rangle$$

with $P_{j_1} \in P_1, \ldots, P_{j_n} \in P_n$ (4)

Example: Consider the fuzzy relation model ending path prediction shown in Table 2. This relation has 5 attributes, such as Object ID, Metadata, Direction, Starting Point or (Starting Name) and representing the degree of certainty that the Object IDa_1 is in the State a_2, and the composite key$a_1 a_2$.

Table 2. Fuzzy Relational Model Database Ending Path Prediction

Actual Variables				Prediction state		
ObjectID	Metadata	Starting Point	Path Predicted point	State Estimation	Total Ending Path prediction	μ
415	1	75790	38152	+0.32	38152.34	0.1
419	1	75793	38156	-1.13	38155.13	0.3
422	2	75796	38159	-2.31	38157.31	0.7
432	1	75806	38169	-2.27	38167.27	0.4
435	1	75809	38172	-2.07	38170.07	1.0
436	1	75810	38173	-2.00	38171.00	0.6

MATERIALS AND METHODS

Inthissection, we propose to extend the ER data model to represent fuzziness. Then, we describe the design methodology for implementing fuzzy relational databasesfrom fuzzy conceptual data definition like Thalheim, B. (2013).

Traditional ER model to aFuzzy ER model

In this critical part of the conceptual data, the model is designed, starting with investigating the issue of designing methods which are twofold, due to separation between the construct, the common ER model and attach 'f' to the entities and relationships that are fuzzy. In addition, the design methodology for fuzzy relational databases is an extension of the design methodologies for crisp relational databases (Fahrner, C., &Vossen, G. 1995).

Common ER data model

The Entity-Relationship (ER) data model developed by Thalheim, B. (2013) is one of the paradigms that are most frequently used for the conceptual data modeling step of the database design process. The work of Teorey et al. (1986) describes a design methodology for implementing relational databases from an ER schema. The steps could be as follows:

- **Method 1: Use ER to model the application domain requirements:** The data requirements are analyzed and modeled using an ER diagram. The ER diagram in Figure 3 shows how the basic concepts of ER modeling are expressed.

- **Method 2: Transformation ER to model to relational tables:** Building relationships is a crucial step that captures the associations or interactions between entities. Relationships define how entities are connected and can be 1-to-1, 1-to-n, or n-to-n. The cardinality and participation constraints are then assigned to specify the number of occurrences and the participation requirements of entities in relationships. Cardinality determines the number of instances one entity can be associated with another, while participation indicates whether participation in a relationship is mandatory or optional.

- **Method 3: Normalization of the relations:** Normalize all relations by following three steps: the first normal form (1NF), the second normal form (2NF), and the third normal form (3NF).

- **Method 4: Validation and iteration:** The designed data model is then validated by examining its accuracy, consistency, and adherence to the requirements. Iterative refinement may be necessary based on feedback and additional requirements. Validation ensures that the data model represents scenarios around the world.

- **Method 5: Documentation of the design:** The document provides a comprehensive overview of the data model's entities, attributes, relationships, constraints, and other relevant details of the data model.

The ER Methodology with a Fuzzy Extension

This section describes the ER process design and extensions of the ER data model to accommodate fuzzy data. The literature normally expects the entities' keys to be crisp or non-fuzzy. This section describes the ER data model extensions and ER design methods for handling uncertain data.

The ER Fuzzy Extension

This section explains the extensions to the ER data model and the ER design methodology to cope with fuzzy data.

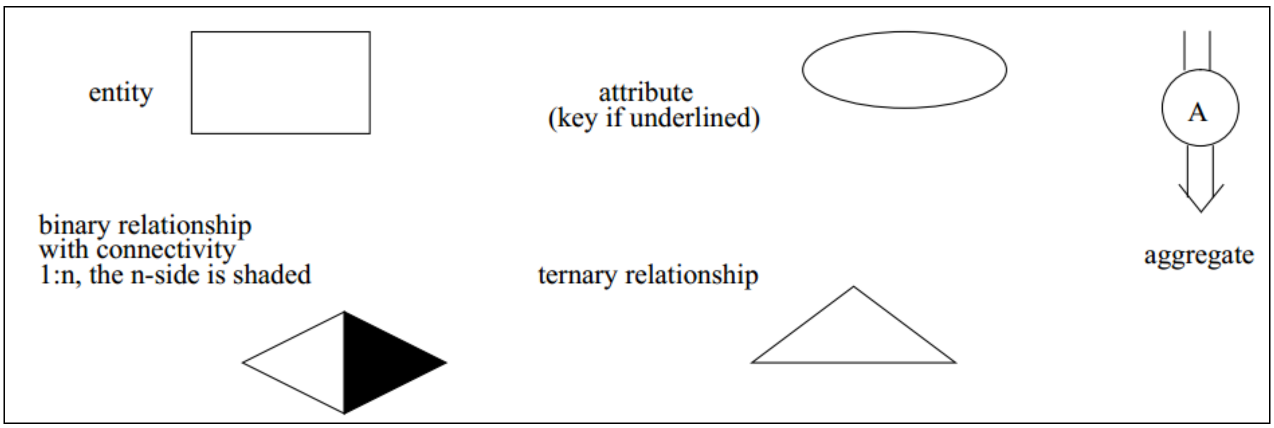


Figure 3: Basics of ER Modeling

Fuzzy Comparison Function: Fuzzy extensions of ER (Entity-Relationship) data modeling design procedures include incorporating fuzzy logic concepts into the traditional ER modeling techniques. The ER data model for the MEP project represents the most comprehensive set of tools and an innovative solution for the enrichment of geographic maps with information about the accessibility of urban areas for people with mobility challenges. As a result, a comparison function has been constructed for each entity that is involved in a fuzzy match for the relevant comparison operator. With the letters "fm_{θ}," which stand for the particular fuzzy match's comparison functions, where θ is the comparison function for the particular fuzzy match.

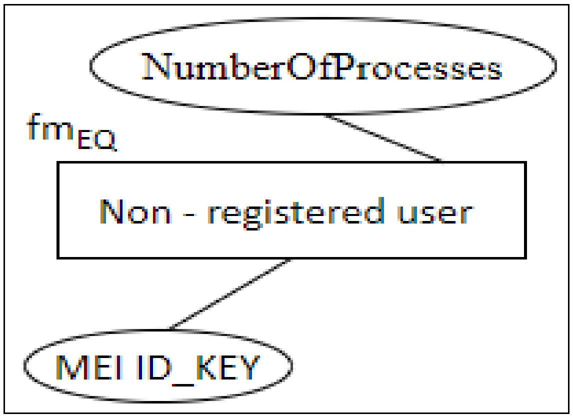


Figure 4: ER Representation of the Entity Non – Registered User

DBFuzzifier: In some circumstances, it is more useful to consider a crisp entity with one or more attributes fuzzified, rather than considering the entity in its original crisp form. In these situations, we suggest that fuzzifying the relevant EN attributes in order to define a new entity, EN^F, on top of EN.

Example: Consider a FuzzyMEP database with two entities, an entity Registered user (disability and active citizen), with 2 attributes no requirement and step_free, with the domain {low, medium, high, very-high}, and the entity Non - registered user which can visualize all information about the accessibility of the paths on their smartphones / tablet / pcwith the attributes EquipmentNum (meiid_key) and NumberOfProcesses with the domain {0,..., 1000000}. A join can be executed between the entities registered user and non-registered user, based on the attributes step_free and NumberOfProcesses, if we can define a match between the attribute values of step_free and NumberOfProcesses. One way of carrying out this translation is to partition the attribute NumberOfProcesses in the entity non-registered user into the crisp sets low, medium, high, very-high. However, a "better" translation employs fuzzy theory, and thus we define a new entity $\text{Non} - \text{registered user}^F$ on top of the entity non-registered user by mapping each instance of non-registered user into the fuzzy sets low, medium, high and very-high based on the attribute NumberOfProcesses.

We adapt the fuzzification operator defined by Lee and Chuen-Chien (1990) for this purpose. This operator has the effect of transforming crisp data into fuzzy data and is defined by:
$\mathrm{x} = \text{fuzzifier}(x_0)$ where x_0 is a crisp input value from a process; x is a fuzzy set.

Note the definition of the fuzzifier function depends upon the application requirements. In particular, this definition is determined by the universe which are fuzzifying to, which in turn determines the mapping of the elements of x_0 to various fuzzy sets.

The constrain the fuzzifier, now called the "**DBFuzzifier**", so that it can be applied to derive a fuzzy relation. This operator takes as its input parameters an entity and a fuzzifier defined on an attribute of this entity and maps this entity to a fuzzified entity.

Definition: $\mathrm{EN}^{\mathrm{F}} =$ DBFuzzifier $(EN,\ fuzzifier(B_0))$, where EN is an entity with attributes $< K, \mathrm{A}_1, \dots, \mathrm{A}_\mathrm{L}, B_0 >$, with key K, non-key attributes A_i for *i*= 1, ..., L, and B_0 the non-key attribute to be fuzzified. For any $Z =< K, B_j, \mathrm{A}_1, .., \mathrm{A}_\mathrm{L}, \mathrm{B}_0 >\in EN$, with $k \in K$, $a_i \in A_i$ for *i*= 1, ..., L, and

$b_0 \in B_0, EN^F$ has the collection of tuples $Z_j^F =< K, B_j, A_1, \dots, A_L, \mu(B_j)$, for j = 1, ..., n, with fuzzifier (B_0) = , i.e., the fuzzifier maps the attribute to a fuzzy set with finite cardinality n.

Example: Assume we need to fuzzify the entity non-registered user from the last example based on the attribute NumberOfProcesses. The domain of NumberOfProcesses in Non - registered user is {0, ..., 1000000}. In Non-register user^F, domain (- NumberOfProcesses) is a fuzzy set over the universe {low, medium, high, very high}. So with Non-register user^F = DBFuzzifier(Non-register user^F, fuzzifier (NumberOfProcesseso)), each tuple in Non - registered user is transformed to up to four fuzzy tuples in A Non-register user^F , one corresponding to each of the four sets low, medium, high, very high. To take a specific instance, the tuple <234, 230000> in non-registered user may be mapped to the tuples < 234, low, 0.1>, <234, medium, 0.9>. The membership grade of 230000 in the fuzzy sets high and very high is zero, so there are no corresponding tuples in the non-registered user relation. The ER construct we propose for the DBFuzzifier concept is shown in Figure 5.

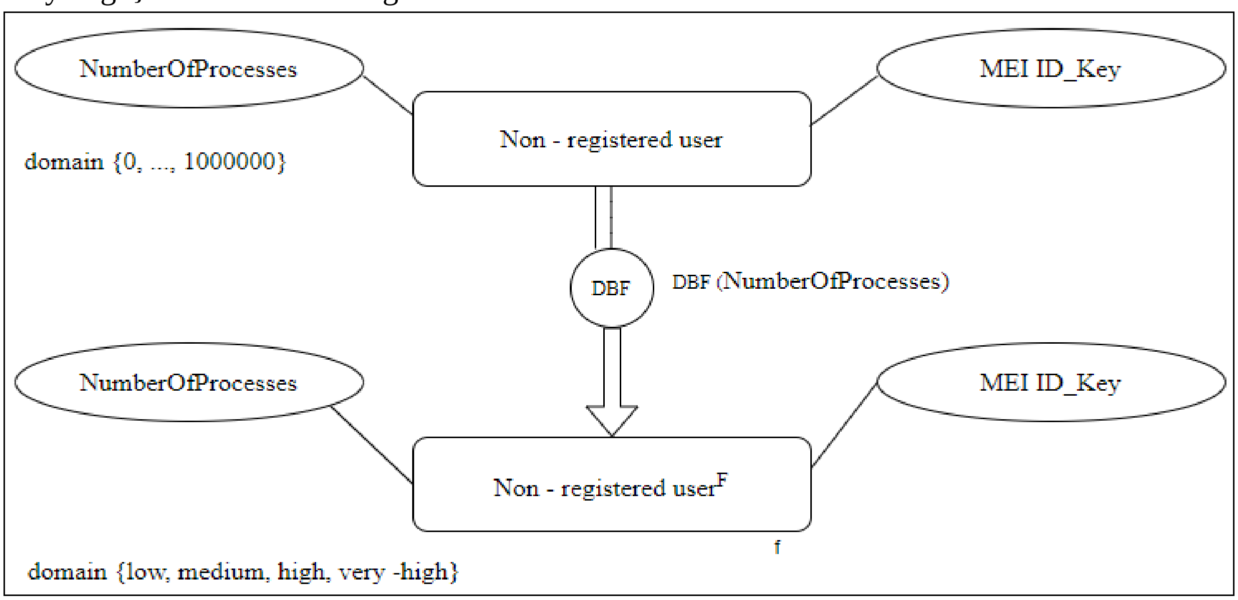


Figure 5 : DBFuzzifier Construct *(**Source :** Sinkonde, et al, 2023)*

Fuzzy ER Model Mapping to Relational Implementation

The mapping of this conceptual model to relations is required after the ER data model has been built.With the exception of adding a further membership property, fuzzy entities and fuzzy n-to-n connections can be mapped to relational databases in the same way as their crisp counterparts (showed in Section 3.1). Nevertheless, the mapping approach for converting fuzzy 1-to-1 and 1-to-n relationships to tables needs to be revised.

Converting the DBFuzzifier component and related entities to tables: Both input entity, EN and output entity, EN^F to the DBFuzzifier should be translated into separate tables. As an illustration, both non-registered user and $\text{Non} - \text{registered user}^F$ in Figure 5 ought to be mapped to different tables.

Methodology for Fuzzy Conceptual design
We now present the FPostGIS database design method that incorporates the additional components mentioned in Section 3.2 into the ER design method (Teorey, Yang, and Fry, 1986).

Method 1: Constructing an extended fuzzy ER data model

- Construct the common ER model.
- Attach 'f' to the entities and relationships that are fuzzy (see Figure 5).
- Show the DBfuzzifier construct for entities whose attributes are fuzzified at various levels.
- Attach 'fm_θ' to entities to be used in a fuzzy match, where θ is the desired comparison operator.

Method 2: Converting the ER model to relational tables.

- Convert crisp entities and crisp relationships to tables in the same way as MEP server (crisp) databases are converted to tables (as described in Section 3.1, Method 2).
- Fuzzy entities denoted by an 'f' must be converted to tables in the same way that crisp entities are, except adding an additional attribute to the fuzzy membership.
- Create fuzzy comparison functions for entities denoted with 'fm_θ'.

Method 3: Normalization of the relations.

- Normalize all relations by following method 2 by using functional dependencies, multi-valued dependencies, and restricted fuzzy functional dependencies.

Method 4: Guaranteeing correct interpretation of the fuzzy relational operators.

- This phase focuses on data operations rather than the data itself. It is needed only if the database management system (DBMS) used does not support fuzzy data. In the absence of a commercially available fuzzy DBMS, fuzzy logic can be applied to define fuzzy rules and constraints that govern the behavior of the entities and relationships in the data model in Section 2 The RDBMS might be extended to provide queries on fuzzy data, or queries embedded in host language programs could modify the results in the host language program.

Method 5: Fuzzy Querying and Reasoning

- By integrating fuzzy extensions into the ER data model design methods, it becomes possible to represent and handle uncertain or imprecise information more effectively, enabling better modeling of real-world scenarios where ambiguity and imprecision are prevalent by Hsieh et al., (2010).

FUZZIFYING THE MEP POSTGIS DATABASE

After each FuzzyMEP run, the rules in the PostGIS-database are evaluated to determine which of them should be invoked and what degree of certainty should be associated with this construction of the rule. Section 4.1 describes rule construction. Section 4.2 outlines our approach to handle conflicting information in rule consequents, while Section 4.3 describes the process for selecting the suitable algorithm based on rule building.

Determining the Grade of a Constructed Rule

As explained in Table 1A and Table 1B, the rules used in the system have the general form:

Rule One:	If the linguistic input term is (comment =metadata is 1) AND (barrier = very low), THEN (accessibility of a path = comment+μp+coordinate is Excellent)
Rule Two:	If the linguistic input term is (comment = metadata is 1) AND (barrier = low), THEN (accessibility of a path = comment+μp+coordinate is Excellent)
Rule Three:	If the linguistic input term is (comment = metadata is 1) AND (barrier =medium), THEN (accessibility of a path = comment+μp+coordinate is ok)
Rule Four:	If the linguistic input term is (comment = metadata is 1) AND (barrier = high), THEN (accessibility of a path = comment+μp+coordinate is poor)
Rule Five:	If the linguistic input term is (comment = metadata is 2) AND (barrier = very low), THEN (accessibility of a path =comment+μp+coordinate is Excellent)
Rule Six:	If the linguistic input term is (comment = metadata is 2) AND (barrier = low), THEN (accessibility of a path =comment+μp+coordinate is Excellent)

*(**Source**: Sinkonde, et al, p.4. 2017*

Therefore, If *predicate* [AND *predicate*] ..., then [NOT] *action*, α.

Consider an arbitrary rule R with $n$predicates on the LHS denoted by: If P_1AND ... AND P_n, then Action, α. To evaluate the LHS, each of these predicates will be matched to facts in the database. These facts may be fuzzy and/or the operand may be fuzzy. We note that the use of the DBFuzzifier allows us to reduce the complexity of the situation, by assuring that each value in the database corresponds to an element, and not a fuzzy set. This will have a positive impact on the performance of the matching process.

