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The Need for a Multi-Pollutant Approach to Model the Movement of Pollutants in Surface-Water: A Review of Status and Future Challenges

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Abstract: ***Significant research on surface water pollution modelling has been carried out over diverse landscapes has sought to explain the sources, transport, and surface water pollution. To date, surface water pollution studies have focused on nutrients, plastics, and chemicals. Consequently, the current review aims to identify and synthesise peer-reviewed literature about integrated contaminants modelling in surface water. Thus, highlighting that modelling potentially multiple sources of a pollutant from the surface water has remained a thought-provoking topic. Studies differed significantly in terms of the type of model application and procedures for reporting findings, making it challenging to separate clear trends and patterns. Accordingly, most studies agree that pollutants such as plastics and agrochemicals can have adverse consequences on surface water quality; these coincide with difficulties in modelling pollutant transport. Consequently, no regional or global estimates are available for the water pollution burden of flood-related pollution, considering the demonstrable modelling techniques, the significance of the concurrent impacts of surface water pollution by contaminants. Multi-pollutant approaches to modelling the potential sources of pollution and encourage protective behaviour are essential. Mainstreaming freshwater pollution concerns into planning strategies will also be needed to lessen anthropological contribution to surface water pollution. While the implementation of these models is constrained by lack of adequate field data, the model output must be analysed within the model inputs' uncertainty, data limitations and methodologically established surface water modelling principles from the literature.***

Keywords: ***Pollutant Sources, Plastic Component, Microbial Component, Nutrient Component, Multi-Pollutant Approach, Contaminant Flow.***

1. INTRODUCTION

Surface water contamination is primarily derived from plastics, nutrients (non-biodegradable), pesticides, and heavy metals. Such contaminants have diverse ecological effects (Kroeze *et al.*,

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2016). For example, hypoxia and harmful algal blooms in coastal areas and rivers can be caused by excess nutrients in the water. Chemical derived contamination can have toxic effects on marine animals. Often surface water bodies are influenced by various contaminants' collective impact (Kroeze *et al.*, 2012; Kroeze *et al.*, 2016). Streams are chiefly contaminated by human activities, including agriculture, urbanisation, industrialisation, and improper sewage disposal (Manoj and Padhy, 2015; Srinivasamoorthy *et al.*, 2011). Contaminants transported to a river via overland flows can be carried to very distant places via river channels and deposited in coastal environments (Kroeze *et al.*, 2012; Kroeze *et al.*, 2016). Contaminants in rivers tend to have a common source. For example, nutrients, pesticides, and heavy metals can be derived from agriculture and sewage released from municipal and industrial sources (Abdalla and Khalil, 2018; Barletta *et al.*, 2019; Yesmeen *et al.*, 2018). It implies that measures that were put in place to lessen a particular contaminant possibly also affect other contaminants (Kroeze *et al.*, 2012; Kroeze *et al.*, 2016).
In wastewater treatment, for instance, concentrations of most contaminants are reduced while recovering water and nutrients. Effective management of water sources' pollution requires to account for the co-benefits and the side-effects (Alves *et al.*, 2019; Wu *et al.*, 2018). It is noteworthy that there are regional variations of causes of stream contamination. Pollution of streams is a global phenomenon as rivers worldwide serve as conduits through which pollutants are collected at the basin scale and transported to the seas (Brusseau *et al.*, 2019; Hoellein *et al.*, 2019; Kellner and Hubbart, 2019). Nearly all the contaminants' sources are well established in advanced nations (Tornero and Hanke, 2016). However, in some regions (i.e., Africa, South America, and Asia), these causes are either poorly known or not well investigated (Dsikowitzky *et al.*, 2016). In this kind of situation, models can be used (Brack *et al.*, 2015). It aids understanding of the problem and provides bases for decision making on environmental management and pollution control. This can be achieved through a multi-pollutant approach to pollutant modelling, which offers estimates of pollutant-load in surface water.

1.1.Why is a multi-pollutant method for modelling surface water required?

It has been argued that an integrated and more comprehensive multi-approach to surface water modelling is required for various reasons:
i). A new and comprehensive model approach is necessary to address the joint exposure of surface water bodies to contaminants.
If possible, these types of models will combine trace metals, nutrients, chemicals, plastics, and pathogens in addition to contaminants like antibiotics and nanomaterials (Kroeze et al., 2016). Also, river temperature is crucial under changing climatic conditions due to its effects on surface water networks (Alvarez-Cabria *et al.*, 2016). Therefore, these models should address at least three aspects that many existing models did not account for: (1) the common origin of contaminants; (2) physical, chemical, and biological interactions between contaminants in river waters; and (3) the combined effects of numerous pollutants. This is depicted in Figure 1. Instances of a common origin of contaminants are industrial and municipal sewage (Harder *et al.*, 2016)—both released chemicals, nutrients and pathogens to rivers. Point pollution is more clearly caused by urbanisation, whereas land use and agriculture are the familiar sources of nonpoint pollution, i.e., diffuse sources (Shen *et al.*, 2015; Yi *et al.*, 2019). Since there are numerous recognisable sources, approaches to lessen individual pollutants may also influence other contaminants' concentration levels (Kroeze *et al.*, 2016).

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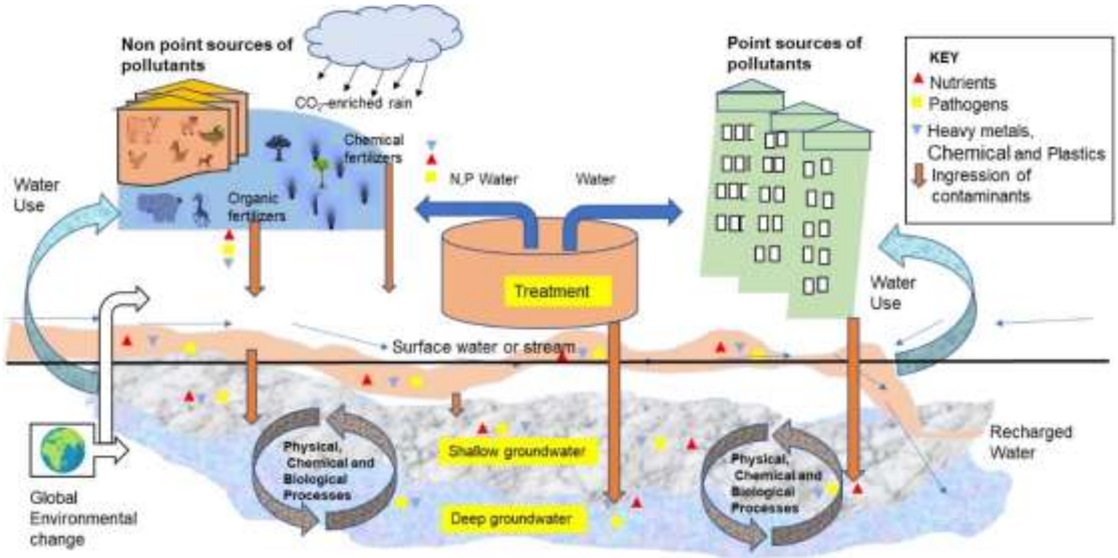

Figure 1. Potential risks to water pollution: Impurities can originate from the same source; Impurities might interact physically, chemically, or biologically; and many impurities may have numerous effects. After Kroeze *et al.* (2016).

ii). Sound knowledge of the interactions between chemical, physical, chemical, and biological processes in streams is essential for pollution management

A good account of interactions between multiple contaminants is vital for gaining insight into ecosystem resilience and functioning. For instance, pesticides and hydrophobic chemicals can be bound by plastics before burial in soils or absorption by plants (Gallo *et al.*, 2018; Geitner *et al.*, 2017). Similarly, nutrients build-up may increase biomass and, consequently, result in lesser chemical load (Koelmans *et al.*, 2001). The interaction among nutrient, pathogen and thermal contaminants could lead to the speedy decline of surface water quality and fast deterioration of the environment (Gillefalk *et al.*, 2018; Mateus *et al.*, 2019; Williamson *et al.*, 2017). Interactions between water quality, water availability and streamflow are quite explicit since various contaminants' concentrations rise under conditions of low flows. Also, compound modelled stressors may add up for a particular ecological receptor (Kroeze *et al.*, 2016). Consequently, new modelling approaches suitable for analysing such interaction impacts and water pollution causes are required. This is particularly vital for gaining insight into future variations in surface water quality.

iii). A multi-pollutant approach to modelling may well aid to predict upcoming ecological gravities better.