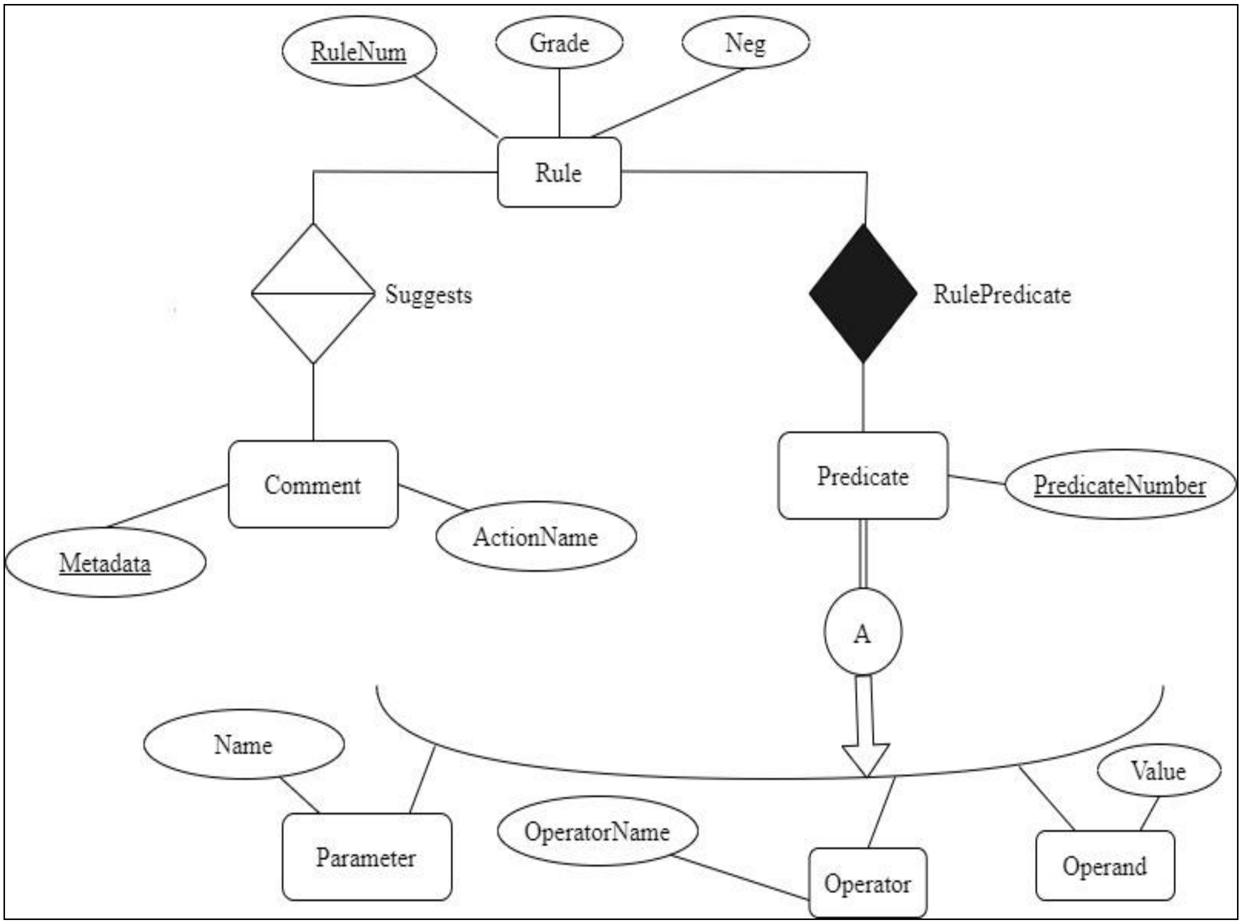


Figure 6: MEP ER Diagram of a Fuzzy Rule
*(**Source:** Sinkonde, et al, 2023)*

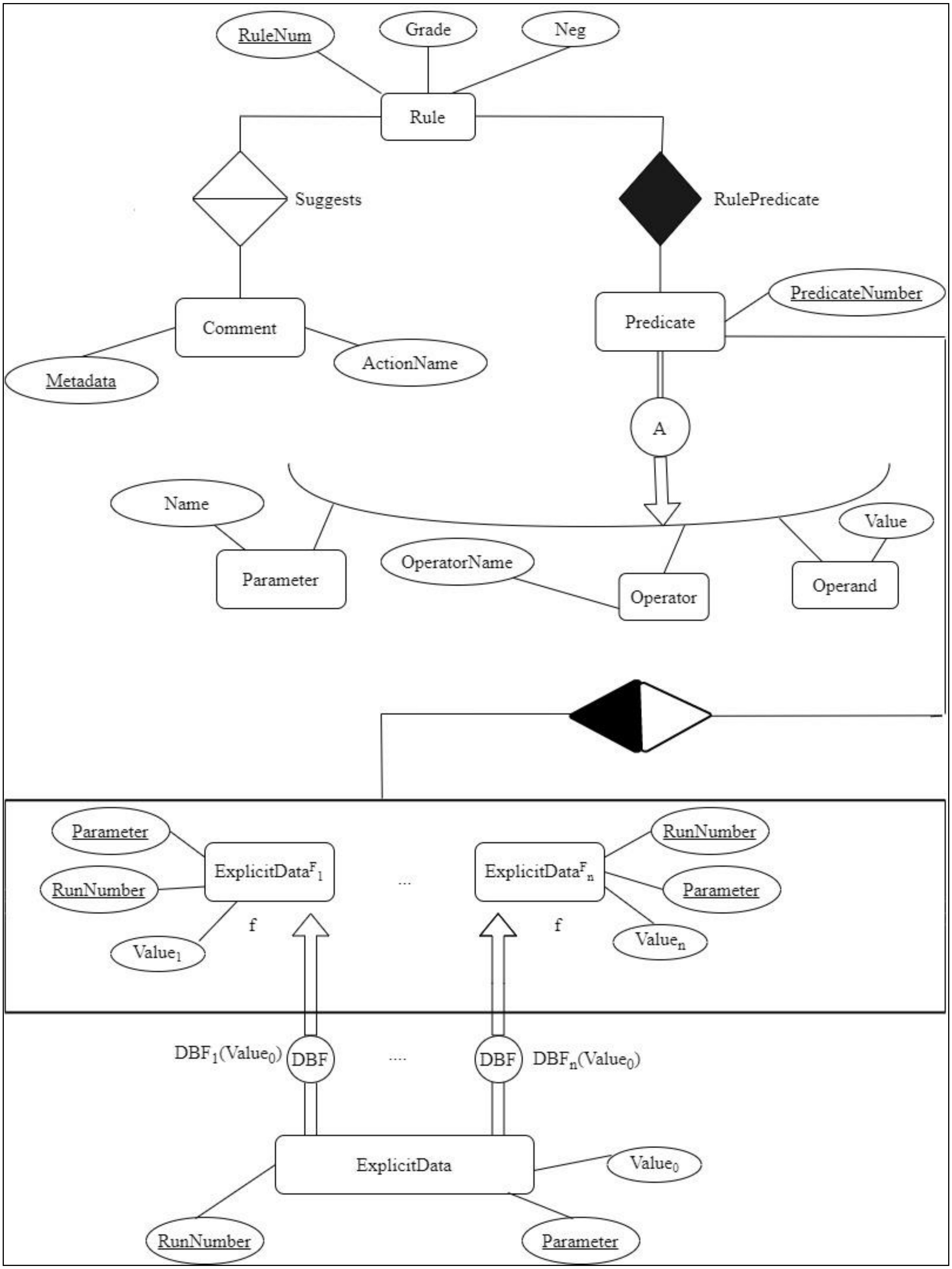


Figure 7: MEP ER Diagram of a Fuzzy Rule Base and the "facts" Data
*(**Source:** Sinkonde, et al, 2023)*

The predicate evaluation of a rule S thus results in $\delta_1, \delta_2, \dots, \delta_n$ which are the grades of match of the predicates $P_1, P_2, \dots, P_n$ of S. For the execution of the rule, an overall confidence γ needs to be calculated. γ is a function of the certainty factor α, and $\delta_1, \delta_2, \dots, \delta_n$. Since the predicates on the LHS are ANDed together, δ, the overall grade of match of the LHS, is defined as the minimum of $\delta_1, \delta_2, \dots, \delta_n$. Finally, we define$\gamma$, which is the confidence of the consequent as a result of the rule firing, as min (α, δ).

Example: Consider the following rule:
Rule 1: if barrier b_1 is reported on path h_1 the precision is high.
Rule 2: if barrier b_2 is reported on path h_2 the precision is low.
Rule 3: if barrier b_1 is reported on path h_2 the precision is high.
Rule 4: If pedestrian X using mobility aid a_1 is passing through path $P$and barrier b_1 is reported to be present across path$P$, then the alternative route h_1 is the most viable one.

Handling Imprecise information

The type of rule mentioned in the previous paragraph in the previous paragraph allows determination of rules that comment against an action. Therefore, when new rules are added to the existing rule base, some rules may be inconsistent in sense that one rule may clearly communicate the instructions of another rule.

Example: Consider that the rule base has the following rule:

Rule 1: If error $> 1\beta$ AND error $< 2\,\beta$, then precision is high, 0.8

New rules are added to the rule base:

Rule 2: If error $< 1\beta$ then the alternative route h_1 is the most viable one, 0.6

Rule 3: If error = low, then NOT precision is high, 0.6

Now Rule 3's consequent is in contradictory information regarding one issue with Rule 1's consequent.

In a review work of Sikchi et al. (2013), reports the main contributions taken from the literature for utilized the concepts used in the fuzzy expert system described how to handle contradictory information. A particular *action* may appear as a consequent in more than one rule. It may appear negated in some rules and non-negated in others. After each run, when the overall confidences for the consequents of all the rules have been evaluated, the grades of each occurrence of an action are unified. This is done by associating each action with two confidence levels, the *Upper Confidence* level and the *Lower Confidence* level.

The Upper Confidence represents the certainty that the particular action is supported by the rules constructed and is defined as the maximum of the overall grade (β) of all the matched rules in which that action appears non-negated as a consequent. The Lower Confidence is a measure of the degree to which the matched rules advise against a consequent. It is defined as 1 minus the maximum of the overall grade (β) of all the constructed rules in which that action appears negated as a consequent.

Note that if an action does not appear negated in any of the rules with a non-zero degree of match, its Lower Confidence is given a special "blank" value, indicating absence of knowledge about the Lower Confidence. Likewise, if an action does not appear non-negated in any of the rules with a non-zero degree of match, its Upper Confidence gets the value "blank".

Decision Making Process

The calculation of the Upper and Lower Confidences unifies the advice of all the rules with non-zero degree of match. At this stage, the large number of actions in our conflict set with varying degrees of support. Now a decision has to be made as to which actions have (not) been given sufficient support by the rule base for the present run, and hence should (not) be executed. To make this decision, we propose the following algorithm:

Let the Lower and Upper Confidences of each action be represented by the two-tuple (X_1, X_2) where X_1 is the Lower Confidence, and X_2 is the Upper Confidence. Both X_1 and X_2 are fuzzy grades, i.e., $X_1, X_2 \in [0, 1]$. The decision problem can then be modeled as defining decision regions on the area (0, 0), (0, 1), (1, 1), (1, 0) with the value of X_1 mapped along the x-axis and that of X_2 mapped along the y-axis [see Figure 8]. Details of the approach can be found in Zhang*et al*., (2012).

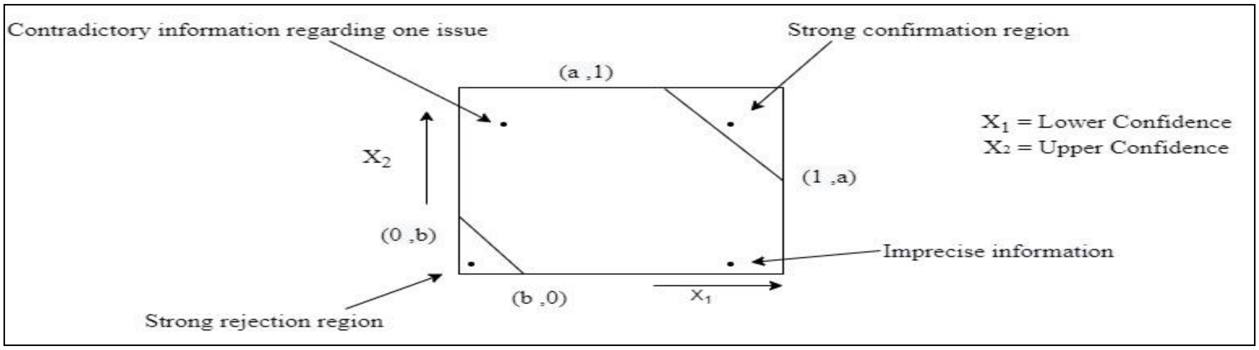


Figure 8: Two-Dimensional Representation of the Action-Related Support FuzzyMEP
Source: Own processing

A point with high X_1 and high X_2 represents an action that is strongly supported by the rules, since the Upper Confidence, X_2, which is the degree of support for taking the action, is high, and the Lower Confidence, X_1, which is 1 minus the degree of support for not taking the action, is also high. Conversely, a point with low X_1 and low X_2 represents an action which the rules strongly advise against. A point near the (1, 0) corner indicates an action for which both the support for and against is low, i.e., a region of *imprecise information*. A point near the (0, 1) corner corresponds to an action for which we have *contradictory information regarding one issue*, since the support for the action is high, and 1 minus the support against the action is low.

We utilize the above regions to employ the following rule selection strategy: Giving equal weight to the Lower and Upper Confidences, a *strong confirmation* region can be defined as the triangular region (a, 1), (1, 1), (1, a). Any action whose (X_1,X_2) representation falls in this region should be executed. Similarly, any action whose (X_1,X_2) representation falls in the *strong rejection* region (0, b), (0, 0), (b, 0) should not be executed. The constants 'a' and 'b' delineate these regions and hence determine thresholds for accepting or rejecting an action. These different regions are depicted in Figure 8.

A scenario where none of the conclusions falls in the strong confirmation region, and not all of the conclusions fall in the strong rejection region, presents us with a special case. In such a case the rule constructing has not ruled out all the conclusions but has also not explicitly suggested a particular set of conclusions. An example of this case is depicted in Figure 9. The conclusion with the maximum support is defined to be the one which is closest to the strong confirmation region. This conclusion with maximum support is taken as the decision reached by the rule invocation. In Figure 10, our algorithm would thus select the action denoted by (Y_1,Y_2).

Since it is plausible that none of the rules in the conflict set have a consequent where an action appears negated, subsequently it is possible that the Lower Confidence is assigned the value "blank". Similarly, the Upper Confidence will be assigned the value "blank" if an action appears negated in some of the rules in the conflict set, but does not appear non-negated in any of these rules. So, an action can have a "blank" for either X_1 or X_2. An action will not be associated with both (X_1,X_2).= ("blank", "blank"), rather it would not be listed at all. Since a "blank" indicates an absence of information, a "blank" as a Lower Confidence is interpreted as the value 1 for X_1, while a "blank" for an Upper Confidence is interpreted as the value 0 for X_2 [see Figure9].

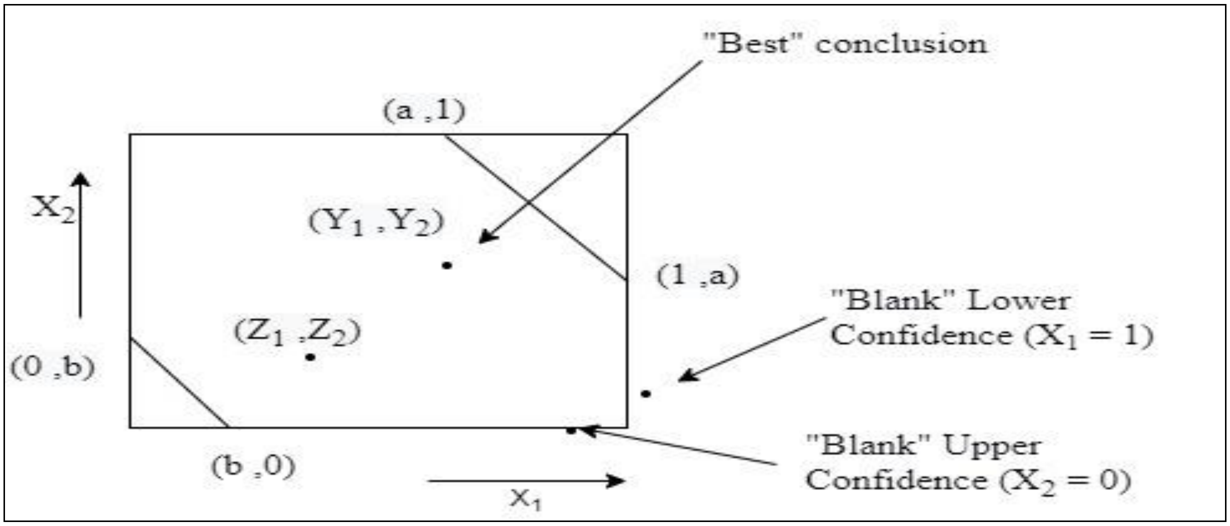


Figure 9: Selecting the suitable algorithm based on rule building.
Source: Own processing

CONCLUSIONS AND PERSPECTIVES

This paper makes an important contribution to the MEP project through the design methodology for fuzzy relational PostGIS databases (FPostGIS). More importantly, no findings from any design methodology for the building of fuzzy relational databases for the accessibility of a path have been published. In this paper, we propose a design methodology for FPostGIS based on accessibility information about a particular path. In this article, we propose a fuzzy extension (both graphical and formal definitions of extensions) to the ER model. Additionally, we describe a novel design methodology for mapping such fuzzy ER models for fuzzy relational databases. To that end, we are enhancing path reconstruction on a set of pedestrian paths by combining fuzzy logic and crowdsourcing methodologies. We show that the MEP server requires capabilities for managing imprecise data. Research has shown that the method has designed for FPostGIS can play a vital role in improving information about the quality-condition of pedestrian walkway accessibility and improving the quality of life for people with mobility challenges in urban areas.

RECOMMENDATIONS FOR FUTURE WORK

The research work in this paper focuses on the MEP project through the design methodology for fuzzy relational PostGIS databases (FPostGIS) for urban pedestrian accessibility. Fuzzy theory demonstrated its superior performance in modeling ambiguous information by Li et al., (2013) and Kang et al., (2020). There are still some open issues to be investigated in the future as an extension of this research. We propose research on the fuzzy information-based decision-making process where a single high confidence in a given conclusion overrides several low confidences in that conclusion. It's also important to research problems with the MEP server, such as issues with imprecise data or imprecise rules.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Reuse of Sludge from Wastewater Treatment Plants in Agriculture: Problem of Heavy Metals in Moshi Municipality Waste Water Treatment Plant

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Abstract
Municipal wastewater treatment plants (WWTPs) have the potential to play a significant role in a circular economy by adopting the principles of reduce, reuse, and recycle (3R). While the primary goal of a WWTP is to decrease the pollution in sewage, this process also produces various potentially valuable byproducts such as treated effluent, biogas, and sludge. The challenge in recycling beneficial nutrients from sludge to agricultural soil primarily arises from the presence of heavy metals, partly due to their toxicity and environmental persistence. This study aimed to examine the concentrations of specific heavy metal contaminants (Cd, Zn, Fe, Cu, and Cr) in sludge from the Moshi municipal WWTP, which is slated for use as fertilizer. The samples underwent analysis using an Atomic Absorption Spectrophotometer (AAS). The examination of sewage sludge revealed a pH average indicating an acidic condition at 5.93 ± 1.05, while iron averaged at 53.32 ± 3.66 mg/kg and copper varied between 0.10 and 3.43 mg/kg, with an average of 1.63 ± 1.18 mg/kg. Environmental assessment involved the application of three pollution indices—Contamination Factor (CF), Index of Geo-accumulation (Igeo), and Pollution Load Index (PLI). These indices collectively confirmed the absence of contamination in the sludge regarding these elements. However, ensuring the elimination of environmental risks and evaluating potential impacts on human and animal health regarding the use of sludge from treatment plants necessitates comprehensive studies across various treatment facilities in the country, considering the chemical composition of these sludges.

Keywords: *Rural Water Supply, Sewage sludge, fertilizer, Moshi Municipal*

INTRODUCTION

Sewage sludge, a by-product from wastewater treatment plants, forms as a diverse blend of solid organic and inorganic elements, along with colloids, separated with varying chemical compositions, treatment durations, and physicochemical conditions (Goldan et al., 2022).

during the treatment process (Gray, 2010). Managing sewage sludge disposal has emerged as a significant challenge in recent years. Adapting sewage sludge for soil enhancement involves a range of methods

The treatment of sewage sludge has become an immediate concern, primarily due to the significant population growth in urban areas and the evolving living standards, which have led to higher water consumption and the consequent release of used water into surface watercourses (Iticescu et al., 2018). Various countries have opted for different disposal methods for urban sewage sludge, such as using it in agriculture as fertilizer, incineration, composting, and landfill. When comparing the costs of these disposal methods, applying sludge to land and agriculture stands out as the most cost-effective compared to other approaches (Mehmood et al., 2022). However, the choice of sewage sludge management method is mainly influenced by the quantity and properties of the sludge itself (Urra et al., 2019).

Wastewater treatment plant sludge finds purpose through compost production, direct application to agricultural and forest land, creating growth substrates, and harnessing energy (Renaud et al., 2017). Due to practical and legal considerations, there's a growing trend to reuse sewage sludge rather than resorting to landfills. This strategy aims to reduce waste generation, foster bioeconomy growth through smart waste management, and aligns with a zero-waste approach (Ruiz-Gomez et al., 2017).

Sewage sludge exhibits fertilizer-like properties and offers potential for enhancing agricultural soils due to its rich content of nitrogen, phosphorus, and organic matter (Metcalf, 1991). Approximately, one ton of dried sludge typically comprises 200 kg of organic matter, 6 kg of nitrogen, 8 kg of phosphorus, and about 10 kg of assorted soluble salts on average (Zhang et al., 2016). This sludge, derived from wastewater treatment, has the capacity to retain moisture and can serve as a pH regulator within specific parameters. Alongside essential elements crucial for plant growth, it may also contain variable quantities of heavy metals and other pollutants (Deenik and Cooney, 2016).

Because of its nutrient richness and substantial organic mass, sewage sludge in significant quantities can positively impact productivity, addressing a critical challenge: the removal of sewage sludge from wastewater treatment plants to prevent incineration, costly procedures, and further pollution. Application methods include liquid form, sludge cake (25% dry solids), or dried sludge granules (95% dry solids). Studies indicate nutrient loss during dehydration and drying processes, favoring the use of the first two forms. However, this recycling approach might pose challenges due to foul odors and potential health hazards from pathogens within the sludge (Tsadilas et al., 2014; Jamil et al., 2006).

Improper management of sewage sludge can lead to environmental contamination and groundwater pollution. The accumulation of heavy metals in the soil poses a significant risk as it profoundly impacts the natural circulation of elements in the environment (Urra et al., 2019). Heavy metals become a substantial threat to the quality of agricultural crops through the food web since consumed plants serve as a primary natural source of these metals for humans and animals. As wastewater treatment progresses, reducing the release of pollutants into receiving water bodies and improving water quality, more potentially harmful compounds are transferred to sewage sludge, rendering it unsuitable for agricultural purposes (Tsadilas et al., 2014).

Heavy metals are recognized as significant environmental pollutants due to their toxicity, extended atmospheric lifespan, and their ability to accumulate within the human body through bioaccumulation. Municipal wastewater, a complex amalgamation of various pollutants from domestic and industrial origins, has emerged as a crucial human-made source of pollution in aquatic environments (Han et al., 2017). Several studies elsewhere have indicated that the application of wastewater sludge to cropland can heighten the accumulation of heavy metals in specific crop plants (Singh and Agrawal, 2017; Singh and Agrawal, 2010; Muchuweti et al., 2006).

The motivation behind this study stems from acknowledging the role of municipal wastewater in contributing to heavy metal pollution in the environment. Its aim is to aid in nationwide estimation and policy formulation in Tanzania. This research specifically quantified the discharge of heavy metals from sewage sludge sourced from the wastewater treatment plant of Moshi Municipality, primarily utilized as manure.

MATERIALS AND METHODS

Description of the Study Area and Sample Collection

The wastewater treatment system of Moshi Municipality, situated in the northern part of Tanzania within the Kilimanjaro region, is overseen by the Moshi Urban Water and Sewerage Authority (MUWSA) (Fig. 1). This system handles domestic sewage from a sewered area covering 46% of the municipality, the highest coverage in Tanzania (Kihila et al., 2014). Additionally, it receives sewage from areas lacking a sewerage network via septic pump trucks. The treatment setup comprises a waste stabilization pond (WSP) interconnected with a constructed wetland (CW) system.

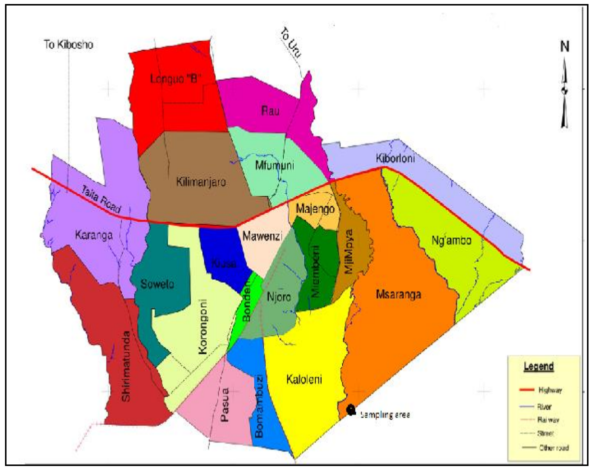

Figure 1: Moshi Municipality Wastewater Treatment System Coverage

The wastewater treatment system of Moshi Municipality is situated in Mabogini ward, approximately 4 km south of the center of Moshi town. The sewage treatment setup of the municipality includes a sequence of oxidation ponds that receive domestic sewage from both the town and its surrounding suburbs.

Volume of Solid Sludge Produced at Moshi Waste Water Treatment Plant

Determining the exact volume of municipal wastewater sludge generated by treatment facilities remains challenging due to fluctuations resulting from standard sludge treatment procedures. As per Metcalf and Eddy (1991), a typical primary and secondary wastewater treatment process yields approximately 0.94 kg of dry solids per 1,000 gallons (3.78 m^3) of treated wastewater. The wastewater treatment system in Moshi Municipality receives domestic sewage from a sewered area covering 46% of the municipality, the highest coverage in Tanzania. The Waste Stabilization Pond (WSP) within this system is designed with a capacity of 4500 m^3/d, comprising an anaerobic pond, two facultative ponds, and six maturation ponds (Kihila et al., 2014). This translates to an average production of 1,251 kg/day of dry solids in the treatment plant.

Sampling Procedure

Sewage sludge samples were gathered from five separate WWTPs located in Moshi Municipal. In each site, four samples were collected monthly between August and November 2018 from the sludge drying beds, amounting to a total of twenty samples. The collection method involved manual sampling through composite sampling taken from the middle depths of identified sludge beds.

Plastic sampling containers with screw caps were employed (Gomez et al., 1986). The sample volumes and necessary sampling conditions followed the guidelines outlined in the Standard Methods for the Examination of Water and Wastewater (APHA, AWWA, WEF 1998). Each sample was gathered in a labeled plastic bag, then stored in a cooler box with ice during transportation and subsequently placed in a refrigerator at 4°C until further analysis.

Preparation of Samples

The collected samples underwent air-drying at room temperature (27°C) in the laboratory for a duration of five days. Following this, the samples were subjected to nitric acid digestion as per the EPA guidelines (Hseu, 2004). Approximately 2 grams of the milled sewage sludge sample was weighed and placed in a conical flask. Subsequently, 20 mL of HNO_3 (55% concentration) was added, and the mixture was heated at 90°C for 45 minutes, followed by an increase in temperature to 150°C for 10 minutes. Throughout the heating and boiling process, 10 mL of HNO_3 (55% concentration) was intermittently added three times to ensure the maintenance of the liquid content.

The blend was permitted to cool at ambient conditions. Subsequently, the samples were filtered into 100 mL volumetric flasks and filled to capacity using distilled water. The mixture was filtered through acid washed Whatman No. 44 filter paper into a 50 mL volumetric flask and diluted to its full volume. The resulting sample solution was then drawn into the Varian AA240 Atomic Absorption Spectroscopy apparatus.

The determination of total nitrogen (N), phosphorus (P), and potassium (K) followed methodologies outlined in existing literature (Arvas et al., 2011; Kihila et al., 2014). A sample underwent digestion in concentrated sulfuric acid (VI) with hydrogen peroxide acting as an oxidant. Subsequently, the sample underwent specific analyses:

nitrogen measured calorimetrically via the hypochlorite method, phosphorus assessed calorimetrically using the vanadium-molybdenum method, potassium, calcium, and sodium determined through atomic emission spectroscopy, and magnesium analyzed using the atomic absorption spectrophotometric method.

Determination of pH

To conduct pH testing, 10 grams of air-dried sample was deposited into a 100 mL beaker. Following this, precisely 40 mL of distilled water was added, thoroughly mixed, and left undisturbed for 30 minutes. Subsequently, the pH electrodes were immersed into the partially settled suspension, and the readings were recorded.

Evaluation of Heavy Metal Pollution

The level of contamination in the sewage sludge from the wastewater treatment plant of Moshi Municipality, primarily utilized as manure, was evaluated using three environmental assessment indices. These indices include the Geoaccumulation index (I_{geo}), the Contamination Factor (CF), and the Pollution Load Index (PLI).

Geoaccumulation Index (I_{geo})

The I_{geo} is a pollution degree evaluation index proposed by Müller and is widely used to evaluate the metal pollution degree in water, ocean, and soil environments (Olumuyiwa, et al., 2014). The calculation formula can be expressed as follows:

$$I_{geo} = Log_2\left(\frac{C_i}{1.5B_i}\right) \quad (1)$$

Where Bi and Ci are the background and measured concentrations of the sludge samples respectively.

In the process of interpreting geochemical data, background values and its choice plays a significant contribution. The most common way is the use of average shale values as suggested by Turekian & Wedepohl, (1961) and average crustal abundance data as reference baselines (Ali, *et al*., 2016). The background values adopted from Edori and Kpee (2017) where: Fe = 47,200; Cr = 90; Cu = 45; Zn = 95 and Cr = 0.3.

Single Pollution Index Models

Contamination factor (C_f) was determined using Single Pollution Index Model. This is a basic and useful tool for detecting toxic metal contamination. The C_f is used to evaluate the individual toxic metal contamination insoil. The standard employed for the interpretation of the contamination factor values was adopted from Edori and Kpee (2017). The contamination factor is given in Eq. (i):

$$C_f = \frac{C_m}{C_b} \quad (2)$$

Where: C_f = Contamination factor; C_m = Is the concentration of the metal and C_b = The background value.

The Pollution Load Index (PLI)

The Pollution Load Index (PLI) is obtainedas concentration Factors (CF). This CF is the quotient obtained by dividing the concentration of each metal. The PLI of the place are calculated by obtaining the n-root from the n-CFs that were obtained for all the metals. With the PLI obtained from sampling site. Generally pollution load index (PLI) as developed by Lacatusu (2000) which is as follows (Eq iii): $PLI = (C_{f1} \times C_{f2} \times C_{f3} \times C_{f4} \times \ldots C_{fn})^{1/n}$ (3)

Where: PLI is Pollution Load Index, C_f contamination factor of respective metal, n = number of metals.

Table 1 shows different classifications into which the contamination factor (C_f), Geoaccumulation Index (I_{geo}) and Pollution load index (PLI) are categorized

.

Table 1: Classification of Different Pollution Indices

I_{geo} value[a]	**Description**	C_f value[b]	**Description**	PLI value[c]	**Decription**
$I_{geo} < 0$	Practically Uncontaminated	$C_f < 1$	Low contamination	$PLI = 0$	Excellent
$0 < I_{geo} < 1$	Uncontaminated to moderate contaminated	$1 \leq C_f < 2$	Low to moderate contamination	$PLI = 1$	Baseline level of pollutants
$1 < I_{geo} < 2$	Moderate Contaminated	$2 \leq C_f < 3$	Moderate contamination	$PLI > 1$	Polluted
$2 < I_{geo} < 3$	Moderate to heavily contaminated	$3 \leq C_f < 4$	Moderate to high contamination		
$3 < I_{geo} < 4$	Heavily contaminated	$4 \leq C_f < 5$	High contamination		
$4 < I_{geo} < 5$	Heavily to extremely contaminated	$5 \leq C_f < 6$	High to very high contamination		
$5 < I_{geo}$	Extremely contaminated	$C_f \geq 6$	Extreme contamination		

[a] Muller (1969), [b] Ma et al., (2022), [c]Mkude et al., (2021)

Quality Assurance

To guarantee the accuracy of the test outcomes, suitable safety precautions and quality assurance protocols were adhered to. All chemicals and reagents employed were of analytical and trace-metal grades. The glassware and utensils were thoroughly cleaned, and distilled water was utilized throughout the study. Samples were handled carefully to reduce cross-contamination risks, and reagent blank determinations were conducted to adjust the instrument readings.

The validation of the sample preparation procedure was accomplished through a recovery study. The mean recoveries (± relative standard deviation) acquired were as follows: Cr: 101 ± 3.4%; Cd: 89 ± 3.1%; Zn: 98 ± 3.3%; Cu: 96 ± 2.7%; and Fe: 94 ± 3.5%. Post-calibration, the sample solutions were promptly drawn into the AAS instrument for direct measurement of the metal concentrations (Table 2).

Table 2: Calibration Curve A vis Conc. of Heavy Metals (mg/L)

Metal	Model for Absorbance vis Conc.	R^2
Fe	y = 0.0362×	0.9946
Cr	y = 0.0791×	0.9951
Cu	y = 0.0834×	0.9938
Zn	y = 0.0214×	0.9973
Cd	y = 0.0168×	0.9972

The AAS sequence included a QC sample and a blank after 10 soil samples. A second identical sequence was run with the duplicate samples.

RESULTS AND DISCUSSION

The pH of the Sludge Used as Manure

The interplay between pH, acidity, and alkalinity holds a crucial role in biological wastewater treatment, emphasizing the importance of monitoring and regulating pH for optimal outcomes (Ekama and Wentzel, 2008). pH variability significantly impacts agricultural productivity as it affects micronutrient availability in the soil. It's widely understood that as soil pH decreases, its capacity to adsorb and retain metals diminishes (Brady and Weil, 2002). The examined sewage sludge revealed an average acidic pH value of 5.93 ± 1.05, with a minimum of 4.59 and a maximum of 7.90 (Table 1).

These recorded values fall notably below recent findings (You et al., 2021), where pH levels ranged between 6.54 and 7.16, indicating weak alkalinity. Shrivastava and Banerjee (1998) highlight the necessity of adjusting the soil pH for this type of sludge within a range of 6.5–7.0 to regulate heavy metal availability in sludged soils. Modifying soil pH to a specific value through liming can diminish the mobile fraction of numerous heavy metals in the soil. To counter potential soil acidification stemming from these alterations, Alvarenga et al. (2016) suggest simultaneous application of sludge treatment and chemicals in agricultural land to create an acid-base buffer system's effect. Such systems maintain soil pH within the boundaries of the acidic component's pKa (Hamdi et al., 2019). Given the pH of agricultural soils in Moshi Municipality at 5.93 ± 1.05, the pKa of the acidic component within the buffer system must align within this range. In the scenario of sludge application on arable lands, the buffer system of $CaCO_3$-$Ca(HCO_3)_2$ was considered, possessing an acid component with a pKa value of 7.48.

The Concentration of Chemical Elements in the Sludge

Concentration of Total Nitrogen (N_t), Phosphorus (P) and Pottasium (K) in the Sludge

The concentration of N_t, P and K observed in Moshi municipality wastewater treatment sludge is shown in Table 3.

Table 3: The **Concentration of Heavy Metals (mg/kg)**

Variable	Minimum	Maximum	Mean	Std Deviation
pH	4.59	7.90	5.93	1.05
K	1.00	2.20	1.67	0.41
P	13.80	39.60	26.81	11.64
N_t	0.21	1.51	0.76	0.60
Cu	0. 10	3.42	1.63	1.18
Fe	b.d.	86.96	53.32	3.66
Zn	b.d	7.91	3.74	2.15
Cr	6.06	8.40	7.49	0.70
Cd	BDL	0.16	0.02	0.05

Source: Researcher (2018); BDL = below detection limit

The obtained sewage sludge sample exhibited substantial concentrations of nitrogen, phosphorus, and potassium. The average quantities of N_t, P, and K in the sewage sludge were 0.76 ± 0.60, 26.81 ± 11.64, and 1.67 ± 0.41 mg/kg, respectively. These figures surpass the recently detected values reported by Głodniok et al. (2021), which recorded Nitrogen at 0.44 mg/kg, phosphorus at 0.30 mg/kg, and potassium at 0.81 mg/kg. Gorlach and Mazur (2002) explain that this discrepancy is expected due to the low pH of the sewage sludge (5.93 ± 1.05), wherein these micronutrients contend more with soluble aluminum (Al) and H^+. The presence of H^+ and Al^{3+} displaces other exchangeable cations such as (N^{3+}, P^{3+}, and K^+), mobilizing them into the soil solution and consequently heightening the potential for leaching.

Concentration of Heavy Metals in the Sludge

The introduction of this sludge, with its acidic pH level (5.93 ± 1.05), contributes to the soil's acidic condition, potentially leading to the liberation of heavy metals bound to metal oxides (Table 3). The concentration of Cd in the sludge samples varies from Below Detection Limit (BDL) to 0.02 ± 0.05. These figures were notably 58 times lower than the values previously identified in Poland (Milik et al., 2017).

Cadmium concentrations were notably lower compared to the recommended soil concentration of 100 mg/kg in Tanzania (TZS, 2003), yet they may still pose risks to human and environmental health. The presence of Cd primarily stems from the mixing of industrial effluents with wastewater channels (Nassef et al., 2007). The frequent utilization of cadmium-based phosphatic fertilizers in various agricultural practices contributes significantly to Cd presence in wastewater bodies. Moreover, Cd is prevalent in rechargeable batteries for household use (Ni-Cd batteries), paints, photography, and urban wastewater originating from diverse sources such as food items, detergents, body care products, and stormwater. Elevated Cd levels can lead to kidney dysfunction, high blood pressure, and organ damage (Nassef, 2007; Rajappa et al., 2010).

Copper, iron, and zinc are essential elements, yet they pose potential toxicity risks at elevated concentrations and can induce deficiency symptoms even at low environmental levels. Iron (Fe) plays a pivotal role in diverse physiological and biochemical processes within plants, serving as an electron carrier, contributing to chlorophyll synthesis, and upholding chloroplast structure and function—making it a crucial trace element for plants (Roy et al., 2013). The average concentration of iron in the sludge samples was 53.32 ± 3.66 mg/kg. This value surpasses the previously recorded values in India, which were 10.5 ± 0.42 mg/kg (Roy et al., 2013), yet remains lower than the values detected in Turkey, averaging at 367.0 mg/kg (Dolgen et al., 2007).

The copper concentration in the sludge derived from the examined sewage treatment plant ranged between 0.10 and 3.43 mg/kg, averaging at 1.63 ± 1.18 mg/kg. These values align closely with previously detected values in Poland (Bowszys et al., 2015), ranging from 1.51 to 1.98 mg/kg. However, they were notably lower than those detected earlier in Poland (Milik et al., 2017), which ranged from 107.69 to 160.36 mg/kg. While copper is an essential trace element for life, its toxicity escalates at higher concentrations. Copper originates from diverse sources like cleaning products, cosmetics, shampoos, fuels, and ointments (Tiruneh et al., 2014). Furthermore, it's present in various food items, oils, lubricants, paints, pigments, and other alloy-related industries. Additionally, copper emissions can arise from small-scale commercial activities, warehouses, and buildings equipped with commercial heating systems (Sternbeck, 2000).

Copper, while essential for numerous organisms, also holds significant toxicity. It's known to elicit several adverse effects on both crops (Baryla et al., 2000) and soil microorganisms, potentially impacting soil fertility negatively.

The sludge samples revealed an average zinc content of 3.74 ± 2.15 mg/kg. These values were lower than previously detected values (Bowszys et al., 2015), ranging from 6.41 to 15.14 mg/kg. Zinc stands as an essential trace element for humans, animals, and plants. However, elevated zinc concentrations pose potential toxicity to plants, humans, and animals (Ohnessorge and Wilhelm, 1991).

Although zinc (Zn) poses relatively low toxicity to humans and animals, studies indicate potential allergies associated with high levels of zinc, and zinc poisoning along the food chain may disrupt copper metabolism (Ohnessorge and Wilhelm, 1991). Zinc originates from natural, domestic, and industrial sources (Solomons, 2001).

Household zinc compounds are commonly present in a variety of products like cosmetics, shampoos, lubricants, medications, and detergents. These sources encompass various industrial processes such as galvanization, brass and bronze alloy production, tire and battery manufacturing, as well as plastics, rubber, fungicides, and textiles. Zinc chloride is utilized in taxidermy, embalming solutions, construction materials, specialized cements like zinc oxide and zinc fluorosilicate, dental applications utilizing zinc oxide, cosmetics, and pharmaceuticals (Solomons, 2001). Industrial zinc sources include wastewater streams from steelworks, fiber manufacturing, wood-pulp production, and wastewater generated from plating and metal processing industries (Obladen et al., 1998).

Chromium (Cr) stands as the seventh most abundant element globally and ranks 21st in the Earth's crust, typically with an average concentration of 100 mg/kg (Puzon et al., 2008). The maximum permissible concentration of chromium in drinking water is 0.10 mg/L due to the toxic effects of Cr(VI) and the potential conversion of Cr(III) to Cr(VI) (WHO, 1996). The sludge samples exhibited an average chromium level of 7.49 ± 0.70 mg/kg. These values are lower than those previously detected (Momeni et al., 2019) with an average of 16.62 ± 2.18 mg/kg and also fall below Tanzania's acceptable soil standard of 200 mg/kg (TZS, 2003).

According to Álvarez et al. (2002), the reduced heavy metal concentrations in sludge may be linked to the weight loss of fresh sludge during anaerobic digestion and, subsequently, an increase in dry matter content during sludge dehydration. The impact of increased dry matter (DM) content on total heavy metal concentrations in sludge was observed in dewatered sludge, characterized by higher DM and metal contents compared to primary or secondary sludge.

Heavy Metals Pollution Levels

Geo-accumulation Indices

Figure 2a showcases the geo-accumulation index employed to gauge heavy metal accumulation in the study area, resulting in values of -0.4091, -4.01714, -5.3748, -5.2543, and -4.4933 for Fe, Cr, Cu, Zn, and Cd respectively. As per Muller (1969), the site is categorized as practically uncontaminated due to all values falling below 0 (refer to Table 1). These values are notably lower than those determined in prior assessments (Jena et al., 2019), where the Igeo values for Cr, Cu, Cd, and Zn were 0.16, 0.37, 0.65, and 0.67 respectively.

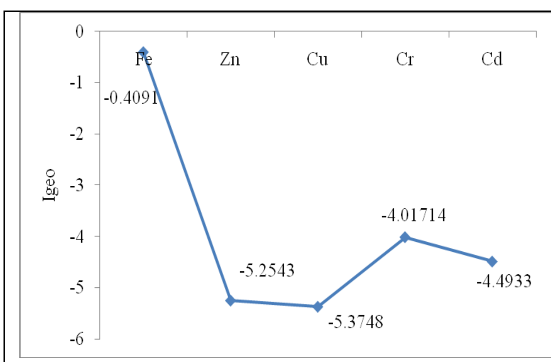

Fig 2a: Geoaccumulation Index Determined

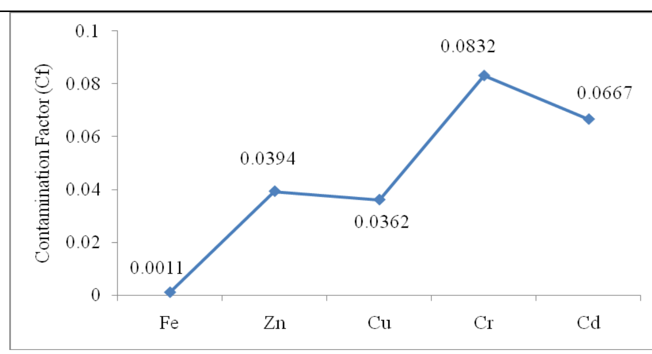

Fig 2b: Contamination Factor (Cf) Determined

Single pollution index analysis of heavy metals

The Contamination factor (CF) pollution index for the five heavy metal elements was computed using the single-factor pollution index method, and the outcomes are displayed in figure 2b. The CF values for Fe, Cr, Cu, Zn, and Cd were 0.0011, 0.0832, 0.0362, 0.0394, and 0.0667 respectively, all falling within the low contamination category (Table 1).