Pressures on surface water systems are expected to rise under impending global change. The river flows in most parts of the globe, particularly in semi-arid and arid areas, are likely to acclimate and reduce climate modification and consequently add to water stress. Summer river flows will change in temperate regions due to earlier snowmelt peaks and unpredictable summer rains (Croitoru and Minea, 2014; Lininger and Wohl, 2019; Marszelewski and Pius, 2016). Precipitation is often decreasing, consequent of reduced surface water flows in the dry season of monsoon climates (Dunning *et al.*, 2018; Taniwaki *et al.*, 2016). Water temperatures will be changed by higher atmospheric temperatures (Kroeze *et al.*, 2012; Kroeze *et al.*, 2016). Those pressure forms can lead to elevated contaminants in rivers and perhaps reduce oxygen

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concentration, even though the nutrients loadings will remain constant. Therefore, it is essential to combine hydrological models with pollution models that are efficient for showing low stream surges in upcoming climate transformation so that imminent scenarios can be optimally simulated (Bailey *et al.*, 2016; Fan and Shibata, 2015; Liu *et al.*, 2016).

iv). Future water quality models might be required to account for pollutants build-up in the environment.

This is particularly essential when investigating options for reducing water pollution in the future. Some contaminants accrue in the sediments and soils, consequently impacting management options. This is practically applicable to contaminants with high capacities to accrue. Microplastics are examples of these pollutants and are persistently high and remain stockpiled in sediments or soils for many years (Andrady, 2011; Cole *et al.*, 2011; Daly *et al.*, 2016; Smith and Zeder, 2013; Villarrubia-Gómez *et al.*, 2018; Zalasiewicz *et al.*, 2018; Zalasiewicz *et al.*, 2016). For this reason, they have large pollutants stock. Tenacious organic contaminants can stockpile in soil or sediments. This is also the case for metals and phosphorus (Sharpley *et al.*, 2013; Strokal and de Vries, 2012). Dependent open their biogeochemical complexity and the attendance of additional biochemical elements such as aluminium and iron oxides that combine organic matter and clay binding metals, e.g. de Vries *et al.* (2007) and phosphorus Strokal and de Vries (2012). Also, this can hold for nitrogen, though it is not subjected to adsorption processes, like metals in addition to phosphorus.

At present, the only available model for river export that considered a global '*retention effects'* of phosphorus (P) and nitrogen (N) build-up in soil and river sediments is IMAGE-GNM (Beusen *et al.*, 2015). The first attempt was by Strokal and de Vries (2012) to report N residue in sediments in the river export using Global NEWS. They followed the modelling method of Langmuir. Also relevant is assessing the dynamics for discovering the time-course of other forms of impurities, per se water pollutants (Roseta and Xepapadeas, 2004), pesticides (Conrad and Lars, 1992), greenhouse gases (Tahvonen, 1997), and industrial substances termed as 'Substances of Very High Concern'(Gabbert and Hilber, 2016). The river export models can be combined with dynamic modelling of impurities. This can provide additional insight into the temporal pattern of chemicals in rivers and consequent threats to aquatic systems.

There are many ways through which a multi-pollutant modelling approach is developed. Rather simple models for basins can be designed for modelling the annual export of various chemicals by streams to coastal environments (Strokal *et al.,* 2019; van Vliet *et al.,* 2019). Coastal water pollution can be traced using such models and is applicable to study scenarios. It investigates the success of managing pollution approaches. The introduction of dispersed grid-based hydrological simulations (or models) extended to take in water quality variables could be another example. These models explain causal processes for regional problems of pollution, and the resultant effects of various chemicals on human society and water stress can be well explained by the aid of such models (Kroeze *et al.*, 2016). Therefore, the appropriateness of any multi-pollutant approach is determined by the objective of the study. Generally, an exact model for modelling various contaminants can improve understanding of significant effects and sources of impending pollutants and prosper correct answers to the entire global surface water pollution problem. These types of models can be applied to (Kroeze *et al.*, 2016):

i. Analyse and quantify the volume and condition of water, in addition to appraisals of future availability of potable water.
ii. They can also aid in enhancing our awareness of water safety.

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iii. These models may perhaps lay the foundation for systematic and management apparatuses that resolve simultaneously various water-related problems.
iv. Empathetic knowledge of the effect of surface water quality on bionetworks as well as humanity is crucial for human development and wellbeing; and
v. Global based multi-pollutant surface water models can provide desirable, innovative knowledge and applicable policy funding and consequently underwrite acceptable Sustainable Development Goals by the United Nations.

1.2. Modeling Surface-water pollutants

The objective of modelling contaminants flow from land to surface water channels (e.g., river, stream, and sea) is primarily on recurring sources of pollutants and their multiple impacts. Surface water pollution models are available worldwide, for instance, thermal pollution, nutrients, chemicals and plastics. For chemicals, continental-scale models are available for salinity, BOD, and faecal indicators. More so, there are several models for discrete river basins. There are limited studies that applied a multi-pollutant approach to modelling multiple pollution sources, but primarily at the continental scale. There is no multi-pollutant analysis on a global scale that accounts for all the outlined contaminants above. In Kroeze *et al.* (2016), some typical universal, unambiguous models were presented to examine surface water quality parameters (instances of universal and regional scale models for surface water quality parameters). They examined surface water quality parameters such as river temperature, chemicals, nutrients, pathogens, and plastics.

Their model summary compares previously designed nutrients models over the past 20 years with recent models for studying chemicals, microplastics, and pathogens. The model comparison summarises existing models for a worldwide or regional approach to pollutant modelling Surface water contamination for nutrients in rivers. The coastal area is an ecological problem, which can lead to the development of harmful algal bloom. At present, the IMAGE-GNM (Global Nutrient Model) by Beusen *et al.* (2016) and Global NEWS Model for (Nutrient Export from WaterSheds) (Kroeze *et al.*, 2012; Kroeze *et al.*, 2016; Mayorga *et al.*, 2010; Seitzinger *et al.*, 2010) are the only available and comprehensive models for multi-pollutant modelling. While a multipollutant approach is required for assessing the global water quality concerns, there are challenges relating to continuous inputs, approaches for modelling multipollutant and evaluation of models. Strokal *et al.* (2019)'s evaluation has illustrated the hotspots of stream contamination with multiple pollutants. These results are highly policy-relevant since the availability of clean water is seldom analysed from a multipollutant viewpoint.