Pollution Load Index (PLI)

The Pollution Load Index (PLI) for the sludge obtained from the Moshi Municipal water treatment plant, used as manure, was determined to be 0.0244. This figure corresponds to values previously detected (Mkude et al., 2021) in the Wami River, ranging from 0.007 to 0.014 across different river sections. Following pollution categorizations (Table 1), the calculated PLI remains below 1, indicating that the manure exhibits an 'excellent' quality regarding the pollution extent from the analyzed heavy metals.

CONCLUSION AND RECOMMENDATIONS

The composition of sewage sludge greatly depends on the quality of the processed wastewater. Analyzing the total concentrations of heavy metals (Zn, Fe, Cd, Cu, and Cr) in sewage sludge remains a critical aspect for evaluating the potential risks these elements pose to the environment and living organisms. It's been observed that the concentrations of heavy metals in sewage sludge fall within the permissible norms outlined by the Tanzania Bureau of Standards (TZS, 2003) for soil, indicating suitability for agricultural use.

The wastewater treatment plants in Moshi Municipality primarily handle domestic wastewater and discharge from consumers engaged in economic activities that don't involve substantial industrial pollution. Typically, any industrial wastewater in the area is initially treated within the sewage treatment plants of major industrial facilities before being introduced into the municipal wastewater system.

This accounts for the notably low levels of heavy metals detected in the analyzed sludge, well below the limits stipulated by current legislation. Another contributing factor to the reduced heavy metal load is the limited industrial activity and relatively modest economic development in the Moshi Municipal area, resulting in very few industries discharging wastewater into the river.

The significance of these detected low heavy metal concentrations shouldn't be underestimated, given their potential to profoundly affect both environmental quality and human health. This is attributed to their persistent nature in the environment and their tendency to accumulate in plants and vegetables. Consequently, it's advisable to ensure proper treatment of sludge from wastewater treatment plants to diminish the levels of contaminants to safe thresholds for the environment and human health before considering its use as fertilizer or manure. This treatment plays a pivotal role in mitigating the risks associated with potentially hazardous substances present in the sludge. Without adequate treatment, these contaminants could pose significant threats to soil quality, water systems, and ultimately human health when applied in agricultural contexts. Thus, ensuring proper treatment is essential to transform the sludge into a safer and beneficial product for land application while minimizing potential adverse impacts.

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Anaemia among schoolchildren; A narrative review

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Abstract
Anaemia is a significant problem in the developing world, such as Sub-Saharan Africa (SSA), with the greatest burden of disease experienced in children. Although extensive research on anaemia has been done among the pre-schoolers, less is documented about schoolchildren. Thus, the current review intends to summarise recent data on the prevalence and risk factors of anaemia among schoolchildren aged 5-18 years across SSA for planning mitigating interventions. A review was conducted on published English articles in Sub-Saharan countries providing estimates on anaemia prevalence and risk factors using databases from PubMed and Google Scholar from January 2010 to April 2021. A total of 41 articles were identified for review. Based on eligibility criteria, 18 articles were included in the current review. The review showed that the prevalence of anaemia among schoolchildren ranged from 11% (Ethiopia) to 83% (Nigeria). Generally, infection (56%), eating less protein and vegetables (33%), age (22%) and sex (16%) of the child were the significant risk factors for anaemia among schoolchildren. The current review established that anaemia is directly associated with infection, less consumption of protein and vegetables, age and sex of the child. Effective public health strategies such as biofortification of food are needed to improve micronutrient intake among older children.

Keywords: *Adolescents, haemoglobin, feeding pattern, predictors, prevalence, risk factors, Sub-Saharan Africa*

INTRODUCTION

Anaemia is the most common nutritional deficiency worldwide and an important public health problem, especially in developing countries. It affects the populations of both rich and poor countries. Globally, 42.6% of children are anaemic, among them 60.2% are from Africa (WHO, 2015). The World Health Organization (WHO) defines anaemia as a low blood haemoglobin (Hb) concentration < 115 g/L for children aged 5–11 years (WHO, 2008). There is limited data about anaemia among schoolchildren in SSA. However, malnutrition persists into the pre-adolescent period affecting school performance and reproductive health during puberty, particularly when child-bearing occurs early in life. The available data revealed that the prevalence of anaemia ranges between 29.3 % and 46% in different studies conducted among schoolchildren in SSA (Gowele *et al.*, 2021, Abizari *et al.*, 2012). Therefore, the rating shows that anaemia is a severe public health problem (WHO, 2015).

Furthermore, children in rural areas are shown to be highly affected compared to children in urban areas. Several strategies have been developed to address the problem of anaemia. This included free dispensing of iron supplements, deworming and iron fortification in foods. All these interventions have addressed the problem among preschool children. The prevalence of anaemia among schoolchildren who are equally affected has received less attention compared with the pre-schoolers in developing countries. Therefore, there is a need to have data on the prevalence and risk factors of anaemia in schoolchildren. This information will assist in developing interventions focusing on this neglected group.

Iron plays vital roles in the body, including cognitive function (MoHCDGEC *et al.* 2016 and Thalanjeri *et al*. 2016) and biological functions, respiration, energy production, DNA synthesis, and cell proliferation (Zhang, 2014). Anaemia can stunt growth and increase morbidity from infectious diseases. It adversely affects several immune mechanisms. Furthermore, anaemia affects the physical development of an individual leading to decreased working capacity (Abizari *et al*., 2012, FAO/WHO, 2001). However, little, if any, comprehensive review of existing literature on anaemia prevalence and its risk factors in schoolchildren has been done for developing counties to cast the overall picture. Therefore, the objectives of this article are (i) to review the existing literature on the status of anaemia in schoolchildren so as to (ii) determine the prevalence and (iii) determine risk factors for anaemia across SSA.

METHODOLOGY

Search strategy and study selection

The current review included two databases, PubMed and Google Scholar. In addition, grey literature, such as reports and dissertations which focused on strategies to improve the iron status of schoolchildren, was consulted. A literature search was performed to identify existing research articles on anaemia. Key search terms were developed and used either singly or in combination. These terms included anaemia, schoolchildren, school-age children, adolescents, micronutrients, iron and SSA. Other articles that were considered are those, which reflected on feeding patterns, overweight and obesity, the prevalence of and determinants or risk factors for anaemia. The reviewer screened all the selected literature's titles and abstracts as a function of age out of the range, studies not from SSA countries, papers without the full text available, irrelevant or those which did not meet the inclusion criteria. The current review included articles published from January 2010 to April 2021. By using the identified phrases, 41 articles were collected based on the established inclusion and exclusion criteria. After the critical scrutiny to obtain the most relevant articles, 18 were qualified and reviewed. The outcome of interest for inclusion was anaemia, determined by the Hb level < 115 g/L (Table 1).

Table 1: Inclusion and exclusion criteria for selecting articles for review

Aspect	Inclusion criteria	Exclusion criteria
Age of subjects	Schoolchildren aged 5-18 years	Children below five and above 18 years No age identified
Publication	Between January 2010 to April 2021	Published before January 2010 and after April 2021
Subjects	Used human subjects	Used animal subjects
Language	Written in the English language	Written in other languages apart from English
Focus	Childhood anaemia, overweight and obesity	Other nutrition problems
Type of articles	Original articles	Review articles, book chapters, conference proceedings, and correspondence letters.
Schooling level	Pre and Primary school	Below pre-primary and above primary school
Participating countries	Countries in SSA	Countries outside SSA

Data extraction

The data extracted from the studies were first transferred into a Microsoft Excel (Microsoft Corporation, Washington, DC, USA) spreadsheet designed for the current review. Relevant information from each study was included, such as the prevalence of anaemia, dietary intake and predictor variables concerning the child, parents, household and community. Other items extracted were the authors, year of publication, and the location/country in which the study was conducted. Prevalence, proportions and confidence intervals (CI) reported by each study were recorded. When prevalence data were given for subgroups such as male/female, age groups, urban/rural, a weighted average across subgroups was calculated to provide one estimate per study.

RESULTS

Description of included studies

The current review assessed articles from the following regions: Burkina Faso (2), Cameroon (1), Egypt (1), Ethiopia (6), Ghana (1), Kenya (2), Nigeria (2) and Uganda (3). The results section reports the risk factors associated with anaemia among schoolchildren in SSA. The data extracted are those reported from the studies investigating both protective and harmful effects, evident from the Odds Ratios. Furthermore, data on schoolchildren were not equally defined, as some authors used pre-schoolers, schoolchildren and adolescents. Therefore, all these categories were considered in the review. The reviewed articles were from all countries in SSA.

Prevalence of anaemia among schoolchildren

Anaemia is a major public health problem in developing countries. Evidence from reviewed articles showed diverse trends of anaemia among schoolchildren across SSA. A study by Daboné *et al*. (2011) among schoolchildren aged 7-14 years in Ouagadougou, Burkina Faso, indicated that 40.4% of schoolchildren had anaemia. The available data indicate that Burkina Faso is still doing worse with an anaemia rate of 56.2% (Teh *et al*., 2018) and 28.6% (Erismann *et al*., 2017). Likewise, Uganda has not done much to reduce the prevalence of anaemia among schoolchildren. For instance, Legason *et al*. (2017) and Turyashemererwa *et al*. (2013) revealed that 34.4% and 37.7% of schoolchildren were suffering from anaemia respectively. In addition, Barugahara *et al*. (2013) reported higher rates of anaemia (46%) among female schoolchildren in Masindi district. Studies in Ethiopia have indicated mixed trends in the prevalence of anaemia. Gutema *et al*. (2014) revealed that 23.7% of children from the Somali region had Hb low than 115 g/dL. Moreover, in the same year, Assefa *et al*. (2014) and Desalegn *et al*. (2014) reported a higher prevalence of anaemia (37.6%) among schoolchildren in Jimma Town. Subsequently, Alelign *et al.* (2015) revealed that 11% of schoolchildren in Durbete Town had anaemia, whereas, in Eastern Ethiopia, the prevalence was 27.1% (Mesfin *et al*., 2015). In another study, Getaneh *et al*. (2017) recorded about 16% prevalence of anaemia among schoolchildren from Gondar town in Ethiopia. Similarly, a higher prevalence of anaemia (30.8%) was reported in the Volta region of Ghana (Egbi *et al*. 2014). Likewise, in Kenya, schoolchildren are equally affected by anaemia (28.8% and 35.3%), as revealed by Ngesa & Mwambi (2014)) and Pullan et al. (2013) respectively. Among the articles reviewed, higher anaemia (82.6%) prevalence was reported in rural communities of Abia State in Nigeria among schoolchildren aged 7-12 (Onimawo *et al*., 2010). In Menoufia Governorate, Egypt, Abdel-Rasoul *et al*. (2014) indicated that 25.6% of primary schoolchildren aged 6-11 years had anaemia. Table 2 gives the prevalence rates of anaemia in SSA.

Table 2. Summary of the prevalence of anaemia among schoolchildren

Author (year)	Location/Country	Age (Yrs)	Study design	(n)	%
(Daboné *et al*., 2011)	Ouagadougou Burkina Faso	7-14	Cross-sectional	649	40.4
(Erismann *et al*., 2017)	Plateau Central and Centre-Ouest regions of Burkina Faso	8-14	Cross-sectional	455	28.6
(Teh *et al*., 2018)	Batoke (Limbe) and Tole (Buea), Cameroon	0-14	Cross-sectional	828	56.2
(Abdel-Rasoul *et al*., 2014)	Menoufia Governorate, Egypt	6–11	Cross-sectional	497	25.6
(Alelign *et al*., 2015)	Durbete Town, Ethiopia	5-15	Cross-sectional	403	10.7
(Mesfin *et al*., 2015)	Eastern Ethiopia	5-14	Cross-sectional	1755	27.1
(Getaneh *et al*., 2017)	Gondar town, Ethiopia	6-14	Cross-sectional	523	15.5
(Desalegn *et al*., 2014)	Jimma Town, Ethiopia	6-12	Cross-sectional	616	37.4
(Assefa *et al*., 2014)	Jimma Town, Ethiopia	6-14	Cross-sectional	423	37.6
(Gutema *et al*., 2014)	The Somali region, Ethiopia	5-15	Cross-sectional	355	23.7
(Egbi *et al*., 2014)	Volta Region of Ghana	6-12	Cross-sectional	143	30.8
(Ngesa & Mwambi, 2014)	Kenya	0-14	Cross-sectional	11,711	28.8
(Pullan *et al*., 2013)	Kenya	4-16	Cross-sectional	16 941	35.3
(Onimawo *et al*. 2010)	Abia State, Nigeria	7-12	Cross-sectional	249	82.6
(Adebara *et al*., 2011)	Ilorin metropolis, Nigeria	5-12	Cross-sectional	246	36.2
(Legason *et al*., 2017)	Arua district, Uganda	1-14	Cross-sectional	342	34.4
(Turyashemererwa *et al*., 2013)	Central Uganda	5-11	Cross-sectional	122	37.7
(Barugahara *et al*., 2013)	Masindi District, Uganda	11-14	Cross-sectional	109	46

Dietary iron intake among schoolchildren

The current study established that in SSA countries, the diets of schoolchildren are very limited in quantity and diversity. The data, furthermore, demonstrated that the feeding pattern is characterised by minimal intake of animal-protein foods (Barugahara *et al.*, 2013) and (Desalegn *et al.*, 2014) fruits and vegetables (Desalegn *et al*., 2014), coupled with an overconsumprion of unhealthy foods such as soda, cookies, cakes, candies and ice pop (Daboné *et al.* 2011). A study in Nigeria suggested that school-age children's energy and nutrient intake was unsatisfactory. For instance, 70% of the children had a total iron intake below the Recommended Daily Allowance (RDA) of 10 mg/day (Food and Nutrition Board & National Research Council, 1989). Another study by Fiorentino *et al*. (2016) reported poor dietary iron intake among 46% of schoolchildren in Senegal. Tidemann-Andersen *et al*. (2011) also reported similar findings in the Kumi district. Children had a predominantly vegetable-based diet, while foods of animal origin were consumed occasionally. In Northwest Morocco, Achouri *et al*. (2015) found that 64.9% of the studied sample consumed plant-based foods at least once a day, whereas animal food was less consumed (at least once a week) by the majority (79.3%). These findings imply that the plant-based foods, which were predominantly consumed, were not being complemented with animal-based food to enhance their nutritional quality.

Risk factors of anaemia among schoolchildren

Studies based on SSA investigated risk factors of anaemia among school-going children are dissected in this subsection. These factors are categorised as a child, parental or caregiver, household and community-related factors.

Child-related risk factors for anaemia

Evidence from reviewed articles showed that there are varied risk factors for anaemia. Table 3 describes the distribution of child-related variables for anaemia in the reviewed articles. Infection was highly (56%) associated with anaemia in schoolchildren (Teh *et al*., 2018; Getaneh *et al*., 2017; Legason *et al*., 2017; Alelign *et al*., 2015; Desalegn *et al*., 2014; Gutema *et al*., 2014; Ngesa & Mwambi, 2014; Barugahara *et al*., 2013; Adebara *et al.* 2011; Onimawo *et al*. 2010). For example, Gutema *et al*. (2014) revealed that infection with an intestinal parasite increased the likelihood of anaemia 2.99 times as compared to uninfected schoolchildren (AOR 2.99, 95% CI: 1.05, 849) in Southeast Ethiopia. Furthermore, anaemia was positively correlated with malaria incidences among female schoolchildren (Ngesa & Mwambi 2014). The malaria diagnosis status of a child was strongly associated with the risk of anaemia (OR 4.022, 95% CI:3.399, 4.759). Barugahara *et al*. (2013) also documented a positive correlation between anaemia and improper deworming among female schoolchildren in Masindi District in Uganda.

The habit of eating less protein and vegetables was specified as a risk factor by 33% for anaemia in schoolchildren (Legason *et al*., 2017; Mesfin *et al.*, 2015; Abdel-Rasoul *et al*., 2014; Assefa *et al*., 2014; Desalegn *et al*., 2014; Turyashemererwa *et al*., 2013). For example, low intake of plant food (OR 3.847, 95% CI:2.068, 7.157) and animal food (OR 2.37, 95% CI:1.040, 5.402) were significantly and independently associated with anaemia (Assefa *et al*., 2014). Several studies (Teh *et al*., 2018; Alelign *et al*., 2015; Mesfin *et al*., 2015; Assefa *et al*., 2014; Ngesa & Mwambi, 2014) have indicated that younger children (1-11 years) were highly affected by anaemia (22%) (Mesfin *et al*., 2015; Assefa *et al*., 2014). With regard to the sex of a child conflicting results were documented. For example, male schoolchildren were indicated to be at a greater risk of anaemia (16%) in Arua district in Uganda and The Somali region in Ethiopia (Legason *et al*., 2017; Gutema *et al*., 2014). In contrast, Barugahara *et al*. (2013) revealed that anaemia affects female children more than their counterparts.

Another risk factor for anaemia among schoolchildren reported by various researchers is nutritional status, including wasting underweight, stunting, overweight and obesity which accounts for 28% (Erismann *et al*., 2017; Getaneh *et al*., 2017; Legason *et al*., 2017, Gutema *et al*., 2014, Ngesa & Mwambi, 2014). For instance, Gutema *et al*. (2014) reported that the Odds of anaemia were 5.5 times higher among stunted children than in non-stunted ones (AOR 5.50, 95% CI: 2.83, 10.72). Underweight schoolchildren were 2.07 times more likely to be anaemic (Hb < 115 g/L) compared to children with normal weight (AOR 2.07, 95% CI: 1.06, 4.05). Other documented factors include fewer meals and food insecurity (Getaneh *et al*., 2017; Barugahara *et al*., 2013; and Turyashemererwa *et al*., 2013), high intake of plant-based foods (Barugahara *et al*., 2013), birth order (Abdel-Rasoul *et al*., 2014), soft drinks, tea and chips utilisation habit (Abdel-Rasoul *et al*., 2014) and irregular legume consumption (Mesfin *et al*., 2015) was least (6%) associated with anaemia in schoolchildren in SSA.

Table 3. Distribution of the child-related risk factors for anaemia

Risk factor	No. of Studies	References
Age of the child (being younger)	4/18 (22%)	(Assefa *et al*., 2014), (Mesfin *et al*., 2015), , (Ngesa & Mwambi, 2014), (Teh *et al*., 2018)
Sex of the child (being a male)	3/18 (16%)	(Gutema *et al*., 2014), (Barugahara *et al*., 2013), (Legason *et al*., 2017)
Intestinal worms/parasites, malaria, illness/infection	10/18 (56%)	(Alelign *et al*., 2015), (Gutema *et al*., 2014), (Adebara *et al*., 2011), (Getaneh *et al*., 2017), (Barugahara *et al*., 2013), (Onimawo *et al*. 2010), (A. Desalegn *et al*., 2014), (Ngesa & Mwambi, 2014), (Teh *et al*., 2018) , (Legason *et al*., 2017)
Nutritional status, BMI, height, weight, stunting, wasting, underweight, overweight, obesity	5/18 (28%)	(Gutema *et al*., 2014), (Getaneh *et al*., 2017), (Erismann *et al*., 2017), (Ngesa & Mwambi, 2014), (Legason *et al*., 2017)
Eating less protein and vegetables	6/18 (33%)	(Assefa *et al*., 2014), (Turyashemererwa *et al*., 2013), (Abdel-Rasoul *et al*., 2014), (Mesfin *et al*., 2015), . (Desalegn *et al*., 2014), (Legason *et al*., 2017)
High intake of plant-based foods	1/18 (6%)	(Barugahara *et al*., 2013)
Fewer meals/food insecurity	3/18 (17%)	(Turyashemererwa *et al*., 2013), (Barugahara *et al*., 2013); (Getaneh *et al*., 2017)
Birth order	1/18 (6%)	(Abdel-Rasoul *et al*., 2014)
Soft drinks/tea/chips utilisation habit	1/18 (6%)	(Abdel-Rasoul *et al*., 2014)
Irregular legume consumption	1/18 (6%)	(Mesfin *et al*., 2015)

Distributions of parental and caregiver-related risk factors for anaemia

Table 4 presents the distribution of the parental and caregiver-related risk factors for anaemia. It was noted that comorbidities of anaemia were associated with the mother's education level in 22% of the studies reviewed. The risk of anaemia was 1.57 times higher in children whose mothers had no education than children whose mothers had post-secondary education (OR: 1.569, 95% CI:1.09, 2.259) (Ngesa & Mwambi, 2014). Fathers' education level had a protective effect on the risk of anaemia in their children (Mesfin *et al*., 2015; Abdel-Rasoul *et al*., 2014). In addition, the occupation of parents (being employed) was a significant determinant in the non-occurance of anaemia in children (Mesfin *et al*., 2015; Abdel-Rasoul *et al*., 2014). However, maternal parity of ≤4 (Legason *et al*., 2017), marital status of parents (being married) and maternal age (being young) (Getaneh *et al*., 2017) were least mentioned in previous studies in associating anaemia among schoolchildren in SSA.