Typically, multipollutant issues cause various consequences on the social and aquatic environments, as illustrated in Figure 2. Although eutrophication of global surface water bodies is caused by nutrients pollution, there is persistent addition of plastic pollutant in surface water. Plastic pollution is further complicated since plastics may contain a chemical additive that can be detrimental to aquatic organisms (Strokal *et al.*, 2019). In low-income nations, pathogen pollution is the leading cause of diarrhoea. Aquatic ecosystems can be disturbed by organic pollutants since they stimulate microbial growth. Other categories of pollutants with potential environmental risks are pharmaceuticals, nano plastics and pesticides(Strokal *et al.*, 2019).

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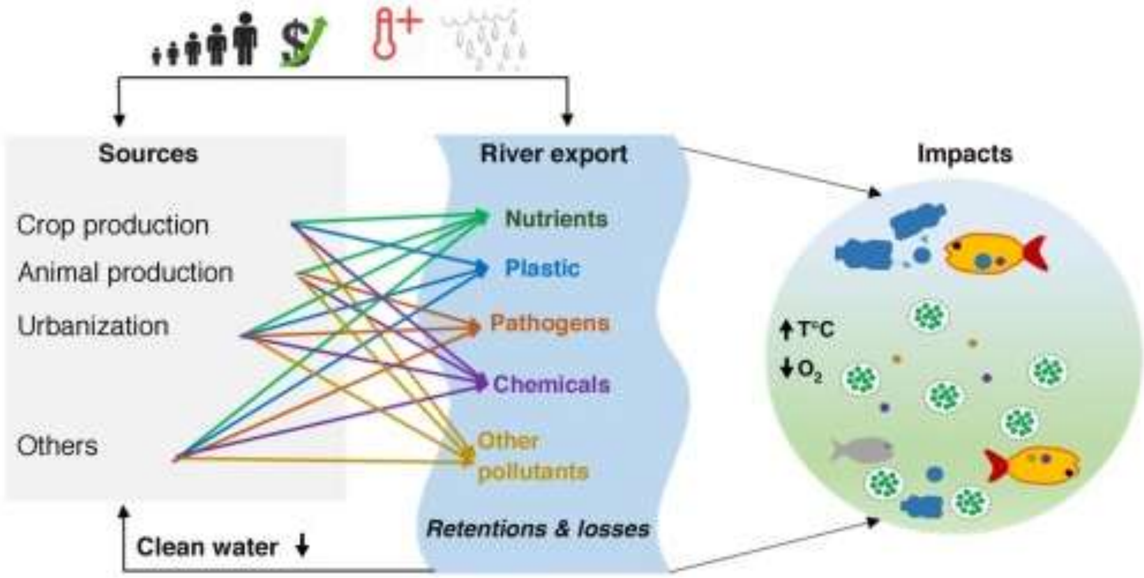

Figure 2. Theorised model showing relationships between pollutants origins and their impacts in surface water, after Strokal *et al.* (2019).

2.1. Modelling Organic and inorganic pollutants in Surface Water

The rivers export to the sea consequent of anthropogenic activities can be estimated using both models summarized in Table 1 (Kroeze *et al.*, 2016). Also, the model includes both the point along with nonpoint sources of contaminants into the river. Nonpoint (diffuse) sources of pollutants include applying animal dung (or organic manure) and synthetic fertilisers in crop fields. More so, nutrient contributions to streams related to land-use changes are termed a dispersed source of pollutants. The models utilise gridded sets of data of Latitude and Longitude (i.e., 0.5 x 0.5) as model inputs. The annual steady-state contaminants exports by the river outlets for particulate and dissolved inorganic types of Phosphorus(P), Nitrogen(N) and carbon(C) was predicted by Global-NEWS utilising typically experiential, primary retention in the land, water systems or linear relationship for sinks (Beusen *et al.*, 2016; Beusen *et al.*, 2015; Kroeze *et al.*, 2016). The N and P retention in-stream river export are estimated using the IMAGE-GNM. It is a physically-based model which uses a nutrient spiralling method, and it is a component of the IMAGE framework that is applied during multiple estimations. It feeds the GLOBIO-AQUATIC and IMAGE-DIVERSITY model. A significant contrast among the Global-NEWS and IMAGE-GNM include:

i. The Global NEWS consists of a small number of standardised or calibrated factors (or parameters). It uses data on nutrient export at the river/stream bay (or entrance). However, the model is (i.e., IMAGE-GNM) is not standardised.
ii. The GLOBAL-NEWS computes the annual nutrients exports for the stream/river basin. The IMAGE-GNM estimates nutrient's movement based on a 0.5 x 0.5-degree network through the nutrient technique's spiralling for the N and P retention by streams.
iii. The IMAGE-GNM was applied only between 1900 to 2000. The GLOBAL-NEWS was used to simulates nutrients exports between 1970 to 2000 and upcoming flows in explicit regions like the African Continent (Yasin *et al.*, 2010), Latin America (van der Struijk and Kroeze, 2010), Bay of Bengal (Sattar *et al.*, 2014; Zinia and Kroeze, 2014), and the Black

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Sea (Beusen *et al.*, 2016; Beusen *et al.*, 2015). A sub-basin edition of the GLOBAL-NEWS model was designed in China (Strokal *et al.*, 2015; Strokal *et al.*, 2016; Strokal *et al.*, 2019).

Table 1. Typical models for analysing variables of water quality. After Kroeze *et al.* (2016).

Model types	GLOBAL_NEWS	IMAGE-GNM	WORLD-QUAL	RBM	GloWPa	Triclosan Model	Model for Plastic
Three-Dimensional (3-D) limit (or extent).	Worldwide	World wide	Regional, e.g., Latin America, Europe.	Worldwide	Worldwide	Worldwide	Regional (Europe)
Three-Dimensional (3-D) upshot (resolution).	Model data input 0.5X0.5 decree. Output River Basin (greater than 6000) streams.	Model data input and output, 0.5x0.5 decree (greater than 6000) streams.	5’	Model data input and output 0.5X0.5 decree.	Model data input and output 0.5X0.5 decree.	Input data 0.5x0.5 decree (Global-News). Output (greater than 6000) streams	Model data input and output 0.5x0.5. output and input data mean unit strength 87.7m
Chronological (temporal) extent.	1970 t0 20150	1900 to date	1990 t0 2010	1970 to 2100	2010 + scenarios	2000 to 2050	1970 to 2050
Time-based resolution	Yearly sums for specific years	Yearly	Monthly	Diurnal	Yearly for certain years	Yearly sums for specific years	Yearly/stream retention, 0.01-day microplastic and Nano plastics.
Contaminants considered	Liquefied and particulate modes of	Total P and N	Total P and N, BOD, TDS,	Surface water temperature	Cryptosporidium, rotavirus	Triclosan	

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	mineral and organic C, P, Si, and N		Fecal coliform bacteria, Movement of nutrients to the streams, lagoons/ ponds, and ocean				
Chemical flows included in the model	Flows of nutrients into the oceans and rivers from land	Flows of nutrients into the oceans and rivers from land	Flows of nutrients into the oceans and rivers from land	Global electric power generation plant's thermal pollutants incorporated as advective sources of heat	Pathogenic contaminants derived from human faces and manure to the streams/rivers	Discharge of Triclosan into streams and oceans	Riverbank transport
Effects of contamination of the model	Potential Coastal Eutrophication marker	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered
Origin of contaminants in the model	Dispersed sources (changes in land use and agriculture). Sewage (point source pollutants)	Distributed sources (changes in land use and agriculture). Sewage (point sources	Dispersed sources (household, industrial, generation of power, agriculture). Sewage (point source of	Thermoelectric power plants (point source of pollutants)	Sewage (point source of pollutants) and manure (slurry) inputs.	Sewage (point source of pollutants)	Sewage (point source of pollutants)

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		, industrial discharge)	pollutants)				
Model application	Historical and future assessment of global trends. For individual continents or regions around the world	Historical trend global trend analysis	Analysis of trends and current loadings globally for large lakes and rivers	Historical and upcoming trend analysis of water temperature globally under the anthropogenic impact (reservoir impact and thermal pollution) and climate change	Applied in India and Bangladesh to analyse human Cryptosporidium and assessment of current scenarios and simulations	Analysis of historical and (2000) and upcoming trends globally	Historical and upcoming assessments of microplastic flow through European rivers; assessments of impacts of polymer density (type), occurrence biofilm on fate, the position of build-up hotspots and retention
Hydrological applications	Water-Balance-plus-Model	PCR-GLOBWB	The WATER-GAP	The VIC Model	Unincorporated, preparing to incorporate VIC Model	Water-Balance-plus-Model	Water-Balance-plus-Model for the European Continent. The St. Venant equation

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							s of momentum and continuity are applied used to calculate the flow rates and water levels in the river retention model
Remarks	The model is applicable in assessing the comparative contribution of pollutant-sources in the entire transport of nutrients transport to the seaside; an edition of the model (the MARINA Model) was developed and used for a sub-basin in China	The model reports the nutrients increasing in rivers	It includes large lakes	The model was used for assessing the effects on global streams/rivers, sea locales—the impact of electricity on the supply and outcomes of thermal pollution globally.	The model is applicable for assessing the proportional contribution of sources of faecal pathogens to rivers. It was applied with SSPs in scenario analysis		The river retention model covers the entire pertinent processes and is implementable for all catchments

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Models weaknesses	It is not essential for the local analysis in lumped basin modelling	Can analyse the total P and N flows; lack future trends	Lacking upcoming trends	They are highly demanding in terms of computational data globally since sub-daily and daily time phase data is required.	Lacking river exports	Initial analysis with several ambiguities. The paucity of data makes substantiation challenging.	Little macro and microplastics yet to be implemented. The paucity of data makes substantiation challenging

The IMAGE-GNM and GLOBAL-NEWS are used to measure pointer eutrophication of coastal areas. It was applied to estimate the consequences of nutrient contributions to coastal regions (Garnier *et al.*, 2010). Scenario analyses and model results have shown that global streams' nutrient export swelled significantly in the past decades and are expected to continue. The rise will be accompanied by increased food production driven by population growth and intensifying contribution of nutrients (or manure) to streams from a point source (Kroeze *et al.*, 2016). Harmful algal blooms possibly will continue to grow consequent of high volumes of nutrients. Analogous findings were obtained with the developed continental-scale models for America and Europe (Grizzetti *et al.*, 2012; Grizzetti *et al.*, 2008; Schwarz *et al.*, 2006 ; Sferratore *et al.*, 2005).

The IMAGE-GNM, in addition to GLOBAL-NEWS, is used to measure pointer eutrophication of coastal areas. It was applied to evaluate the impacts of nutrient contributions on coastal regions (Garnier *et al.*, 2010). Scenario analyses and model results have shown that global streams' nutrient export swelled significantly in the past decades, and I expected to continue. The rise will be accompanied by increased food production driven by population growth and intensifying contribution of nutrients (or manure) to streams from a point source (Kroeze *et al.*, 2016). Harmful algal blooms possibly will continue to grow consequent of high volumes of nutrients. Analogous findings were obtained with the developed continental-scale models for America and Europe (Grizzetti *et al.*, 2012; Grizzetti *et al.*, 2008; Schwarz *et al.*, 2006 ; Sferratore *et al.*, 2005).

Currently, the capable models for forecasting total phosphorous (TP) loading and transport in global rivers comprise three families of peer-reviewed models (Harrison *et al.*, 2019). These are Global-NEWS, WaterGAP and IMAGE-GEM. The specific versions of these models, as presented by Harrison *et al.* (2019), represent the most recent model, which is capable of forecasting the loading and transport of TP in global rivers (i.e., IMAGE-GNM-TP, Global-NEWS-2-T, and WaterGAP3.2) for each respective modelling family. Additionally, the NEW-DIP-HD, which is a half-degree (high-resolution) edition of NEWS-2-DIP can be considered and detailed by Harrison *et al.* (2019), are comprised of explicit

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representation of point and nonpoint sources of P. Converelly these models attempt to explain both the natural and anthropogenic sources of P and they all attempt to explain P sinks on rivers. Theoretically, these models can be prospectively and retrospectively applied, even though. Currently, only the GlobalNEWS-2-TP has been employed to predict future scenarios (Harrison *et al.*, 2019). However, these models differ in some aspects. For instance, the IMAGE-GNM-TP can estimate TP transport but do not estimate the various P contribution types (i.e., organic, inorganic and dissolved P) to TP loading. In contrast, the total P constituents types can be estimated by Global NEWS-2TP. It measures TP as the total of P constituents predictable using Global NEWS-2 sub-models (Global NEWS-2- dissolved inorganic P (DIP), Global NEWS-2 dissolved organic P (DOP), and Global NEWS-2 particulate P (PP) (Harrison *et al.*, 2019).

2.2. Bacteriological pollutants

Waterborne microbial pollutants (or pathogens), e.g., *Cryptosporidium* (parasitic protozoa), are a primary source of diarrhoea globally. A review of outbreaks of waterborne transmission of protozoan parasites between 2011-2016 showed that at least 381 occurrences are credited to the parasitic transmission of waterborne protozoa during that period (Efstratiou *et al.*, 2017). The GloPa-Model (Global Waterborne Pathogen Model) by Hofstra *et al.* (2013) remained a single model for waterborne microbial pollutants (Table 1). Modelling the microbial contaminants causing diarrhoea through the Oral-Fecal-Route constitutes the main objectives of the model. This model was applied to model *Cryptosporidium* (GloWPa-Crypto) and *Rotavirus* (GloPa-Rota). The model was separated into animal and human modules. Dung derived from various animal species (Spp) were loaded where microbes decompose (Kroeze *et al.*, 2016). This, in addition to human faeces, passes into the water from land or sanitary networks and surface runoff to surface water bodies (Hofstra and Vermeulen, 2016; Kiulia *et al.*, 2016).

For instance, the agricultural and population inputs to GloPa are 0.5 x 0.5 − grid together with statistics output form individual countries are surface water pathogen loads on a 0.5 x 0.5 − grid. The GloPa was applied only for the year 2010 (Kroeze *et al.*, 2016). The existing model computes microbial origin inputs to streams and can be combined with a hydrological model to calculate microbe's concentration in stream/river. The GloWPa-Crypto Model application by L. C. Vermeulen *et al.* (2019) presented the first global model of *Cryptosporidium* intensities in rivers. It paves the way for modelling waterborne pathogen on a global scale. The regional-scale water quality model (i.e., WorldQual) was applied for faecal coliform analyses in regions such as Europe and South America. It has a similar procedure to GloPa (Reder *et al.*, 2015). While *Fecal Coliforms* can grow in an environment, they are not pathogenic. The WorldQual model ignored this process (Kroeze *et al.*, 2016).

Although water quality models differ in temporal and spatial resolutions and domains, van Vliet *et al.* (2019) presented an illustrated comparison of spatially specific organic contamination, concentrating on simulated mean BOD intensities derived from four grid-based water quality models comprising of GWAVA-WQ, WaterGAPWorldQual, VIC-QUAL and global BOD model. As shown by Figure 3, their computational results indicated that though the organic pollution flashpoints are generally comparable, some disparities occur due to variations in model input datasets, structure, and the considered sources of pollution. The modelled lower BOD, for example, can be explained by the fact that the existing model

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concentrates only on BOD transport from livestock and urban population, whereas the remaining models also account for organic pollution from manufacturing.