Table 4: Distribution of the parental and caregiver-related risk factors for anaemia

Risk factor	No. of Studies	References
Paternal education level	2/18(11%)	(Mesfin *et al*., 2015), (Abdel-Rasoul *et al*., 2014)
Education of mothers	4/18 (22%)	(Assefa *et al*., 2014), (Ngesa & Mwambi, 2014), (Abdel-Rasoul *et al*., 2014), (Getaneh *et al*., 2017)
Occupation of parents	2/18 (11%)	(Abdel-Rasoul *et al*., 2014), (Mesfin *et al*., 2015)
Occupation of mothers	1/18 (6%)	(Getaneh *et al*., 2017)
Marital status of parents	1/18 (6%)	(Getaneh *et al*., 2017)
Maternal parity	1/18 (6%)	(Legason *et al*., 2017)

Distributions of household-related risk factors for anaemia

Among household-related risk factors, socio-economic status (SES) has been frequently associated with anaemia in schoolchildren in 33% of the studies (Table 5). A study conducted in Southern Ethiopia revealed that the Odds of being anaemic among children whose family's monthly income was less than 500 Ethiopian Birr (about 9$) were 9.44 times higher than among children whose family's monthly income was greater than 2000 Ethiopian Birr (AOR 9.44, 95% CI:2.88, 30.99) (Gutema *et al*., 2014). Several studies (Legason *et al*., 2017; Alelign *et al*., 2015; Desalegn *et al*., 2015; Abdel-Rasoul *et al*., 2014; Gutema *et al*., 2014; Ngesa & Mwambi, 2014) have associated various SES with anaemia in children from SSA. Anaemia was also observed to increase with the increasing number of children in a household (11%) (Mesfin *et al*., 2015). A similar pattern was recorded by other researchers (Legason *et al*., 2017; Abdel-Rasoul *et al*., 2014), who indicated bigger families of ≥ 5 members were at a greater risk of anaemia. Household food insecurity (Getaneh *et al*., 2017) and level of sanitation (Mesfin *et al*., 2015) were the least (6%) reported household-related risk factors for anaemia in schoolchildren.

Table 5: Distributions of household-related risk factors for anaemia

Risk factor	No. of Studies	References
Number of children	2/18 (11%)	(Mesfin *et al*., 2015)
Family size	2/18 (11%)	(Abdel-Rasoul *et al*., 2014), (Legason *et al*., 2017)
Food insecurity	1/18 (6%)	(Getaneh *et al*., 2017)
SES	6/18 (33%)	(Alelign *et al*., 2015) , (Abdel-Rasoul *et al*., 2014), (Gutema *et al*., 2014), (A. Desalegn *et al*., 2014), (Legason *et al*., 2017), (Ngesa & Mwambi, 2014)
Level of the practice of sanitation	1/18 (6%)	(Mesfin *et al*., 2015)

Distribution of community-related risk factors for anaemia

Community-based risk factors were the least reported factors for anaemia in schoolchildren in all the articles reviewed (Table 6). A place where a school was located (urban/rural) was associated with child anaemia in SSA. For instance, a study by Barugahara *et al*. (2013) revealed that the prevalence of anaemia was twice as high in urban schools compared to rural schools. Furthermore, Abdel-Rasoul *et al*. (2014) revealed that anaemia was higher in children from urban areas (63.8%) than in rural areas (36.2%). Other factors, such as school management system and altitude, were reported to be the least (6%) associated with anaemia among schoolchildren of SSA.

Table 6: Distribution of community-related risk factors for anaemia

Risk factor	Number of Studies	References
School management (Government, private)	1/18 (6%)	(Daboné *et al*., 2011).
Location (rural, urban)	2/18 (11%)	(Barugahara *et al*., 2013), (Abdel-Rasoul *et al*., 2014)
Altitude (high/low)	1/18 (6%)	(Teh *et al*., 2018)

DISCUSSION

The review aimed to determine the prevalence and risk factors for anaemia across SSA. Anaemia is one of the significant public health problems among schoolchildren of SSA, ranging from 11% (Ethiopia) to 83% (Nigeria). The findings from the current review agree with various studies (Alaofè *et al*., 2017; Ayogu *et al.*, 2015; Ngui *et al*., 2012). The higher prevalence of anaemia in the current review was partly caused by low consumption of iron-rich foods (Bakar, 2016; Ochola and Masibo, 2014). Therefore interventions to prevent and correct anaemia are necessary. Some of these interventions are dietary diversification and iron fortification. Another intervention includes nutrient supplementation, especially iron and vitamins, in schoolchildren who are at higher risk of developing anaemia.

Analysis of the findings on the risk factors indicated that child-related factors were the most associated with an increased risk of developing anaemia among schoolchildren in SSA. Most of the reviewed studies reported that infection was significantly associated with anaemia among schoolchildren. This experience is almost similar to what was reported by other researchers. For instance, infections such as general infection (Alaofè *et al*., 2017), intestinal parasites (Ayogu *et al*., 2015; Al-Zabedi *et al*., 2014; Ngui *et al*., 2012) and malaria (Ayogu *et al*., 2015; Foote *et al*. 2013) were significantly associated with anaemia among schoolchildren. Possible reasons for the association could be chronic intestinal blood loss, increased nutrient demand, reduced intake and malabsorption of food nutrients resulting from an illness. Therefore, measures for improved health services and sanitation are necessary to prevent worms and other infections, which will likely facilitate anaemia development among older children. Available data show that infrequent intake of protein and vegetables was linked to anaemia in children. This is in line with earlier reflection by other researchers (Purba *et al*. 2019; Alaofè *et al*. 2017; Choi *et al*. 2011). Inadequate consumption of protein and vegetables may contribute to low protein and micronutrient intake, both of which play an important role of a carrier and enhancer of iron absorption. Therefore, inadequate supply may lower iron absorption in the body.

Most of the reviewed articles documented that younger and older children were equally affected. These findings concurred with the results from Nigeria, whereby both younger children (<10 years) (Al-Zabedi *et al*., 2014) and older children (≥10 years) (Olumakaiye, 2013) were equally affected by anaemia. This was attributed to the fact that most children in developing countries mainly consume plant-based diets, predominantly from cereals, roots and tubers. Overconsumption of plant-based food with limited animal source foods rich in bioavailable iron and Vitamin B_{12}, is likely to increase the risks of developing anaemia (Rauber *et al.*, 2014 Tidemann-Andersen *et al*., 2011). The risk of anaemia among children was significantly greater with nutritional status. For example, stunting was found to be significantly associated with anaemia among Beninese schoolchildren (Alaofè *et al*., 2017). This might be due to the long-term effect of low intake of macro and micronutrients, especially iron, vitamin B12, folate and other minerals and vitamins associated with anaemia. In addition, being overweight and obese was a significant predictor of the development of anaemia. Obesity is associated with iron deficiency partly because anaemia may lead to fatigue, reducing physical activity and further aggravating weight gain.

In the present review, maternal education was an important factor in the non-occurrence of anaemia among schoolchildren. This supports findings from studies by various authors (Achouri *et al*., 2015; Al-Zabedi *et al*., 2014; Foote *et al*., 2013; Abubakar *et al*., 2012; Choi *et al*., 2011). Maternal education status (being educated) greatly affects child health, nutrition, growth and development. An educated mother will likely plan better meals than mothers with no formal education. In addition, educated mothers are financially well, hence likely to purchase an animal based food and their products, which are richer in haem iron (Choi *et al*., 2011). Furthermore, mothers with no formal education are likely to be negatively affected by low income, limiting food purchasing power. Hence, their children's access to haem iron sources is limited.

Mothers with no formal education are unlikely to practice proper health-seeking behaviours. As a result, a child is left susceptible to infection. As with African culture, the review revealed that fathers' education status is the least predictor of anaemia in schoolchildren. The fact that fathers are not directly involved in child-caring practices such as meal planning, preparation and health seeking, their contribution to improved nutritional status is generally negligible, hence not a strong determinant for anaemia. It was further noted that low household income contributes to anaemia among schoolchildren. This agrees with several studies (Alaofè *et al*., 2017; Rani & Bandrapalli, 2017; Cardoso *et al*., 2012; Ngui *et al*., 2012). One of the assumptions is that households from lower SES are unlikely to be able to purchase foods with haem iron in comparison to their counterparts.

Anaemia has extremely negative implications for children at risk of impaired growth and cognitive development, lower mental and motor function, poor work capacity and a generally lower quality of life. The results of the current review have made a novel contribution to the area of schoolchildren who were less researched. Considering higher rates of anaemia among schoolchildren, mitigating strategies are necessary. This includes interventions such as promoting dietary diversity, supplementation, fortifications and treatment of malaria and worm infestation. Iron supplementation is one of the effective ways however, it is mostly focusing pregnant and lactating women. This review indicates that infection and poor iron-rich food sources are major predictors of anaemia among schoolchildren. It is further suggested that iron supplementation with infection treatment, especially in malaria-endemic areas, should be administered concurrently in addressing anaemia incidences. Some of the avenues for future research could be to explore the implementation of the proposed intervention, whether continuous or periodic considering issues of toxicity and cost implications.

Strengths and limitations of the current review

The strength of the current review is its focus on anaemia among schoolchildren who are most vulnerable because of their higher iron need to meet the demands of puberty and adolescence. Anaemia is associated with Schoolchildren from SSA are highly affected by anaemia. This review established that the occurrence of anaemia was largely associated with infection. Furthermore, children who consumed protein and plant-based foods less frequently were more likely to develop anaemia than those who frequently used these foods. In addition, age of a child, the nutritional status, such as wasting underweight, stunting, overweight and obesity were predictors of anaemia in schoolchildren from SSA. Effective public health strategies such as biofortification of poor growth and cognitive development, lowered immunity, increased risk of infectious diseases, and reduced work productivity. Furthermore, little attention has been paid in this age group of 5-18 years in most of SSA countries, despite its significance in the development. There are a few limitations to this review. First, the current review restricted itself to published English-language articles. Therefore, the inclusion of non-English published articles may have affected the findings of this review. The use of data from a cross-sectional study design might not reflect a true cause-and-effect relationship between the variables. In addition, the findings from cross-sectional study might also have been affected by recall bias. Furthermore, the definition of schoolchildren differs across articles. Some studies started with pre-scholars, while others started with primary school and others with lower secondary levels. This very wide age gap is likely to bring discrepancies in the study findings. For example, a three-year-old child is quite different from a ten-year-old plus child.

CONCLUSION

Food are needed to improve micronutrient intake among older children.

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Competing interests

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Abundance and Distribution of Microplastics in Fish and Sediments from Coastal River Watersheds of Dar es Salaam, Tanzania

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Abstract

Different reports indicate that microplastics have been environmental pollutants which are engulfed by aquatic organisms also are carriers of other toxic chemicals. This study aimed to characterize and determine the spatial distribution of microplastics in sediments and fish in Dar es Salaam. The study had to indicate the extent of plastic pollutants in the urban watersheds. Fish and sediment samples were collected from river watersheds and ponds. Gastrointestinal parts were digested using 10% KOH and incubated at 65 °C for 24 hours while sediment samples were extracted using the floatation method in 4 M NaOH and 3 M NaI solutions. The identity of microplastics was determined by an attenuated Fourier transform infrared spectrophotometer. The concentrations of microplastics were 94 ± 24 particles/kg for fish samples from River Msimbazi watershed ponds and 46 ± 16 particles/kg for fish samples from River Mzinga watershed ponds. The concentrations of microplastics in sediments were: 64 ± 35 particles/m^2 for the River Mzinga watersheds and 25 ± 18 particles/m^2 for River Msimbazi watersheds. The microplastics observed were polypropylene, polyethene, polyurethane, polyamide, polyvinyl chloride, polyethene terephthalate, and polytetrafluoroethylene. The microplastics were in the form of fragments, sponges, and fibres. The results confirmed that fish living in river watershed ponds in Dar es Salaam were exposed to microplastics and that sediments had microplastics. Further studies need to be performed to find out micro-pollutants adsorbed by microplastics in the river watersheds.

Keywords: *Dar es Salaam River watersheds; Microplastics; pond fish; spatial distribution; sediments*

INTRODUCTION

World plastic production has increased from 1.7 million tons to 348 million tons which has led to approximately 14 million tons of plastics being dumped as waste which degrade into microplastics (Mistri, 2022). Large proportions of plastic wastes are mismanaged so they enter the aquatic environments where they evolve into microplastics via progressive fragmentation

(Gewart, 2015; Zhang, 2017; Wang 2018; Adams *et al.,* 2021). Microplastics have a size which is less than 5 mm which can be primary in origin (purposely made) or secondary in origin (obtained through the degradation process) (Carson, 2013; Vermeiren *et al.,* 2016). Microplastics have been observed in freshwater and marine sediments, for example in the River Thames catchment in the United Kingdom, sediment samples had microplastics with an average abundance of 165 particles/kg (Tibbetts *et al.,* 2018). Microplastics in rivers remain in the watersheds during physical transport by stormwater while some are carried into the ocean.

Microplastic pollution in water and sediments has a potential life impact on aquatic organisms. Microplastics can be ingested by aquatic organisms like crustaceans and fish because of their small size (Oladejo, 2017; Turra *et al.,* 2014; Wang, 2018). Studies have shown microplastic presence in the fish gut, for example, fish from the northern Bay of Bengal in Bangladesh had microplastics with a range of 5.80 ± 1.4−8.72 ± 1.54 particles/kg (Hossain *et al.,* 2019). Animals exposed to microplastics in a laboratory setting have shown several adverse effects like histological alterations, lesions in the gastrointestinal tract, intestinal inflammation, neurotoxicity, oxidative stress, damage, immuno-regulation, feeding behavioural change, and developmental alterations (Jovanovic, 2017).

Most studies about microplastics in fish and sediments in African regions have been performed in seawater compared to fresh water like lakes, dams, ponds, and rivers. That means there is little information documented about microplastic contamination of freshwater bodies in many countries in Africa. Tanzania is one of the African countries that produce and utilize plastic goods in large amounts. Plastic waste has been a current problem in Tanzania's urban regions. Dar es Salaam City in Tanzania is one of the regions that are much affected by the disposal of plastic wastes in its water bodies. Solid waste generation that includes plastics has been increasing in Dar es Salaam City from less than 2000 tons per day in 2011 and the waste composition is 27% plastics (Fassin et al. 2017). This leads to the occurrence of microplastics in water bodies (sea and river water). Microplastics in river streams are carried to the ocean but during the rainy season are also distributed in the watersheds and watershed ponds where they can be engulfed by pond fish (Cole et al. 2011). This study was conducted to assess the abundance and distribution of microplastics in freshwater fish and sediments from river watersheds of Dar es Salaam.

MATERIALS AND METHODS

Sampling Areas

The research was carried out in Dar es Salaam river watersheds and their ponds. The coastline of Dar es Salaam is located between latitudes 6° 27'S and 7° 15'S and longitudes 39°E and 39° 33'E. Samples of sediments for microplastic determination were collected from the River Mzinga and River Msimbazi watersheds (Figure 1), while samples of fish were collected from ponds found in the watersheds of Dar es Salaam. River Mzinga and Msimbazi were selected for study because of various anthropological activities and rainstorms accompanied by plastic wastes (Figure 2).

Figure 1: A Map showing the locations of River Msimbazi and River Mzinga

Figure 2: Plastic waste along River Msimbazi Watersheds in Dar es Salaam

Methods of Sample Collection

Fish samples from River Mzinga were collected at Toangoma ward while those from River Msimbazi were collected between Jangwani Valley and Kijitonyama Valley during the dry season. Three ponds were selected for the collection of fish samples from each river watershed using fish nets. A total of 32 fish samples were collected from the river watersheds: 18 fish samples from River Mzinga and 14 fish samples from River Msimbazi ponds. The samples were stored in an ice box and later were kept frozen in the laboratory. On the next day, the gastrointestinal parts (from the buccal cavity to the anal part) were removed and then separately frozen ready for microplastic determination.

The samples of sediments from the River Mzinga and River Msimbazi watersheds were collected during the dry season. Eight sampling points were identified along River Msimbazi; Buguruni Mivinjeni A, Buguruni Mivinjeni B, Kigogo Bridge, Car wash bridge area, Jangwani truck haulage area, Jangwani bridge area and Jangwani opposite to Muhimbili National Hospital area, Jangwani and Mwananyamala areas. For the case of River Mzinga, ten sampling points were identified at Zakiem Bridge, Car wash, Zakiemu Valley, Gardening, Mpangule, Zakiem, Mbagala Kuu, and Mbagala Mountain, Kibonde Maji A and Kibonde Maji B. The river sediment sampling points were at a distance of 100 m from one point and the next. The samples were collected downstream toward the ocean. At each sampling point, 1000 g of sediment sample was collected in the area of 50 cm x 50 cm, and at 1 cm and 5 cm depth respectively, using shovels, and were then kept in aluminium foil. The number of sediment samples collected from River Mzinga were 20 samples and from River Msimbazi were 16 samples.

Extraction

Extraction of Microplastics in Fish

The reagents (potassium hydroxide and sodium iodide salts) which were used in the extraction of microplastics were Analar compounds which were purchased from Chem Precur Company Limited. The gastrointestinal parts were placed in a 250 mL beaker then 150 mL of 2 M KOH (10% KOH) was added (Hermsea, 2018). The mixture of gastrointestinal parts and 2 M KOH in a beaker was then covered with aluminium foil to avoid contamination from outside and then warmed in a water bath at 64 °C for about 24 hours. The warmed mixture containing organic matter and other solid particles was left to cool followed by filtration using Whatman filter paper with the help of a filter pump. The particles in filter paper were collected in a 250 mL beaker, and then 50 mL of 3.3 M NaI solution was added for floatation of microplastics. The upper portion was decanted in a beaker followed by filtration using the Buchner funnel fitted with Whatman filter paper (a qualitative grade 1 filter paper with a pore size of 11 µm). The microplastics were preserved in vials for analysis using a stereomicroscope and an Attenuated Fourier Transform Infrared Spectrophotometer (At-FT-IR).

Extraction of Microplastics in Sediments

The extraction of microplastics in sediments followed manuals (Frias et al. 2019). The collected sediment samples were air dried in a laboratory until a constant weight. Then samples were sieved on a mesh (5 mm) so that the floatation could be handled more easily. An accurately weighed sediment sample (200 g) was placed in a 1000 mL beaker, thereafter, 300 mL of 4.4 M NaCl solution was added followed by a quick stirring for floatation of microplastics for 2 min. The mixture was left to settle down for 2 min to allow particles less than 1.2 g/cm^3 (the density of NaCl) to float. Later, the solution part containing debris and microplastics was decanted in a 500 mL beaker. A total of 300 mL of 3.3 M NaI (density of 1.8 g/cm^3) was then added to the remainder of the decantation to obtain microplastics with a density less than 1.8 g/cm^3. The two salts were used in the extraction of microplastics from the same sample to minimize costs. The extracts using NaCl and NaI were mixed to form one component, followed by filtration using Whatman filter paper (a qualitative grade 1 filter paper with a pore size of 11 µm). The microplastics on the filter paper were air-dried and collected in a 250 mL beaker ready for the next stage.

Recovery of Microplastics from Sediments

Polyethene (which is less dense than NaCl, 0.98g/cm^3), polyethene terephthalate (which is denser than NaCl, 1.38 g/cm^3), and polyvinyl chloride (denser than NaCl, 1.38 g/cm^3) microplastic pellets were selected for the recovery study. The Polyethylene pellets (20 particles) were spiked in 200 g sand sediments and then mixed thoroughly to get a uniform distribution of particles. The PE was extracted from the sand sediments using a solution of 4.4 M NaCl (300 L) in a 1000 mL beaker, followed by stirring, settling, decantation, filtration, drying, and counting. PETE and PVC were extracted using 3.3 M NaI solution because of their high density compared to NaCl solution. The process of extraction was done in triplicates. Microplastic recovery was 95% for PE, 80% for PVC, and 100% for PETE. That showed that the method was adequate for the extraction of microplastics.