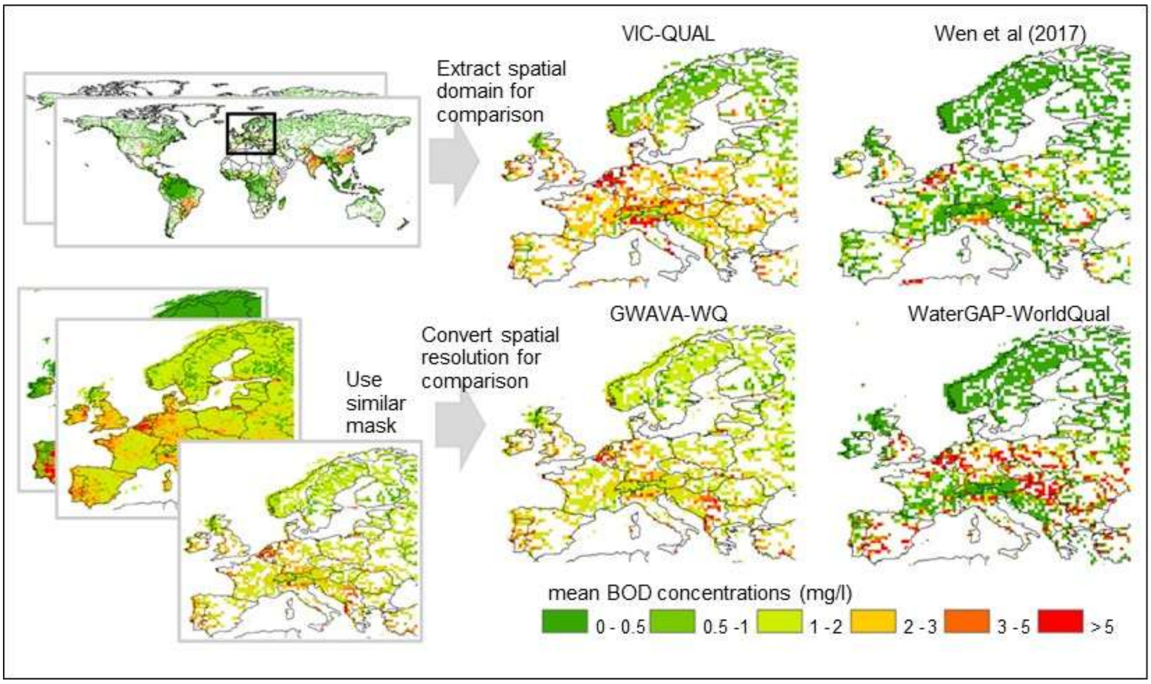

Figure 3. The model analogy of modelled mean BOD intensities for Europe transformed spatial domains and resolutions and aggregates to mean values between 1990-2000, after van Vliet *et al.* (2019).

Owing to data availability, for example, in the Global Environmental Monitoring System (GEMS), Faecal Coliform models are easily validated and calibrated compared to pathogens' models (Kroeze et al., 2016). Data on pathogens in streams/rivers remain scanty, particularly in third world countries. Current studies on pathogens are often carried out in more advanced countries (Kashefipour *et al.*, 2006; Niazi *et al.*, 2015; Wei *et al.*, 2019). A significant distinction between WorldQual and GloWPa is that the former is calibrated (Kroeze et al., 2016). Alternatively, WorldQual can measure pathogen intensities in the stream/river by applying WaterGap for hydrology. However, the contribution of pathogens to streams/rivers is exclusively measured by GloWPa. While the GloWpa runs for only1-year, the WorldQual produces results monthly (Kroeze *et al.*, 2016; van Vliet *et al.*, 2019).
In Bangladesh and India, a measurement of anthropoid *Cryptosporidium* fluxes was conducted using GloWPa (Kroeze *et al.*, 2016; Lucie C. Vermeulen *et al.*, 2015). Global trend assessment of release of *Cryptosporidium* to surface water (Lal et al., 2019; Vermeulen et al., 2019) shows that anthropoid pathogen piling to surface waters may perhaps decline in more significant parts of the globe when cleanliness and wastewater treatment are upgraded, despite the growing population (Kroeze et al., 2016). If improved hygiene conditions do not keep with sewage treatment, the pumping of pathogens will considerably increase in the environment (Hofstra *et al.*, 2013; Hofstra and Vermeulen, 2016; Hofstra *et al.*, 2019). Other applications such as faecal and health risk measurement and waste management trend analysis (Korajkic *et al.*, 2019; Kroeze *et al.*, 2016; Mayer *et al.*, 2018; Wei *et al.*, 2019) are significant components of the

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model. Modelling faecal pathogen transport and health risk following Mills *et al.* (2018) showed sensitivity to and a prerequisite for additional proof on log reduction values for various sanitation practices under contrasting performance circumstances, pathogen movements under inundating situations as well as pathogen moulting and individual exposure in characteristic low-income urban backgrounds (Foster *et al.*, 2021).

It is noteworthy to understand the influence of environmental pollution on the dynamics of waterborne pathogen models. The global stability analysis using numerical modelling enables understanding of environmental pollution's impact on pathogens' fundamental reproduction frequency and dynamics. Increases influence the rise in infections in the tress parameter, which has successfully demonstrated the rapid spread of waterborne infections by environmental pollution (Sharma and Kumari, 2019). Global dynamics of a reaction-diffusion waterborne pathogen with general incidence rate using a nonstandard finite difference scheme was modelled by Zhou *et al.* (2018). It enabled the development of the discrete counterpart of the continuous model. Their analysis showed that the discretisation scheme could conserve the global properties of solutions for the initial continuous model, comprising the positively, ultimate finiteness and global solidity of the equilibria. However, analysis of a diffusing host-pathogen model with universal prevalence and different dispersal rates indicates that hosts' nominal and substantial diffusion rate has a considerable effect in devising the pathogen's spatial circulation (Jinliang and Renhao, 2021).

2.3. Compound pollutants

Volatile compounds like endocrine, heavy metals and pesticides can equally contaminate surface water bodies. Stream pollution models that can be implemented for organic micropollutants and heavy metals on a continental or global scale are lacking (Bieber *et al.*, 2018; Nezikova *et al.*, 2019; Posthuma *et al.*, 2016). Meta export models are few at a basin or regional scale. Tiktak *et al.* (2004) developed a model for measuring pesticide leakage to groundwater. Simulating pesticide runoff from crop fields to surface water channels worldwide is quite challenging. The first global-scale model (Triclosan), presently in progress for chemicals contaminating coastal areas and streams, as indicated by Table 1. The Triclosan (TCS) is an illustration of endocrine-disrupting-compounds. It is an antibacterial substance that is regularly derived from personal care goods (Dann and Hontela, 2011; Kroeze *et al.*, 2016). As shown by toxicological tests, the TCS is safe for humans (Perez *et al.*, 2017). However, it poses a probable hazard to several organisms in the aquatic environment (Hofstra and Vermeulen, 2016). A large amount of TCS (150 tone TCS) is generated annually. The per capita TCS use is ~210 mg (Singer *et al.*, 2002).

A universal spatially explicit TCS model (Jikke van Wijnen *et al.*, 2018; J. van Wijnen *et al.*, 2019) was designed after the Global-News model (Mayorga *et al.*, 2010). It measures TCS transport by streams to seas, employing TCS contributions to streams from sewage (Table 1). A more significant portion of the TCS (50-98) from the river waste can be removed by modern wastewater treatment plants (Heidler and Halden, 2007). However, in several regions (including Africa, Asia, and South America), sewage systems are lacking; often, untreated waste is released into river channels. Concerning hydrology, residents sewage systems and population density, the Global TCs model applied the datasets from the Global-News model (Kroeze *et al.*, 2016). The Global-TCS model comprises significant parameters such as removing TCS throughout the process and biodegradation of TCS and wastewater treatment.

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The model output shows that the TCS export by the river is rising. It presents a possible ecological hazard in the shoreline ecosystem. The global spatially unambiguous model by Jikke van Wijnen *et al.* (2018) can simulate TCS transport by the rivers to coastal regions. The model predicts decreasing river export of TCS in Europe and a significant increase in Southeast Asia for impending scenarios.

2.4. Pliable pollutants

There is a rising quantity of pliable pollutants (i.e., plastic) litter in our ecosystem (Gallo *et al.*, 2018; Kroeze *et al.*, 2016). Estimates show that a large volume of pollutants (4.8 - 12.7 million tons) of plastics waste by-products from land surface is added to the ocean yearly. Concerns about the dangers and potential adversative impacts of micro-plastic pollutants on aquatic creatures, human health and wellbeing and ecosystems are growing. Presently, a first spatially explicit model for plastic export to the river (to European oceans), which is based on the Global-NEWS has been out (Siegfried *et al.*, 2017), signifying that car tyre dust (plastic from car tires released during driving) is a significant contributor of micro-plastic pollutants in oceans and rivers across Europe. It models river export of microplastics derived from wastewater treatment, population, sewage network, and river-retention. It also measures the microplastic pollutants from sewage systems. Subsequently, J. van Wijnen *et al.* (2019) developed the GREMiS model to examine the riverine export of microplastic to the oceans. The model results show that the river export of microplastics to the marine environment varied considerably with regions. Significant sources of microplastics are the fragmentation of and sewerage discharges. By 2050, the export of microplastics is expected to increase unless adequately mitigating measures are implemented.

The first described river model that resolved spatiotemporally hydrological model for microplastic that is comprised of the advective conveyance of microplastics and Nano plastics, as well as their accumulation, sedimentation, and resuspension, presence of biofilm, plastic degradation, and entombment in the soil, was presented (Everaert *et al.*, 2018; Kroeze *et al.*, 2016; Li *et al.*, 2018; Siegfried *et al.*, 2017). Nevertheless, the model lacks global coverage. Excluding the add-on efficiency for hetero aggregation measured methodologically, data from the literature were applied to parameterise the model. Using the spatial aspect of 477 units of an average of 87.7 meters and unit girths between 8 and 228 meters, a 40 km river section were modelled (Kroeze *et al.*, 2016).

With known hydrology, the model can be applied without difficulty for any catchment. A mean plastic mass concentration in the upstream was employed instead of the mean reported microplastic concentrations in surface water. The modelling of river retention was carried out, which largely depends on particle size (Kroeze *et al.*, 2016). The model can measure the location of pollutant hot spots or build-up in the river sediments. Retention of intermediate particles of ~5mm was remarkable, suggesting retention of the minor submicron elements and larger micro-meter sized plastics, including high costs for dispersal of micro-meter sized plastics deposited into seas (Besseling *et al.*, 2017; Kroeze *et al.*, 2016).

2.5. Temperature fluctuations in surface water

Variation of temperature between 5 to 10˚C affects TDS levels. It ultimately disrupts ion exchange capacity, the solubility of gasses, sorption processes, redox reaction, complexation, speciation, and pH level (Wali *et al.*, 2018). Climate change can cause changes in the temperature of surface water. Weather is a vital physical property of surface waters that

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influences the rates of a chemical reaction and the concentrations of other parameters of water quality, including microbial activity, conductivity (EC), dissolved oxygen (DO) and nutrients (Ozaki *et al.*, 2003; Webb and Nobilis, 1997). There are multiple modelling methods, differing in complication. Their input data requirements were designed to model the stream's water temperature worldwide (Breitburg *et al.*, 2018; Bullerjahn *et al.*, 2016; Kroeze *et al.*, 2016). Based on air temperature and streamflow (van Vliet *et al.*, 2011), a non-linear regression model on stream/river temperature was implemented to estimate water temperature on daily and monthly time intervals.

A simple regression analysis model comprising river flow was used to measure the thermal capacity to mirror the energy budget differences. The predictor variable used was the air temperature (van Valiet *et al.*, 2012; Webb and Nobilis, 1997). Regression approaches to water temperature are magnificent for their limited prerequisite for hydrological and meteorological imposing data. Even though it is still considered for highly described variance levels (van Valiet *et al.*, 2012; Webb and Nobilis, 1997). Water temperature models that are Physics-based (e.g., heat transport equations) tend to be more complex since they require a lot of hydrological and meteorological data input (Lu *et al.*, 2017; Stryker *et al.*, 2018; Tavakoly *et al.*, 2019).

Nevertheless, these models are usually more suitable for assessing the impact of changing climate-related regression models of stream/river temperature for scenario studies. These are designed for historical epochs. Global-scale regression models of water temperature are available. Both models solve the I-D heat advection equation (Kroeze *et al.*, 2016). These physics-based models are; PCR-GLOBWB model (van Beek *et al.*, 2012) and the VIC-RBM model (van Vliet, 2012). Based on the spatial resolution of 0.5 x 0.5-degree, streams' water temperature can be modelled using a PCR-GLOBBWB model. The model measures water temperature daily (Kroeze *et al.*, 2016). It consists of ice-coverage influences then rejects every anthropogenic influence (e.g., thermal contaminants) on the stream's water temperature.

After validation of the PCR-GLOBWB model (mean absolute error-1.6 to7.6 ^{o}C), it was applied to model stream's water temperatures for the current global climate (Kroeze *et al.*, 2016; van Beek *et al.*, 2012). The river basin model (or RBM) for measuring the stream's temperature is part of the VIC-RBM model (Yearsley, 2009). It is related to the hydrological model's Variable Infiltration Capacity (VIC) (Liang and Lettenmaie, 1994; Lohmann *et al.*, 2009). These joined models were implemented worldwide and incorporate influences of thermoelectric power generation plants (thermal pollutants) and the lake's impacts on stream/river temperature (van Valiet *et al.*, 2012). The model framework operates daily based on 0.5 x 0.5 – degree. It was authenticated for Global-River-Basins (mean error = -0.3 oC; RMSE = 2.8 ^{o}C) as reported by Kroeze *et al.* (2016).

To evaluate the thermal smog consequences from thermoelectric power plants on global rivers. The VIC-RBC model was used (Raptis *et al.*, 2016). It was also used to analyse the effects of changing climate on streamflow and water temperature worldwide. This displays a robust increase in surface water temperature anticipated for eastern Asia, southern Africa, the United States, and Europe. However, global streamflow and surface water temperature forecasts of VICRBM were used to measure the significances of electricity supply and cooling water use (van Vliet *et al.*, 2013; van Vliet *et al.*, 2016) and effects on fishery ecosystems worldwide (van Vliet *et al.*, 2013). Recent application includes Tangdamrongsub *et al.* (2017); and Sutanudjaja *et al.* (2018) .