Recovery of Microplastics from Fish

Fish from Farmers were collected for laboratory quality assurance of microplastic extraction. Gastrointestinal parts of the fish were accurately weighed and then spiked with selected microplastics (polyvinyl chloride, polyethylene and polyethylene terephthalates). The gastrointestinal parts were placed in a 250 mL beaker then 150 mL of 2 M KOH (10% KOH) was added. The procedure of extraction was the same as that of section 2.3.1. Microplastic recovery was 85% for PE, 77% for PVC and 91% for PETE. The results showed that the method was adequate for the extraction of microplastics from fish.

Analysis of Microplastics

Analysis of microplastics involves the determination of size, enumeration, and identification of microplastics (Frias *et al.* 2019).

Determination of Number and Size of Microplastics in Fish and Sediments

Large and visible microplastics (1000–5000 µm) were counted using the help of a hand lens (5x magnification) and a scalpel. The microplastics less < 1000 µm were placed in a Petri dish, and then a stereo binocular microscope (10 x magnification) was used to visualize the particles and count their numbers. All microplastic enumeration was recorded as the number of particles/kg for fish and particles/m^2 for sediments, according to the microplastics analysis protocol (Frias *et al.* 2019). It has to be noted that all sediment samples were collected at 0.5 x 0.5 m^2 while fish samples were weighed then the wet weights were recorded. Microplastic size analysis was performed using sieves of different pore sizes. Fibres were measured using a veneer calliper with the help of a hand lens and stereo microscope. In this study, microplastics were grouped into sizes of 100–500 µm, 500–1000 µm, and 1000–5000 µm for all fragments, fibers and sponges.

Identification of Plastics

Identification of microplastics was performed using an Attenuated Fourier Transform Infrared Spectrophotometer (At-FT-IR, Bruker, Massachusetts, USA), available at Chemistry Laboratory, University of Dar es Salaam. Standards of polypropylene (PP), polyethene (PE), polyvinyl chloride (PVC), polystyrene (PS), polyethene terephthalate (PET), polyurethane (PU) and polyamide (PA) microplastics were run in the At-FT-IR instrument to obtain their spectra before the analyses of microplastics samples. The resolution was set at 4 cm^{-1}. The Attenuated total reflection (ATR) crystal was cleaned with acetone and a background scan was performed between each sample. Microplastic particles which were analysed for identity were extracts of 62 sediment samples and 18 fish samples. Each particle was compressed against the diamond to ensure good contact between the particle and the ATR crystal, according to the manufacturer's specifications. The At-FT-IR instrument collected spectra from 4000 cm^{-1} to 450 cm^{-1} at a data interval of 1 cm^{-1}. The spectra were collected using Micro lab computer software in transmittance mode. The absorption bands of microplastics which were identified using a peak height algorithm within the Bruker software were recorded and compared to the absorption bands of each polymer reported in the literature and the standard spectra.

Data Analysis

Excel Analysis ToolPak was used for summarizing the raw data into means, standard deviation and range of microplastic concentrations in sediments and fish samples. The one way-ANOVA was used to compare the mean concentrations of sediment microplastics from different sampling points, depths and sites where the number of laboratory bench sediment samples (n); for River Mzinga, n = 62 and River Msimbazi, n = 42.

RESULTS AND DISCUSSION

Microplastic Occurrence in Watershed Sediments and Fish

Microplastic Occurrence in Watershed Sediments

The concentration (mean ± standard deviation) of microplastics in sediments from River Mzinga at 1 cm was in the range of 14 ± 0 particles/m^2 to 106 ± 0 particles/m^2, while at 5 cm was in the range of 14 ± 9 particles/m^2 to 128 ± 11 particles/m^2. The overall average concentration of microplastics in the River Mzinga watersheds was 64 ± 35 particles/m^2. The statistical analysis (one way-ANOVA) indicated that there was no significant difference in mean concentration between depths ($p = 0.38$) also there was no significant difference between points in River Mzinga ($p = 0.9$).

The concentration (mean ± standard deviation) of microplastics in River Msimbazi at 1 cm was in the range of 6 ± 0 particles/m^2 to 54 ± 8 particles/m^2 while at 5 cm was in the range of 6 ± 0 particles/m^2 to 86 ± 8 particles/m^2. River Msimbazi watersheds had an overall average concentration of 26 ± 18 particles/m^2 (Table 1). The statistical analysis (one-way ANOVA) indicated that there was a significant difference in mean concentration between the depth ($df = 31$, $p = 0.01$) and that there was no significant difference in the mean concentration of microplastics between points in River Msimbazi ($p = 0.9$).

The mean concentration of microplastics in watersheds (River Mzinga and River Msimbazi) was 45 ± 27 particles/m^2. The statistical analysis (one-way ANOVA) indicated that there was no significant difference in mean concentration ($p = 0.06$) between River Mzinga and River Msimbazi.

The occurrence of microplastics in all sampling points in River Mzinga and River Msimbazi is an indication that watersheds in Dar es Salaam urban being contaminated by microplastics. There were anthropological activities like plastic waste disposal, agricultural practices, motor vehicle garages and plastic goods industries which were performed near and far from the river valleys. Rainstorms collect plastic wastes into River Mzinga valley from Mbagala, Toangoma and Mzinga urban areas which are highly populated by human settlements and industries. This also was the same with River Msimbazi where there were various anthropological activities which were performed along the valley of Msimbazi (Figure 2). Rainstorms collect plastic wastes into River Msimbazi from various industrial, markets, garages and populated domestic areas of Buguruni and Chang'ombe. Msimbazi Valley extends to Jangwani Valley which receives plastic wastes from Magomeni populated settlements and River Ng'ombe which passes through Mwananyamala Valley. Either the differences in geographical physical features along the river had a great influence on retaining microplastics at the point, for example, River Mzinga has a large land plain which has many bushes and grasses. The results for concentration levels of microplastics in river watershed sediments in this study are similar to those reported in urban rivers from other parts of the world. For instance, the study on River Thame and four of its tributaries in Birmingham city in the UK reported that all sediment samples were found to contain microplastics with an average abundance of 165 particles/kg (Tibbetts *et al.,* 2018). Li et al., (2019) also reported that microplastic concentration in river estuaries in Maowei Sea ranged from 520 ± 8 to 940 ± 17 items/kg. Furthermore, Hitchcock and Mitrovic, (2019) reported that microplastics were in the pattern in such a way that the lowly human-impacted estuary in Bega in Australia had 98 particles/m^3 and the highly human-impacted estuary had 246 to1032 particles/m^3. In this study, microplastics have been found in all sampling points in River Mzinga as well as in River Msimbazi. These results are similar to the study in the River Thames Basin (UK) by Horton *et al.,* (2017) which reported the presence of microplastics at all four sites where one site had a significantly higher number of microplastics than other sites in a range of 16 to100 particles/kg. The microplastic concentration levels in this study did not differ much downstream as was reported in other similar studies by Widigdo et al., (2017) in Citanduy River, West Java, where the highest microplastic abundance was in the downstream area, followed by the upstream with the concentration of 18, 70−190, 405 particles/m^2. This might be due to geographical features like vegetation cover found along the river watershed area.

Table 1: Concentration (mean ± standard deviation) of Microplastics in Sediments at Different Points and Depth

River Msimbazi Average Microplastics (mean ± standard deviation), particles/m^2					
	Depth		**Depth**		
Point	**1 cm**	**n**	**5 cm**	**n**	**Point Mean**
1	6 ± 3	3	6 ± 3	3	6 ± 0
2	26 ± 14	3	36 ± 0	3	31 ± 7
3	8 ± 0	3	18 ± 3	3	13 ± 7
4	8 ± 3	3	ND	3	8 ± 0
5	8 ± 0	3	14 ± 3	3	11 ± 4
6	20 ± 6	3	86 ± 8	3	53 ± 47
7	42 ± 8	3	46 ± 19	3	44 ± 3
8	54 ± 8	3	26 ± 3	3	40 ± 20
Mean	38 ± 18		33 ± 30		26 ± 18

River Mzinga Average Microplastics, particles/m^2					
	Depth		**Depth**		
Point	**1 cm**	**n**	**5 cm**	**n**	**Point Mean±std**
1	106 ± 3	3	ND	3	106 ± 0
2	14 ± 8	3	ND	3	14 ± 0
3	70 ± 59	3	ND	3	70 ± 0
4	54 ± 3	3	34 ± 8	3	44 ± 14
5	26 ± 3	3	70 ± 14	3	48 ± 31
6	ND	3	128 ± 11	3	128 ± 0
7	26 ± 3	3	102 ± 8	3	64 ± 54
8	52 ± 17	3	14 ± 8	3	33 ± 27
9	60 ± 11	3	36 ± 7	3	48 ± 17
10	60 ± 11	3	118 ± 8	3	89 ± 41
Mean ± std	52 ± 28		72 ± 45		64 ± 35

ND= Not Detected, std = standard deviation, n = number of laboratory bench sediment samples.

Microplastic Occurrence in Watershed Fish

The concentration (mean ± standard deviation) of microplastics in fish from ponds in the River Mzinga watershed was in the range of 32.54 ± 26.1 to 50.32 ± 20.67 particles/kg while in River Msimbazi watershed was in the range of 17.5 ± 13.44 to 35.67 ± 16.20 particles/kg. The average concentration of microplastics in fish from all ponds was 33.81 ± 7.66 particles/kg (Table 2). The statistical analysis of samples of fish, one way-ANOVA, from ponds in watersheds indicated that there was no significant difference in the mean concentration of microplastics ($p = 0.2$).

The results in this study for the occurrence of microplastics in fish imply that freshwater fish engulf microplastics. The study was performed during the dry season; therefore these results also imply that there is the distribution of microplastics in both watershed sediments and watershed ponds during the rainy season which in turn were engulfed by fish. There is a similarity between the results for an abundance of microplastics in fish in this study and those from other studies. For instance, the concentration of microplastics in fish from the Northern Bay of Bengal in Bangladesh was 443 particles/kg (Hossain et al., 2019). Mistri *et al.*, (2022) reported that 47.8% of examined fish from the Adriatic Sea contained 233 fragments of microplastics with a mean concentration of 4.11 ± 2.85 particles/kg. From the Southern Northern Sea, Witte *et al.,* (2022) reported that fish had a concentration of 0.48 ± 0.81 to 0.26 ± 0.64 particles/kg.

Table 2: Mean Concentration of Microplastics in Fish from Watershed Ponds

	Mean Concentration in Ponds, /Particleskg-1			
Pond	1	2	3	Mean
Mzinga	32.54±26.1	50.32±20.67	34.79±0.00	39.22±8.00
Msimbazi	32.00±28.15	35.67±16.2	17.5±13.44	28.39±9.61

Physical Properties of Microplastics in Watershed Sediments and Fish

Physical Properties of Microplastics in Watershed Sediments

Microplastics in sediment samples from watersheds were in the form of fragments, fibres, and pellets. Fibres had size of 1000-5000 µm which had a concentration (mean ± standard deviation) range of 4 ± 3 to 40 ± 6 particles/m^2. Fragments had sizes of

100−500 µm for small microplastics and 1000−5000 µm for large microplastics. The fragments with the size of 100−500 µm had a concentration range of 4 ± 1 to 44 ± 3 particles/m^2. Fragments with the size of 1000−5000 µm had a concentration range of 4 ± 3 to 60 ± 5 particles/m^2 Pellets had a size range of 1000−5000 µm (Table 3). In River Mzinga watersheds, microplastics in the form of fragments were more abundant at 46.30% of the total mean concentration of microplastics followed by fibres which had 31.48% of the total mean concentration and lastly, pellets which had 22.22% of the total mean concentration. In the River Msimbazi watersheds, microplastics in the form of fibres were more abundant by 56.10% of the total mean concentration of microplastics and fibres had 43.90% of the total mean concentration (Figure 3). Generally, in watersheds, fragments were more concentrated at a depth of 5 cm by 59.02% of total fragment concentration while 40.02% of total fragment concentration was at a depth of 1 cm. Fibers were 100% concentrated at 5 cm as well as pellets (Table 3). Therefore, microplastics were highly found at depths greater than 1 cm which might be because of burial effects by physical factors like wind and sediment movements.

Table 3: Distribution of Shapes, Size and Concentration (mean ± standard deviation) of Microplastics in Sediments

Size and Shapes of Microplastics in Sediment Samples from River Mzinga

			Point										
Depth	Shape	Size Range	1	2	3	4	5	6	7	8	9	10	Conc
1 cm	Fragment	100-500	12±3	ND	ND	ND	ND	ND	ND	ND	ND	ND	12±0
		1000-5000	20±2	12±1		36±3	4±3	ND	16±7	ND	24±23	8±3	17±11
	Fibers	100-500	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
		1000-5000	17±4	ND	ND	ND	ND	ND	20±2	12±8	4±3	10±8	13±6
	Pellets	100-500	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
		1000-5000	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
5 cm	Fragments	100-500	ND	ND	ND	ND	ND	ND	44±4	ND	ND	44±3	44±0
		1000-5000	ND	ND	12±6	22±20	8±0	60±5	ND	20±7	16±6	32±0	24±18
	Fibers	100-500	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
		1000-5000	ND	ND	ND	ND	32±5	40±6	4±2	ND	12±0	32±5	21±16
	Pellets	100-500	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
		1000-5000	ND	ND	ND	ND	ND	12±2	ND	ND	ND	ND	12±2
		Mean±sdev	16±4	12±0	12±	29±10	15±15	37±24	21±17	16±7	14±8	25±16	

Size and Shapes of Microplastics in Sediments from River Msimbazi

			Point								
Depth	Shape	Size Range	1	2	3	4	5	6	7	8	Conc
1 cm	Fragments	100-500	4±1	12±2	ND	ND	ND	16±3	ND	24±2	14±7
		1000-5000	ND	244±3	8±2	ND	8±2	ND	ND	ND	87±136
	Fibers	100-500	ND	ND	ND	ND	ND	ND	ND	ND	ND
		1000-5000	ND	32±1	ND	8±1	ND	4±1	40±2	24±1	22±15
5 cm	Fragment	100-500	ND	4±0	ND	ND	ND	60±3	ND	20±3	28±29
		1000-5000	12±0	ND	36±2	ND	4±0	4±1	48±2	4±1	18±19
	Fibres	100-500	ND	ND	ND	ND	ND	8±2	ND	ND	8±0
		1000-5000	ND	ND	ND	ND	20±1	ND	ND	4±0	12±11
		Mean±sdev	8±6	73±115	22±20	8±0	20±11	18±24	44±6	15±10	

Conc = Concentration

Microplastics in form of fragments from sediments originated from degradation of large plastics utilized in markets, domestics, garages, industries, agricultural and other fields which were carried by rain floods from different urban areas to River Mzinga and Msimbazi. Examples of degraded plastics were films, plastic bags, soft drink bottles, jugs, buckets, food packages, cups, and pipes which were common in Dar es Salaam good plastic market. Microplastics in form of fibers mostly originate from plastic degradation of ropes, carpets, toothbrushes, fishing nets, clothes, saloon wigs, bags and other plastics which were also common in the Dar es Salaam plastic good market.

The results for forms of microplastics conform with reports from other studies for example from River Thames and its distributaries in Birmigham city in United Kingdom where it was seen that the forms of microplastics in sediments were 22% fibers, 49% fragments and 15% sponges and at each sampling location the size < 1mm was the greatest abundance and 2-4 mm was least abundant (Tibbetts *et al.*, 2018), while from River Thames Basin in United Kingdom 91% were fragments and the rest were fibers (Horton *et al.*, 2017). Fragments are reported in studies to be in most abundance compared to other forms of microplastics, Hoellein *et al.*, (2018) at the University of Notre Dame's, USA, due to reason that depositional velocity is highest for fragments, intermediate for fibers and lowest for pellets.

Physical Properties of Microplastics in Fish

Microplastics in fish from watershed ponds were in the form of fibers, fragments and sponges. Fragments had size range of 100−500 µm for small microplastics, while large microplastics had size of 500−1000 µm. The fragments with size 100−500 µm had concentration range of 8 ± 0 to 50 ± 29 µm with mean of 31 ± 15 particles/kg while those with size of 500-1000 µm had mean concentration of 120 ± 26 particles/kg. Fibers had size range of 1000−5000 µm. The concentration range of fibers was 27 ± 0 to 53 ± 0 particles/kg with mean of 33 ± 5 particles/kg. The sponge size was 1000−5000 µm with mean concentration of 17 ± 23particles/m^2 (Table 4). The fragments in fish were more abundant with 75.12% of total concentration, fibers 16.42% and sponge 8.46 % of the total concentration. This indicates that fish could engulf different forms of microplastics in water. Mayoma et al. 2020 also reported the occurrence of microplastics in 48% of all collected cockles' samples in East African Coastline Beaches (138 microplastics in tissues), although the different forms were not indicated in the report.

Table 4: Concentration (mean ± standard deviation) and Forms of Microplastics in Sediments and Fish from River Watersheds

		River Mzinga		River Msimbazi	
		Size	Particles/m^2	Size	Particles/m^2
Pond	Fragments	100−500	33 ± 26	100−500	29 ± 10
I	Fibers	ND	ND	1000−2000	37 ± 33
Pond	Fragments	100−500	50 ± 29	500−1000	120 ± 26
II	Fibres	4000−5000	53 ± 0	2000−3000	35 ± 16
	Sponges	ND	ND	500−1000	33 ± 0
Pond	Fragments	100−500	35 ± 0	500−1000	8 ± 0
III	Fibres	ND	ND	1000−1500	27 ± 0

Microplastics in the different forms found in fish are an indication that fish can engulf microplastics without selection. The results show that fragments are engulfed in large amounts may be due to the great occurrence in the environment as has been found in sediments in section 3.2.1. This was because the fishponds were within the watershed area. The findings in this study are similar to those found in other studies in sizes although there are some differences in concentrations. For example, Hossain *et al.*, (2019) reported that fibre dominated in *S. gibbosa* with 55%, followed by fragments (26%) and particles (19%) (fibres up to 5810 µm and fragments up to 4333 µm were retained in gills of the studied specimens. The overall size of microplastics closely overlaps with those documented in other studies, such as 100 to 1000 µm, from gills of Minho estuary fish microplastics had size of 159–5810 µm (Abbasi et al., 2018).

Identity of Microplastics in Fish and Sediments

Identity of Microplastics in Sediments

The polymer types for microplastics in sediments from River Mzinga and Msimbazi watersheds were polyethene, polypropylene, polyurethane, polyamide, and polyvinyl chloride (Figure 4). The concentration (mean ± standard deviation) of polyethylene was in the range of 4 ± 2 to 84 ± 0 particles/m^2. The concentration of polypropylene was in the range of 4 ± 0 to 68 ± 0 particles/m^2. The concentration of polyamide was in the range of 4 ± 3 to 36 ± 0 particles/m^2. The mean concentration of polyurethane was 20 ± 28 particles/m^2. The concentration of polyvinyl chloride was in the range of 1-0 to 8 ± 17 particles/m^2 (Table 5). Polyethene was more abundant at 29% of the total concentration, polyamide at 28.49%, polyurethane was 17.15% of the total concentration, polypropylene at 19.83% and lastly, polyvinyl chloride that had 5.17%.

Table 5: Type of Microplastics and concentration (mean ± standard deviation) in Sediment and Fish from River Watersheds

Site	Type	Sampling Point										
River Mzinga		1	2	3	4	5	6	7	8	9	10	Conc
	PU	40±0	ND	ND	4±0	ND	ND	ND	ND	ND	ND	22±25
	PA	ND	ND	ND	12±0	ND	ND	4±0	28±28	22±8	32±26	32±20
	PE	ND	12±0	24±0	28±11	45±45	96±0	24±0	16±0	44±6	84±0	41±30
	PP	68±0.	8±0	4±0	16±0	40±11	32±0	20±0	ND	ND	ND	27±22
	PVC	ND	ND	ND	ND	ND	ND	52±73	ND	ND	ND	8±17
River Msimbazi	PA	ND	36±0	ND	ND	ND	ND	ND	32±0			34±3
	PE	47±64	4±0	36±0	ND	8±0	12±6	60±0	24±0			27±21
	PP	ND	32±0	8±0	8±0	20±0	ND	40±0	4±0			19±15
	PVC	ND	ND	ND	ND	8±0	ND	ND	ND			1±16

Conc = concentration

The analysis of the particles demonstrated infrared absorption over the entire region of absorption from 4000−450 cm^{-1}. The polymer identity of the particles was determined by using the spectra microplastics absorption peaks mainly the functional group region of the IR spectrum (4000-1500 cm^{-1}) and in the fingerprint region (1500−500) cm^{-1}. Examples of absorption of which were extracted from fish and sediments were polyamide, polyethylene, and polypropylene (Figure 4).