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4.0. Recent studies in surface water pollutants modelling

Investigation of dangerous microplastics in natural water resources is insignificant when equated to seafood, sea salt, and marketed water. Selvam *et al.* (2021) presented outcomes of the first baseline study of microplastics in surface and groundwater water from coastal south India. The study estimated the heavy metal adsorption capacities of various polymers. The microplastics (up to 19.9 particles/L) were comparatively bigger in surface water (0.34–4.30 mm) than in the groundwater (0.12–2.50 mm). Nylon (polyamide), polypropylene, polyester, polyethene, cellulose and polyvinyl chloride were the ordinary polymers, and all of them exhibited various capacities of heavy metal adsorption. In two distinct investigational locations, the polypropylene exhibited greater capacity of adsorption than other polymers in the following orders: (i) Cd > Mn > Pb > S; and (ii) Mn > Zn > As > Pb > Cu. However, the polyamide showed better adsorption only for Mn. Analogous to other latest results, their results correlate microplastics as the main vector to carry heavy metals in the water system. Design of policies to lessen particulate plastics' ecological risks as a compelling vector for conveying the toxic trace elements and the consequent effect on human health via the OSPRC context (origins→sources→ pathways→ receptors→ consequence) is required.

In recent times, a succession of innovative photocatalysts has been built to fight various bio-recalcitrant pollutants and bacteria's deactivation. Simulating photocatalytic processes is essential to evaluate these substances and to comprehend and enhance their presentation. Ateia *et al.* (2020) reviewed the current literature to discover and evaluate modelling photocatalytic concert techniques. The Langmuir–Hinshelwood model (L-H) was applied in several research types to justify the dilapidation kinetics of specific pollutants since it is the most accessible model containing both the degradation rates and adsorption equilibrium. More studies report the advancement of more complex options of the L-H model that consist of catalyst innervation rates, production of reactive oxygen species (ROS), recombination of electron-hole pairs, and development of by-products. Several scholars applied amended Chick-Watson (C-W) and Hom models to incorporate lag stages of bacteria to explain decontamination kinetics. Artificial neural networks (ANNs) were used to study the impacts of operating conditions on photocatalyst performing. Likewise, response surface methodology (RSM) was applied for trial-design and optimisation of operating conditions. Their study analysed all accessible articles that model photocatalytic activity in the direction of water contamination, reviewed and put them in perspective, and suggested future research paths.

The research outcome of contaminants from an oil spill in seawater via multimedia environmental modelling showed that 30,000 tons of crude oil leakage add 58% discharge of naphthalene toxin in receiving water body (Chughtai and Asif, 2020). However, two elements, i.e., toluene and benzene, are profusely present in the air phase adding 83% and 85% discharge in air, correspondingly. Generally, naphthalene stayed constant in the environment for over seven years, contaminating most of the underneath residues through advection trends and bio-accumulating in marine species. Consequently, the model offers valuable results to analyse the fate of toxins discharged in the ecosystem because of leakage and help to choose the redress approach for spills occurrences in time (Chughtai and Asif, 2020).

Identifying micro-pollutants and their removal have forever been a difficult task. Mathematical modelling of deprivation events needs high computational abilities and a detailed understanding of the fundamental theories of micro-pollutant degradation in the natural environment. Panidepu *et al.* (2020) emphasised the value of modelling and its expanding usage in evaluating micropollutants' degradation. Moreover, various modelling methodologies and their fundamental theories and ideas need to be discussed further by setting the climate for a more comprehensive mathematical analysis. Biodegradation of micro-pollutants with specifics on how expanding and nongrowing microorganisms decompose the contaminants and how this leads to variations in devising the mathematical equation need further investigation. The kinetics of biodegradation with a specific case report on biofilters is offered. It is a targeted system that might be devised to deal with toxins.

Samaneh *et al.* (2020) evaluated the water quality index and water quality model ($QUAL_2K$) to assess toxins. It revealed that a proposed $Qual_2k$ model is a suitable tool for water quality evaluation and future projection. Also, a Mathematical analysis of diffusion and degradation of contaminants as a fundamental problem in stream water pollution was proposed by Farahbod (2020). It indicated that the rise in the fabrication time of pollutants in both x and y directions was due to wave depletion in 40 s. Discharge absorption of the contaminant slowly declines. Also, boosting the time to 40 s rises the concentration of impurity in the x and z direction by eradicating the wave after 40 s. Ultimately the contamination of the toxins declines because of chemical effluence and diffusion by dispersion. Results also indicate the impact of the rate of reaction constant rising from $k = 0$ to $k = 0.04\ min^{-1}$ on the distribution of pollutant absorption in the *x*-direction at specific times. Further results reveal that if the reaction rate was 0, there is no mass application within the system. Likewise, the findings show that the contaminant intensity will rise by boosting contact time from 0.003 to 0.197 $mmol/cm^3$.

Hazard-based decision making to estimate contaminant decline scenarios were presented by Ahmadisharaf and Benham (2020). It indicated that achieving water quality goals with very high reliability was impossible, even with intense contaminant decrease levels. The risk-based framework offered illustrated a technique to promulgate watershed model uncertainty. It also evaluates the performance of substitute contaminant decrease scenarios. The model employed existing tools, and the objective was aiding decision-makers to comprehend the dependability of a given scenario in accomplishing water quality goals.

Recently, there is cumulative evidence for the incidence of geogenic chemicals in the water. The emergence of trace elements and an upsurge in the usage of wastewater has emphasised the susceptibility and intricacies of the chemistry of irrigation water and its starring role in safeguarding suitable crop growth, human health and long-term food quality (Malakar *et al.*, 2019). Investigative abilities to quantify vanishingly insignificant concentrations of biologically dynamic organic impurities, comprising of pharmaceuticals, plasticisers, steroid hormones, plasticisers, and personal care products, in diverse sources of irrigation water, offer the methods to assess uptake and incidence in crops. However, it does not solve queries linked to impacts on human health or food safety. Normal and artificial nanoparticles are now identified in several water sources, possibly modifying food standard and plant growth. The precipitously modifying water sources' quality immediately requires more robust consideration to comprehend and envisage long-term impacts on food crops and soil in a progressively more freshwater worried planet (Malakar *et al.*, 2019).

Self-depuration monitoring of surface water and spatiotemporal characterisation of surface water evaluating the impact contaminant origins using chemometrics has led to the recent development of e a sensitive and significant discriminant model with a 93% non-error rate (Jurado Zavaleta *et al.*, 2021). The model is cable of analysing and predicting the self-depuration of the streams. Water quality monitoring can be achieved using this model for its excellent predictive ability (Jurado Zavaleta *et al.*, 2021). Despite the recent advances in surface-groundwater interactions, the impact of surface-groundwater interactions is yet to be fully understood and often underestimated (Lewandowski *et al.*, 2020). The poor understanding was due to inadequate knowledge, awareness and experience regarding the suitable measurement and analysis models. This lack of knowledge application from research into management practices implies that more energies are required to publish scientific findings and methods to policymakers and practitioners.

Understanding the occurrence and fate of emerging contaminants in the aquatic environment and their removal options present a significant challenge that is yet to be fully addressed. Their environment's occurrence gradually generates more severe problems (J. Wang *et al.*, 2021). However, source reduction and substituting the emerging contaminants with inventions of lower toxicity products that are easier to remove from water can reduce the impacts of emerging contaminants on the environment, though not possible in all cases (J. Wang *et al.*, 2021). Significant advances have been made on promoting graphene-based materials for the adsorption of oils, dyes, heavy metals, and the co-adsorption of their mixture from water (Vasilachi *et al.*, 2021). The major challenge lies with the fact that future technologies must be more effective and eco-friendly treatments, efficient for removing a broader spectrum of emerging contaminants, with low costs and energy consumption. Besides, the treatment's efficiency should be adjustable to emerging contaminant's intensity in water and make recovering treated water possible (Vasilachi *et al.*, 2021).