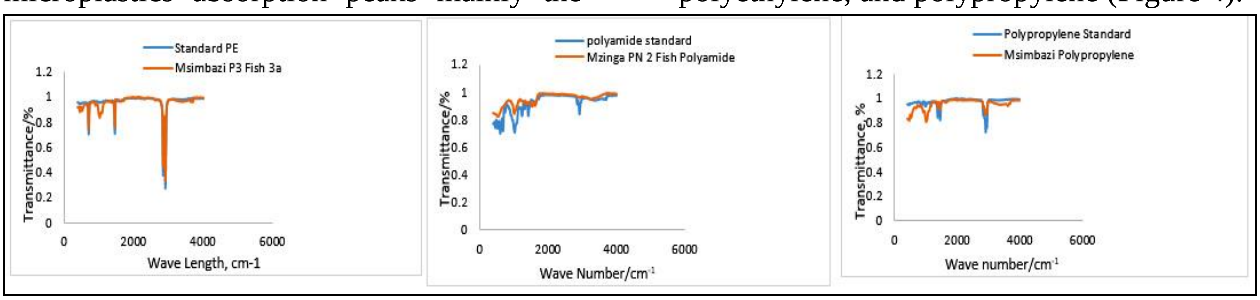

Figure 4: Superimposed At-FT-IR Spectra for standards and their matches from samples for polyethylene from fish, polyamide (nylon 6, 6) from fish and polypropylene from sediments

The identified microplastics in this study are similar those which have been reported in other studies in the light of commonly applied plastics. For example, the type of microplastics in sediments from river estuary in Maowei Sea and River Thames Basin in United Kingdom were reported by Li *et al.*, (2019) to be polyethylene and polypropylene: Polyethylene and polypropylene in this study were dominant in the occurrence because of their wide application in the market in Tanzania. Polyethylene is used in formation of plastics like shopping bags, film wrap, bubble wrap, bottles, buckets, cups, pipes and ropes. Polypropylene is used for formation of plastic ropes, carpets, fertilizer bags, bottle lids, plastic chairs, and sterile containers. There has been large amount of polyurethane microplastics which originate from degrading and deformed foam materials. The polyamide reported in this study might be originating from degradation of plastic fibers used in saloon and other utilities for clothes, fishing nets and ropes which were carried into the River Mzinga and Msimbazi.

Identity of Microplastics in Fish

The identified microplastics in Mzinga and Msimbazi River watersheds were polyurethane, polyethylene, polyamide and polyvinyl chloride. The concentration (mean ± standard deviation) of polyurethane was in the range of 19.64 ± 20 to 69.77 ± 0.00 particles/kg with average concentration of 39 ± 11 particles/kg, polyethylene was in the range of 28.57 ± 0.00 to 35.00 ± 0.00 particles/kg with average concentration of 33 ± 1 particles/kg, polyamide was in the range of 18.00 ± 30.00 to 53.63 ± 0.00 with mean of 33 ± 1 particles/kg and polyvinylchloride was in the range of 5.00 ± 0.00 to 68.57 ± 96 particles/kg with mean of 27.30 ± 35.78 particles/kg (table 6). Polyurethane was more abundant in watershed fish by 29.77% of total concentration, followed by polyamide with 25.19%, polyethylene with 24.43% and polyvinyl chloride 20.61% of total concentration. The type of microplastics found in pond fish are linked to those occurring in river watershed sediments, although they differ in concentration (Section 3.3.1).

Table 6: Type of Microplastics and concentration (mean ± standard deviation) in Fish from River Watersheds

	River Mzinga			River Msimbazi			
	PU	PA	PE	PU	PA	PE	PVC
Pond 1	32.53 ± 26.10	ND	ND	19.64 ± 20.71	41.06 ± 26.44	35.00 ± 0.00	5.00 ± 0.00
Pond 2	69.77 ± 0.00	52.63 ± 0.00	28.57 ± 0.00	33.34 ± 0.00	35.38 ± 16.23	33.34 ± 15	68.57 ± 96.92
pond 3	ND	ND	34.78 ± 0.00	ND	26.67 ± 0.00		8.33 ± 0.00
Mean±sdv	51.15 ± 26	18 ± 30	32 ± 4	26.49 ± 9.7	34.37 ± 7.2	34.17 ± 1.17	8.33 ± 358

The results indicate that fish could engulf different types of microplastics from the water environment. The source of microplastics in fish could be attributed to water, sediments, or other organisms in the food chain. The results which indicate the presence of microplastics in fish have been reported also in different kinds of literature although from different environments, for example, Hossain *et al.,* (2019) report that 13 particles/kg of polyethene terephthalate and 66 particles/kg of polyamide were found in fish from Northern Bay of Bengal at Bangladesh.

CONCLUSION

The purpose of this research was to determine the occurrence and speciation of microplastics in sediments and fish from watershed environments. Microplastics were found in sediments from all study sites (River Msimbazi and River Mzinga) in Dar es Salaam. However, all sampling points had sediment microplastics with different concentrations but a high concentration of microplastics was at 1 cm compared to 5 cm depth. The different forms of microplastics which were found contaminating sediments were fragments, fibres, sponges, and pellets. The type of microplastics identified were polypropylene, polypropylene, polyvinyl chloride, polyurethane and nylon 6.6. The study also indicated that the fish in watershed ponds had been contaminated by microplastics. The form of microplastics in fish were fibres of the type of polyamide and polypropylene, sponges of the type of polyurethane and fragments of the type of polyethene and polyvinyl chloride. These results indicated that the river watersheds were polluted with microplastics whose sources were more attributed to anthropological activities in the urban area together with the influence of rainstorms. The occurrence of microplastics in watersheds and watershed pond fish implies that there is a need for further studies on the dissemination of other toxic chemicals which tend to be adsorbed by microplastics in freshwater bodies.

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Human Health Risks from Exposure to Heavy Metals in Water from Great Ruaha River Serving Domestic Purpose in Pawaga Division

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Abstract
River water and banks could be very busy with varied activities ranging from farming to small industrial activities and other domestic household activities. The present study aimed at investigating the potential human health risks from selected heavy metal contaminants in Ruaha River water at the Kilolo division. To assess potential human health risks the concentration data for six heavy metals (Fe, Mn, Cu, Pb, Zn, and Cd) during the wet and dry seasons from four (4) villages were analyzed using Atomic Absorption Spectrophotometer. The observed mean concentration of heavy metals during the wet season is in the following order: Fe > Zn > Cu > Mn > Pb > Cd > Al. During dry season is in the following order: Fe > Cu > Zn > Mn > Al > Cd= Pb. The HQ_{ing} of Cd ranges from 0.000 – 9.000 while Pb ranges from 2.143 – 32.143. The maximum carcinogenic risk (CR) from ingestion of Cd was 9.429×10^{-4} and Pb was 4.714×10^{-3}. According to risk assessment standard these values are in grade five and six respectively. About 54.2% of the analyzed samples are at grade seven which is extremely high-risk position, while the rest are at high-risk side. Though most levels did not exceed critical values for human health risk from heavy metals, there is still a potential human health risk from chronic exposure to low heavy metal concentrations due to long-term exposure and potential metal interactions. Results of this study inform water pollution remediation and management efforts designed to protect public health in polluted urban area waterways common in rapidly developing regions.

Keywords: *Heavy metals, Kilolo, Carcinogenic risk, Permissible limits, Great Ruaha*

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INTRODUCTION

Water is absolutely essential not only for the survival of all living things also in development of industries and agriculture (Razo *et al.,* 2004; Su *et al.*, 2004). River water pollution by toxic heavy metals is one of the important environmental concerns due to rigorous anthropogenic pressure on the aquatic environment. The anthropogenic activities along riverbanks lead to rapid population growth, urbanization and rapid industrial development, hence accelerated water pollution. Most significant anthropogenic sources such as domestic, hospital and industrial wastewater effluents are poorly treated or not treated at all and sometimes discharge directly to the open space or rivers (Assubaie, 2015).

Heavy metals released into the aquatic environment can enter food chains; persist in the environment, bioconcentrate, and bio magnify (Li *et al.,* 2017; Li *et al.,* 2018). However, some metals, such as copper, zinc, iron, and cobalt are essential elements play an important role in the metabolic processes of living organisms. These elements are only considered dangerous when they reach higher concentrations than required. Toxic heavy metals may be released into water bodies through anthropogenic activities such as mining and smelting operations, industrial production and use, domestic and agricultural use of metals and metals containing compounds (He *et al.*, 2005). Industrial sources include metal processing in refineries, coal burning in power plants, petroleum combustion, nuclear power stations and high-tension lines, plastics, textiles, microelectronics, wood preservation and paper processing plants (Goyer, 2001). Environmental contamination can also occur through atmospheric deposition, metal corrosion, soil erosion of metal ions and leaching of heavy metals, sediment re-suspension and metal evaporation from water resources to soil and ground water (Herawati *et al.,* 2002).

Other heavy metals are non-essential, and they are not required by living systems (Honest *et al.,* 2020). They can be toxic even in trace amounts, these include: cadmium, antimony lead, titanium, arsenic, bismuth, and mercury (Tchounwou *et al.,* 2012). However, whether essential or non-essential, all heavy metals are toxic at higher concentrations with their toxicity linked to chronic diseases such as renal failure, liver cirrhosis, brain syndrome, *itai-itai* and many others (Kobayashi *et al.*, 2009). These heavy metals continue to pile into higher levels especially when they are discharged into natural waters from agricultural, industrial, and domestic wastes, pesticides, or mining operations. As a result, they end up having severe toxicological effects on humans and the aquatic ecosystem (Underwood, 2002).

Lead interferes with functions performed by essential mineral elements such as calcium, iron, copper and zinc. It also inhibits red blood cell enzyme systems (Vasudevan and Streekumari, 2000). Similarly, lead can displace calcium in the bone to form softer denser spots and can inactivate the cysteine-containing enzymes, allowing more internal toxicity from free radicals, chemicals, and other heavy metals (Underwood, 2002). Moreover, hyperactivity and learning disorders have been correlated with lead intoxication in children. A relationship between lead levels and learning defects (like daydreaming as well as being easily frustrated or distracted) was found to exist. Other defects include a decrease ability to follow instructions and poor learning focus in children (Underwood, 2002).

Heavy metals are known to cause carcinogenic and non-carcinogenic effects in the human body (Mohod and Dhote, 2013). The term carcinogenic risk means the probability that an individual will develop cancer over a lifetime of exposure, whereas the term non-carcinogenic risk means the body can sometimes be able to cope with or recover from the exposure (EPA, 1999).

Iron is an essential trace element used for hemoglobin formation and has a role in oxygen and electron transfer in human body (Kaya and Incekara, 2000). Also, it plays an important role in the normal functioning of the central nervous system and in the oxidation of carbohydrates, proteins, and fats (Odhav *et al.,* 2007). The element cadmium is known to be carcinogenic and considered to be a non-essential element in foods and natural waters and it accumulates principally in the kidneys and liver (Divrikli *et al.*, 2003). A high concentration of cadmium than the maximum permissible limit is known to cause severe diseases such as kidney damage, tubular growth, cancer, diarrhea, and incurable vomiting (Divrikli *et al.,* 2003).

Manganese occurs naturally in many surface and groundwater sources as well as in the soils. Anthropogenic activities are also responsible for manganese contamination in river water. Basically, manganese is used in the manufacture of iron and steel alloys and manganese compounds can be an ingredient in various products such as fertilizers and pottery glazes (Venugopal and Luckey, 1978). Manganese dioxide and other manganese compounds are used in products such as dry-cell batteries, glass, and fireworks. Manganese neurotoxicity is associated with motor and cognitive disturbances known as Manganism (Cortez-Lugo *et al.,* 2015).

Zinc is one of the most important elements for normal growth and development in human beings. It is an essential element for the normal functioning of various enzyme systems of human beings and its deficiency, particularly in children, can lead to loss of appetite, growth retardation, weakness, and even stagnation of sexual growth (Saracoglu *et al.,* 2009).

The main objective of this study was to analyze the concentration of heavy metals in Ruaha river water from four different sampling sites at Pawaga division. Based on the concentrations of heavy metals detected, the human risk in terms of carcinogenic and non-carcinogenic was then evaluated.

MATERIALS AND METHODS

Study Area

This study will cover the Pawaga division, the area graphically situated downstream of Great Ruaha Rivers, and is one of the six divisions in the Iringa District Council in the Iringa region (Figure 1). Pawaga division has the smallest land area, just 684.3 km (3.3%) of the total district land area. It has a total of 12 villages and 60 hamlets. The main economic activities in this division are agriculture and pastoralism.

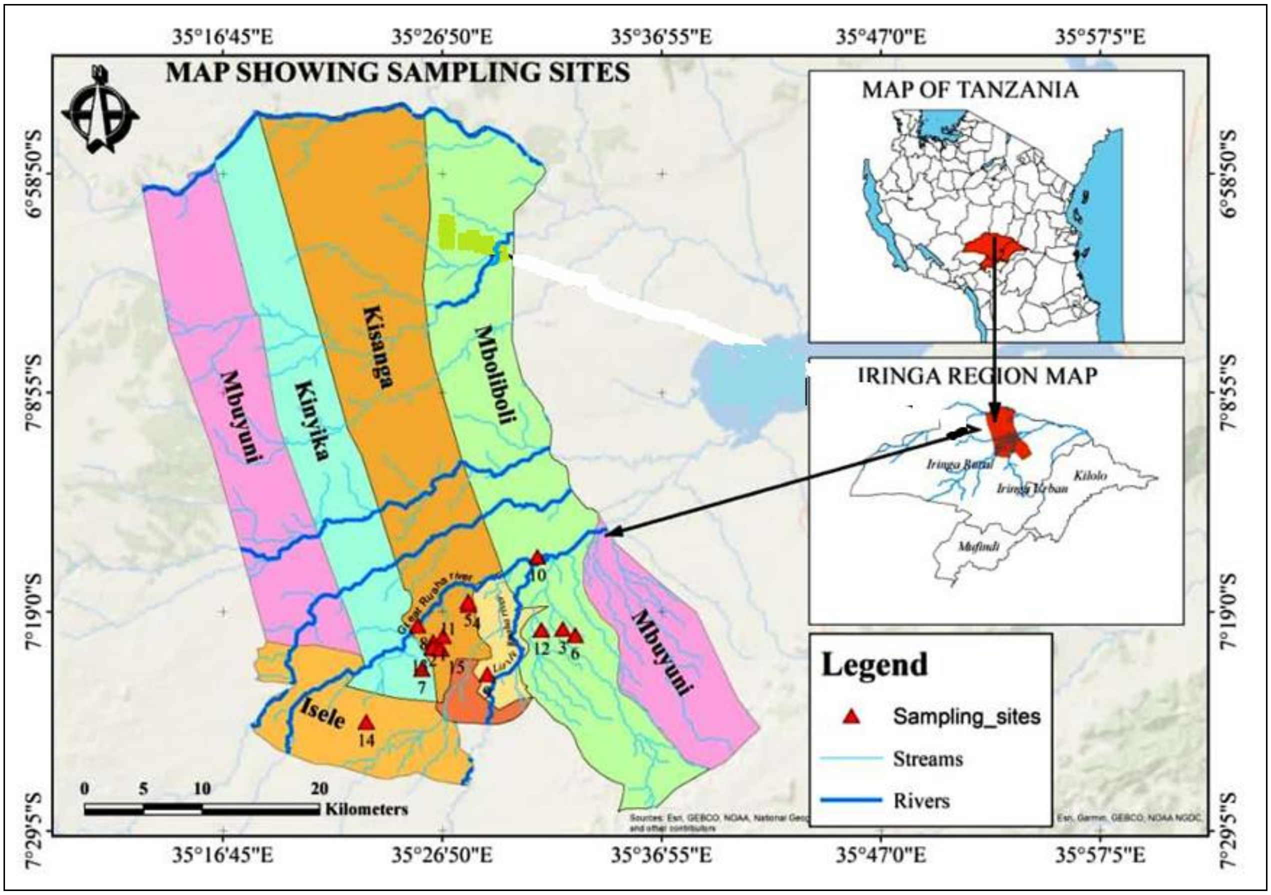

Figure 1: Map of Pawaga Division Showing Sampling Sites

The climate of the Pawaga division is semi-arid with low mean rainfall ranging from 500 – 600 mm, with temperatures over 25ºC. Water demands at the Pawaga division are extremely high due to agricultural activities being dominant and accounting for 85% of the region's gross domestic product (GDP) (Lufingo, 2019). Water scarcity in this region with many water resources has attracted research studies on water quality consumed by the communities around the Pawaga division.

Sampling, Analytical Determination, and Quality Control

Water samples from four different villages were obtained four sites in the Great Ruaha river. Samples were taken four (4) times during the wet season and three (3) times during the dry season (from July 2018 to April 2019) for every 2 months. At each sampling site, the polyethylene sampling bottles were rinsed at least three times before sampling was done. River water samples were collected at a depth of 30 cm in the center of the river (Meng *et al.*, 2022). Four mL of Conc.HNO_3 was added to all water samples to stabilize the samples until pH < 2 and then sealed with parafilm to prevent water evaporation (Meng *et al.*, 2022).

The standard solution of metals was supplied by Merck (Germany) with the highest purity level (99.98%). The commercial analytical grade 1000 ppm stock solutions of Fe, Mn, Cu, Pb, Zn, and Cd were diluted in a 25 mL standard flask and made up to the mark with deionized water to obtain the working standard solutions of 2.0 ppm, 3.0 ppm, and 4.0 ppm of each metal ion.

About 200 mL of each collected water sample was first concentrated on a sandy oven at 80 ºC until the volume reached 50 mL. Then 4 mL of Conc. HNO_3 was added to each sample and digested for 3 minutes. Then 10 mL Conc. H_2O_2 (Merck, 30%) was then added and heated at at 80ºC in the fume hood until oxidation was completed. After cooling, each sample filtered by filter (Whatman filter Merck, 0.45 μm). The filtrate was diluted by deionized water to a final volume of 50 mL (Meng *et al.*, 2022).

Instrument Calibration

Appropriate working standards were prepared for each of these metal solutions using a dilution of the intermediate solutions using distilled water in 2M HNO_3. Using the instrument operation manual (Perkin-Elmer, 1996), to attain its better sensitivity, the working standards were aspirated one after the other into the flame atomic absorption spectrometry (FAAS) and their absorbance was recorded. Calibration curves were plotted with different points for each of these metal standards using absorbance against concentration (mg/L). Immediately after calibration, the sample solutions were aspirated into the AAS instrument, and a direct reading of the metal concentrations was made (Table 1).

Table 1: Calibration Curve A vis Conc. of Heavy Metals (mg/L)

Metal	Model for Absorbance vis Conc.	R^2
Fe	y = 0.0172×	0.9976
Mn	y = 0.0691×	0.9952
Cu	y = 0.0814×	0.9948
Pb	y = 0.0185×	0.9967
Zn	y = 0.0204×	0.9983
Cd	y = 0.0168×	0.9952

Human Health Risk Assessment

Risks of individual heavy metals

Risk assessment is defined as the method of evaluating the probability of occurrence of any given probable amount of harmful health impacts over a determined time period (Wongsasuluk *et al.*, 2014). The health risk assessment of each contaminant is normally based on the estimation of the risk level and is classified as carcinogenic or non-carcinogenic health hazards (Custodio *et al.,* 2020). To estimate the heavy metal contamination and potential carcinogenic and non-cancer health risk caused via ingestion and dermal absorption of heavy metals in the great Ruaha river water; Hazard Quotients (HQ) and Hazard Index (HI) to adults were used (Wang, et al., 2005).

According to EPA (2005), the human health risk assessment estimates the human health effects that could arise from the combined exposure to carcinogenic and non-carcinogenic chemicals. The risk assessment was performed on the basis of exposure doses (D) to heavy metals in river water by ingestion and dermal pathways using Equations (i) and (ii).

$$D_{ingestion} = \frac{C_{ingested} xIRxEFxED}{BWxAT} \qquad (1)$$

$$D_{der} = \frac{C_{derm} xSAxKPxETxEFxEDxCF}{BWxAT} \qquad (2)$$

where, $D_{ingestion}$ is the exposure dose through water ingestion (µg/kg/day), D_{der} is the exposure dose through dermal absorption (µg/kg/day), $C_{ingested}$ is the measured metal concentration in water (µg/L). IR is the ingestion rate per unit time (L/day) estimated to be 2.2 L/day for adults, 1.8 L/day for children; EF is the exposure frequency (350 days/year); ED is the exposure duration (70 years for adults, 6 years for children); BW is the average body weight (70 kg for adults, 15 kg for children). AT is the average life expectancy of people, which is 66×365 = 25,550 for child and for the adult the average exposure time is 24,090 days. SA is the exposed skin area (18,000 cm^2); ET is the exposure time (0.58 h/ day); CF is the unit conversion factor (0.001 L/cm^3), and Kp is the dermal permeability coefficient (cm/h).

The standard parameters and input assumptions for exposure assessment of metals through ingestion and dermal pathways are given on Table 2 (Zakir *et al.*, 2020; Custodio *et al.*, 2020).

Table 2: Standard Constant Parameters (USEPA, 1991; USEPA, 2005).

Parameter		Fe	Mn	Cu	Pb	Zn	Cd
Kp (cm/h)		0.001	1.03×10^{-7}	0.001	0.004	0.006	0.001
Rfd	Ing.	0.7	0.01	0.04	0.0014	0.3	0.001
(mg/kg.day)	Derm.	0.3	0.0008	0.012	0.00042	0.06	0.000025
Parameter		**Unit**	**Ingestion**		**Dermal adsorption**		
Daily average intake (IR)		L/day	2.2		-		
Skin-surface area (SA)		cm^3	-		18000		
Exposure time (ET)		h/event	-		0.58		
Exposure frequency (EF)		day/year	365		350		
Exposure duration (EP)		year	70		30		
Conversion factor (CF)		L/cm^3	-		001		
Body weight (BW)		kg	70		70		
ABS		All	001		001		
Average time (AT)		days	25550		25550		

Non-carcinogenic Risk Assessment

The non-carcinogenic risk was evaluated using the hazard quotient (HQ), which was calculated by dividing the exposure value by the reference dose (Custodio *et al.,* 2020).

$$HQ_{ing(derm)} = \frac{D_{ing(derm)}}{RfD_{ing(derm)}} \quad (3)$$

Where $HQ_{ing(derm)}$ is the hazard quotient for ingestion or skin contact, $D_{ing(derm)}$ is daily intake ingestion or contact. The R_fD are standard values for ingestion or skin contact (Custodio *et al.,* 2020). A value of HQ ≤ 1 indicates that adverse health effects are unlikely. When HQ > 1 reveals probable adverse health effects, while when HQ > 10 indicates high chronic risk. The general potential for non-carcinogenic effects has been assessed by integrating the HQs calculated for each element and expressed as a hazard index.

$$HI = \sum_{i=1}^{n} HQ_{ing(derm)} = HQ_{Pb} + HQ_{Cd} + HQ_{Zn} + HQ_{Cu} + HQ_{Fe} + HQ_{Mn} \quad (4)$$

where $HI_{ing/der}$ is the hazard index for ingestion or dermal contact, n is the total number of chemical elements considered. If HI < 1, the non-carcinogenic adverse effect due to a particular route of exposure or chemical is assumed to be insignificant.

Carcinogenic Risk Assessment

According to Li and Zhang, (2010), the chronic daily intake (CDI) was calculated using the formula:

$$CDI = \frac{C_{water} xDI}{BW} \quad (5)$$

C_{water}, DI, and BW represent the concentration of metal trace in the water (mg/kg), mean daily water intake and body weight, respectively.

The cancer risk (CR) was calculated using the formula:

$$CR = \frac{CDI}{SF} \qquad (6)$$

Where SF is the slope factor of cancer where for Pb = 8.5, Cd = 6.1 both in µg/kg/day (Li and Zhang, 2010).

RESULTS AND DISCUSSION

Concentration of Selected Heavy Metals

The statistical concentrations of heavy metals in the Great Ruaha River during wet season and dry season are given in Table 3 and 4 respectively.

Table 3: Heavy Metal Concentration during Wet Season (mg/L)

Name of Village		Fe	Mn	Cu	Pb	Zn	Cd
Kinyika	Min	0.02	0.10	0.03	0.02	0.23	0.01
	Max	0.87	0.22	0.40	0.42	6.78	0.06
	Mean	0.82	0.14	0.17	0.15	2.07	0.03
	Std	0.70	0.08	0.17	0.19	3.16	0.02
Mboliboli	Min	0.04	0.01	0.00	0.00	0.01	0.00
	Max	1.34	0.13	0.07	0.02	1.20	0.01
	Mean	0.57	0.06	0.02	0.01	0.36	0.01
	Std	0.58	0.06	0.04	0.01	0.56	0.01
Kisanga	Min	0.01	0.11	0.00	0.01	0.01	0.00
	Max	1.09	0.12	0.02	0.01	0.29	0.00
	Mean	0.58	0.08	0.01	0.01	0.12	0.00
	Std	0.52	0.05	0.01	0.01	0.11	0.00
Isele	Min	0.11	0.03	0.01	0.00	0.04	0.01
	Max	0.99	0.10	0.23	0.02	0.69	0.00
	Mean	0.44	0.06	0.07	0.01	0.26	0.00
	Std	0.43	0.03	0.10	0.01	0.29	0.00

Table 4: Heavy Metal Concentration during Dry Season (mg/L)

Name of Village		Fe	Mn	Cu	Pb	Zn	Cd
Kinyika	Min	0.12	0.01	0.02	0.01	0.03	0.01
	Max	0.32	0.04	0.08	0.05	0.08	0.06
	Mean	0.20	0.03	0.05	0.03	0.05	0.03
	STD	0.11	0.02	0.03	0.02	0.02	0.03
Mboliboli	Min	0.04	0.02	0.01	0.01	0.01	0.00
	Max	0.25	0.07	0.08	0.02	0.13	0.03
	Mean	0.14	0.04	0.03	0.01	0.07	0.01
	STD	0.11	0.03	0.04	0.01	0.06	0.01
Kisanga	Min	0.05	0.02	0.02	0.01	0.02	0.00
	Max	0.18	0.02	0.03	0.01	0.10	0.04
	Mean	0.14	0.01	0.02	0.01	0.05	0.01
	STD	0.08	0.02	0.01	0.01	0.04	0.02
Isele	Min	0.03	0.01	0.04	0.01	0.01	0.01
	Max	0.44	0.02	0.07	0.02	0.12	0.04
	Mean	0.19	0.01	0.06	0.01	0.01	0.02
	STD	0.22	0.001	0.02	0.001	0.001	0.01

The observed mean concentration was high during wet season than during dry season. Kilolo division area is semi-arid land, during wet season agricultural activities are at peak where farmers apply more chemicals to their farm as well as migration of animals towards Usangu area. During wet season river water at Kinyika is more contaminated followed by river water at Kisanga village than at Mboliboli and the last at Iseke. During dry season river water at Kinyika is more contaminated and the last is at Mboliboli village. The observed mean concentration of heavy metals during wet season is in the following order: Fe > Zn > Cu > Mn > Pb > Cd > Al. During dry season is in the following order: Fe > Cu > Zn > Mn > Al > Cd= Pb.

Iron is used in industries added to brass to enhance its mechanical strength and produce hard and tough alloy. People at Kilolo are engaged in small industries like garage and industrial waste directed to Ruaha river which has led to iron contamination in the river. The average concentration of Fe during the wet season was in the range of 0.44 – 0.82 mg/L, while during dry season it ranges from 0.14 – 0.20 mg/L. These values correspond to values detected earlier (Bala *et al.,* 2008) ranging from 0.08 – 0.217 mg/L. However, the concentration is higher than the WHO permissible limit of 0.01 mg/L (WHO, 2011).

Manganese occurs naturally in many surface water and groundwater sources (from the dissolution of manganese oxides, carbonates, and silicates in soil and rock). Anthropogenic sources (from industrial discharges, mining activities, and landfill leaching) can also be a source of manganese contamination in water (Adhikari and Mal, 2021) and is often considered as one of the least toxic metals. The mean concentration level fluctuated between 0.06 – 0.14 mg/L which is higher than maximum permissible limits in drinking specified to be 0.05 mg/L (WHO, 2020). The mean concentration during the wet season ranges from 0.06 – 0.14 mg/L and 0.01 – 0.04 mg/L during dry season. These values are lower than maximum acceptable limit WHO (2020). The lower level of manganese tends to be lower in flowing rivers and streams due to presence of dissolved oxygen in water, which limits the amount of manganese that is dissolved (WHO, 2020).

The maximum mean values of Cu from both seasons are 0.17 mg/L (wet season) and 0.06 mg/L (dry season). These values are higher than those detected earlier (Mahugija, 2018) which was 0.04 mg/L. Similarly, the highest mean value of Pb during wet season was 0.15 mg/L and during dry season was 0.03 mg/L. These values are higher than those detected in Dar es Salaam ranges from 0.012 – 0.08 mg/L (Mahugija, 2018). Also, values are higher than WHO maximum permissible limit in drinking water 0.01 mg/L (WHO 2011).

During dry season, the highest mean concentration of Pb was detected at Kinyika village (0.002 mg/l). The same village detected highest concentration during wet season (0.15 mg/L). The high level of Pb in water samples indicate disposal in the effluents in the study areas, which may be attributed to the large number of tanning industries found in along the river. Lead is normally found in dyes and pigments used in industries (Idrees *et al.,* 2018).

The highest mean concentration of Zn was detected during wet season (2.07 mg/L), which is below the WHO maximum permissible limit of 5 mg/L (WHO, 2011). These values were below the values detected earlier (Idrees *et al.*, 2018) which ranges between 0.04 – 0.07 mg/L. These results may be because these areas at Kilolo are densely populated, having small, developed hubs of electronic industries. The illegal dismantling of E-wastes materials is high within these areas. The dispose or recycling of E-wastes is either by open-air burning, dissolving by acid, or other methods to get valuable parts from the waste and hence find their way into the river.

Human Health Risks Assessment

The non-carcinogenic health risk owing to ingestion and dermal exposure to the studied heavy metals are shown in Table 5. Average levels of non-carcinogenic risk (HQ) via ingestion of river water were observed in the descending order wet season > dry season. For the heavy metals the trend for HQ via ingestion, were observed in the ascending order Fe < Zn <Cu < Mn < Pb < Cd.

Table 5 Non-carcinogenic Risk by Ingestion (HQ_{ing}) of Heavy metals in River Water

Village name	Season	Fe	Mn	Cu	Pb	Zn	Cd	HI
Kinyika	Wet	0.037	0.447	0.136	32.143	0.221	9.000	51.984
	Dry	0.009	0.096	0.040	6.249	0.005	9.000	15.399
Mboliboli	Wet	0.026	0.192	0.016	2.143	0.038	3.000	21.399
	Dry	0.006	0.128	0.024	2.143	0.007	3.000	5.308
Kisanga	Wet	0.026	0.256	0.075	2.143	0.013	0.000	2.513
	Dry	0.006	0.032	0.150	2.143	0.005	3.000	5.623
Iseke	Wet	0.020	0.192	0.056	2.143	0.028	0.00	2.439
	Dry	0.009	0.300	0.048	2.143	0.001	0.639	3.140

There is little exception at Kinyika and Kisanga villages, where the HQ_{ing} for Pb is higher than HQ_{ing} for Cd. According to Liang *et al.,* (2011) the heavy metal pollutant can pose potential adverse health effects when the HQ_{ing} value of a metal is higher than 1. The HQ_{ing} of Cd ranges from 0.000 – 9.000, while Pb ranges from 2.143 – 32.143. Other metals in the present study have the HQ_{ing} values lower than 1 via ingestion of water.

Therefore, the studied metals were capable individually to pose adverse health effect through ingestion in the water of Ruaha River. During wet season, river water at Kinyika village indicates high chronic risk as the value of HQ_{ing} of Pb > 10, while other villages has revealed probable adverse health effects as 1< HQ_{ing} > 10. The heavy metal HQ_{ing} values studied were below the permitted limit and indicated that adverse health effects are unlikely.

The HQ_{ing} values of Zn, Cu, Mn and Fe obtained in this study indicate that adverse health effects on the inhabitants who consume water from the rivers evaluated are unlikely. Stelmashook, et al., (2014), indicated attention must pay to Zn levels due to possible consequences of excessive Zn intake. It is well indicated *(*Kuo *et al.,* 2013) that Zn can affect the gastrointestinal tract, before it is distributed throughout the body. Another study also reported that, metal ions imbalance such as Zn and Cu play an important role in the pathogenesis of many neurodegenerative diseases (Yang and Wang, 2018). Intake of high concentrations of Fe may cause a variety of disorders that can lead to pathological conditions, including diabetes mellitus (Huang, 2003), liver disease, and cardiovascular disease, as well as neurodegenerative disorders (Kuo *et al.,* 2013).

However, the combined hazard index for ingestion registered HI > 1 values in all the rivers sites evaluated, indicating that the adult population is at risk of suffering non-carcinogenic effects due to the combined effects of heavy metals analyzed. The HI > 10 values were recorded in Kinyika village during the wet and dry season and at Mboliboli during the wet season. People at these two who consume river water are at very high-risk to their health.

Table 6 shows the non-carcinogenic skin contact risk of heavy metals in water for adults. The results reveal a risk considerably below the permitted limit (HQ_{derm} and HI less than 1), indicating that there is no evident risk to the population in the study area via the dermal pathway. The trend of HQ via dermal contact was in the order Mn < Fe < Cu < Zn < Cd < Pb.

Table 6 Non-carcinogenic Risk by Contact (HQ_{derm}) of Heavy metals in River Water

Location	Season	Fe	Mn	Cu	Pb	Zn	Cd	HI
Kinyika	Wet	3.909×10^{-4}	2.578×10^{-6}	2.026×10^{-3}	0.204	2.960×10^{-2}	0.172	0.408
	Dry	9.534×10^{-5}	5.524×10^{-7}	5.959×10^{-4}	0.041	7.151×10^{-4}	0.172	0.221
Mboliboli	Wet	2.717×10^{-4}	1.105×10^{-6}	2.384×10^{-4}	0.014	5.148×10^{-3}	0.057	0.0767
	Dry	6.674×10^{-5}	7.365×10^{-7}	3.575×10^{-4}	0.014	1.001×10^{-3}	0.057	0.0724
Kisanga	Wet	2.765×10^{-4}	1.473×10^{-6}	1.19×10^{-4}	0.014	1.716×10^{-3}	0.000	0.016
	Dry	6.674×10^{-5}	1.841×10^{-7}	2.384×10^{-4}	0.014	7.151×10^{-4}	0.057	0.072
Iseke	Wet	2.097×10^{-4}	1.105×10^{-6}	7.151×10^{-4}	0.014	3.718×10^{-3}	0.000	0.019
	Dry	9.058×10^{-5}	1.841×10^{-7}	7.151×10^{-4}	0.014	1.430×10^{-4}	0.114	0.129

Overall, the results reveal that adults are not vulnerable to acute and chronic effects of heavy metal intake. This was consistent with the previous study (Alidadi *et al.*, 2019) they reported that non-carcinogenic risk (HI) of heavy metals for adults' dermal contact with heavy metals ranges from 0 016 – 0.244. Although the results in this study indicated that there was no obvious non-carcinogenic risk observed at the Kilolo division among selected trace elements analyzed, routine monitoring must be done.

Carcinogenic Risk Assessment of Trace Elements

Carcinogenic risk is the product of daily exposure dose and cancer slope factor, which is shown in Equation (v). Under the assumption that there is no antagonism and synergism between pollutants, the integrated carcinogenic risk can also be identified as the sum of carcinogenic risks exposure by various pollutants via different pathways. Table 7 shows the carcinogenic risks for adults by ingestion of heavy metals from river water at sampling villages.

Table 7: Carcinogenic risk by ingestion of heavy metals in river water at different sites in Kilolo division

Village	Season	Fe	Mn	Cu	Pb	Zn	Cd
Kinyika	Wet	2.577×10^{-2}	4.4×10^{-3}	5.343×10^{-3}	4.714×10^{-3}	6.506×10^{-2}	9.429×10^{-4}
	Dry	6.286×10^{-3}	9.429×10^{-4}	1.571×10^{-3}	4.714×10^{-3}	1.571×10^{-3}	9.429×10^{-4}
Mboliboli	Wet	1.791×10^{-2}	1.886×10^{-3}	6.29×10^{-4}	3.143×10^{-4}	1.131×10^{-2}	3.143×10^{-4}
	Dry	4.400×10^{-3}	1.257×10^{-3}	9.43×10^{-4}	3.143×10^{-4}	2.200×10^{-3}	3.143×10^{-4}
Kisanga	Wet	1.823×10^{-2}	2.514×10^{-3}	3.14×10^{-4}	3.143×10^{-4}	3.771×10^{-3}	0.000
	Dry	4.4×10^{-3}	3.143×10^{-4}	6.290×10^{-4}	3.143×10^{-4}	1.571×10^{-3}	3.143×10^{-4}
Iseke	Wet	1.383×10^{-2}	1.886×10^{-3}	2.2×10^{-3}	3.143×10^{-4}	8.171×10^{-3}	0.000
	Dry	5.971×10^{-3}	3.143×10^{-4}	1.886×10^{-3}	3.143×10^{-4}	3.143×10^{-4}	6.286×10^{-4}

The carcinogenic risk of heavy metals through ingestion of river water varied from $0.00 – 6.505 \times 10^{-2}$. According to Li *et al.*, (2017), carcinogenic risk values can be rated in seven levels which is extremely high risk (Table 8).

Table 8: Levels and values of risk assessment standards (Li *et al.*, 2017)

Risk Grade	Rating of risk	Range of risk value	Acceptability
Grade one	Extremely low risk	$CR < 10^{-6}$	Completely acceptable
Grade two	Low risk	$1 \times 10^{-6} < CR < 1 \times 10^{-5}$	Not willing to care about the risk
Grade three	Low-medium risk	$1 \times 10^{-5} < CR < 5 \times 10^{-5}$	Do not mind about the risk
Grade four	Medium risk	$5 \times 10^{-5} < CR < 1 \times 10^{-4}$	Care about the risk
Grade five	Medium-high risk	$1 \times 10^{-4} < CR < 5 \times 10^{-4}$	Care about the risk and willing to invest
Grade six	High risk	$5 \times 10^{-4} < CR < 1 \times 10^{-3}$	Pay attention to the risk and act to solve it
Grade seven	Extremely high risk	$CR > 10^{-3}$	Reject the risk and must solve it

About 54.2% of the analyzed samples are at grade seven which is an extremely high-risk position, while the rest are at high-risk side. These results suggest that the carcinogenic risk of heavy metals from ingestion of water contaminated by different heavy metals makes adults be at risk due to cancer.

The maximum carcinogenic risk (CR) from ingestion of Cd was 5.546×10^{-4} and Pb 1.546×10^{-4} (Table 9).

Table 9: The carcinogenic risk (CR) from ingestion of Pb and Cd in the water

Site	Season	Pb	Cd
Kinyika	Wet	5.546×10^{-4}	1.546×10^{-4}
	Dry	1.109×10^{-4}	1.546×10^{-4}
Mboliboli	Wet	3.697×10^{-5}	5.152×10^{-5}
	Dry	3.697×10^{-5}	5.152×10^{-5}
Kisanga	Wet	3.697×10^{-5}	0.000
	Dry	$3.697 \text{ x } 10^{-5}$	$5.152 \text{ x } 10^{-5}$
Iseke	Wet	$3.697 \text{ x } 10^{-5}$	0.000
	Dry	3.697×10^{-5}	1.030×10^{-4}

Caspah *et al*,. (2016), indicated there are difference in determination of maximum threshold according to country or continent. For example, the USA recommends 1×10^{-6} to 1×10^{-4} (USEPA 1992; 1999) the United Kingdom generally adopts 1×10^{-5} (*Zakir et al.,* 2020), in practice, and the Netherlands suggests a 1×10^{-4} (Liyin, *et al*, 2018). Therefore, the maximum carcinogenic risk (CR) in this study was within acceptable limit ranges of $1 \times 10-6$ to $1 \times 10-4$. These values are similar to values observed earlier in China by Liyin, *et al.*, (2018) where the CR values exceeded the 10^{-4} level of concern. The levels of Cd near old industrial areas exceeded the Cd exposure standard (2.6% of CR values > 10^{-4}).

CONCLUSION AND RECOMMENDATIONS

The Great Ruaha river watersheds in the southern highland of Tanzania are exposed to contamination by heavy metals and metalloids from natural and anthropogenic sources and agricultural activities are the main sources. The magnitude of heavy metal contamination in the studied rivers requires more frequent monitoring and supervision of the household (who discharge their liquid waste into water bodies).

The assessment of carcinogenic and non-carcinogenic risks due to exposure to heavy metals through the routes of ingestion and dermal contact showed adults are more risks. These findings demonstrate the urgent need for effective policies to control and reduce the pollution levels of the rivers whose waters are destined for a variety of uses. Therefore, further studies on other heavy metals in the Great Ruaha and sediments are recommended.

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