Another challenge to surface water pollution modelling is data assimilation (DA). Thus, understanding the controls, intensities, and uncertainty sources is a critical DA research field (Cho *et al.*, 2020). Although more novel and numerous DA websites are becoming accessible, more needs to be studied with simultaneous water quality state and parameters updates. The DA appraisal is of interest to changes in the prediction skills related to the surface water quality update modelling. The need and possibility of widening the DA applications exist and can be further explored (Cho *et al.*, 2020). It will help develop an integrated surface water quality assessment by aggregating multiple contaminants and time (Schuwirth, 2020). Consequently, an immission-oriented assessment method for surface water quality based on multicriteria decision supports approaches are recommended. It aggregates over multiple contaminants and time and enables surface water modelling with actual micropollutant data (Schuwirth, 2020). This helps in modelling solute transport to supervise subsurface water contamination from surface water sources (Mustafa *et al.*, 2020). Such models enable the determination of the suitable site for groundwater mining and pumping rate, so that pollutant curl never reaches the pumping well. This is useful in constructing riverbank filtration sites (Mustafa *et al.*, 2020).

4.0.Implications for surface water quality management

The models discussed above have implications for whether and how accurate surface water contaminants can be estimated in rivers and oceans. Typical examples of models used for estimating pollution in surface water are summarised in Table 1. It appears that several models are existing, even though they are primarily based on continental or basin-scale (Schwarz *et al.*, 2006; Yen *et al.*, 2016). Perhaps, the global river water quality appraisal models are complete for specific water quality parameters. The current review of regional-scale water quality models comprises illustrative examples for assessments of river water pollution. Therefore, it is believed that the recent model highlight is comprehensive for the justification

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of multipollutant methods for modelling surface water pollution. Other models are designed for nutrients, yet their procedures are various, and they are primarily applied for a particular basin or continental scales. The River Trailer Model, for instance, used a mechanistic method like IMAGE-GNM but then with adjusted parameters. RIVERSTRAHLER also modelled nutrient flows; the model is mainly applied to the Red basin (Garnier *et al.*, 2010) and basins in Europe (Billen *et al.*, 2005; Ruelland *et al.*, 2007).
The SPARROW Model is a spatially referenced regression for watersheds nutrients exports by the river through sources of nutrients as per the IMAGE-GNM and Global-NEWS (Kroeze *et al.*, 2016). It is mainly applied for assessing North American basins (McCrackin *et al.*, 2013). The Mike-She hydrological model is an illustration of physically-based models. It requires adjustment before implementation in specific watersheds or divides (Frana, 2012; Zhang *et al.*, 2008). However, the model lacks global reporting as, for instance, VIC does. Likewise, for other water quality parameters such as pathogens and plastic, the current model framework presents illustrative instances of modelling methodologies.
The level of pollutants can be simulated and predicted using surface water quality models. The models can also show the distributions and assess the risk of contaminants in surface water (He *et al.*, 2008; McKnight *et al.*, 2010; Obropta and Kardos, 2007; Q. Wang *et al.*, 2013). Simulated results from these models under diverse pollution scenarios are essential components of environmental impact assessment. It can also provide basis and technical support for environmental management agencies to make appropriate decisions. Accurate results are required since findings can impact the empiricism and rationality of the approved construction projects and the existence of pollution control measures (Norton *et al.*, 2007; Q. Wang *et al.*, 2013; Y. Wang *et al.*, 2018). The development of surface water quality models can be viewed from three steps that analysed the precisions, suitability, and methods between diverse models. Environmental management agencies can be more efficient if water quality models are standardised (Alshuwaikhat and Abubakar, 2008; Paliwal *et al.*, 2007; Q. Wang *et al.*, 2013). They can guarantee the reliability of the model's application for regulatory purposes. There is a need to infer the status of standardisation of water quality models in developed and developing countries. Available measures should be put forward to standardise water quality models, particularly in third world countries (Horn *et al.*, 2004; Strobl and Robillard, 2008; Q. Wang *et al.*, 2013).
The dearth of adequate data on water quality in many countries impedes the modelling of surface water quality, especially in developing countries. Therefore, it affects the entire process of water management. Elshorbagy and Ormsbee (2006) discussed the prospect of an object-oriented modelling environment for managing surface water quality. It was based on the concepts of system dynamics (OO-SD). The potential application of the proposed method, particularly in data-poor environments and the tasks faced by hydrologists to take advantage of such modelling technique, was identified. Though it is not a substitute for traditional models, it can be a viable substitute in data-poor countries. It can be a possible runner when the participation of decision-makers is essential for a modelling project.

2. CONCLUSION

The literature is undivided on the significance of identifying how surface water is polluted. However, the rate at which contaminants are transported is mainly dependent on many factors.

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These include climate, geology, topography, and land use. These are highly variable in space and time. Consequently, modelling contaminant transport has presented a taught provoking topic that requires an understanding of the nature of contaminants themselves, their sources or origin, how they interact with other elements and their movement in surface water. Equating the surface water quality model types summarised in Table 1 leads to the remarks:

i. Currently, universal models for water quality were established for various reasons. These can be applied in data-scarce areas to identify pollution sites. They can be used for impact analysis and make available an evidence baseline for managing surface water quality and assessing potential pollution risks.
ii. Nutrients export river models are still being designed for the past 20 years (Kroeze *et al.*, 2012), for some chemicals and plastics, e.g. TCS (Kroeze *et al.*, 2016);
iii. The pioneer global-based models are presently being established (Besseling *et al.*, 2017; Siegfried *et al.*, 2017) and for pathogens less than fifteen years (Hofstra *et al.*, 2013; Hofstra and Vermeulen, 2016).
iv. However, physical, chemical, and biological interactions between impurities or combined effects are yet to be modelled.
v. There are similarities in the movements of pollutants in the existing models. Generally, contaminants are released into waterways via municipal and industrial sewage (point sources) and through leaching and runoff (diffuse sources).
vi. Numerous chemicals are a consequence of similar anthropological sources, including family circles or food production. Also, climate change will continue threatening water quality (Michalak, 2016).
vii. Instances include increased precipitation that can wash many chemicals from crop fields and via drainage runoffs to river networks, and the temperature rises, leading to algal growth and consequent nutrient contamination of streams (Michalak, 2016).
viii. Data availability presents another challenge. There is limited data to scale water quality approaches and authenticate models for global-scale water quality analyses.
ix. A significant distinction between existing global models is the retention process of impurities in rivers or on land.
x. The models apply diverse hydrological models as a starting point, and they vary in detail both with temporal and spatial levels. The components on the spatial level from the network to combine river-basin models with more information on temporal deviations ranging from days to years (Kroeze *et al.*, 2016);
xi. While some models are chiefly designed to analyse future trends, other models can analyse the past.
xii. One more distinction is in the modelling approaches: consolidated, steady-state-models, e.g., Global-News, versus dynamic-process-based, e.g., IMAGE-GNM).
xiii. River pollution models at the global scale usually concentrate on a single pollutant, as shown in Table 1. However, generally, this is characteristic of most water pollution. This may perhaps be amazing, owing to the resemblances among the water quality models.
xiv. Consequently, water quality models of specific contaminants cannot be related easily, owing to the discrepancies in temporal and spatial detail, and differences in data input, parameters and how the river processes are patterned; and

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xv. As a result of these, a modern invention of cohesive water quality models that amalgamate sources of data, impacts, and products for various contaminants is required.

The rationality of contaminant modelling using pollutant transport models is mostly hard to authenticate because appropriate field data is unavailable for broader evaluation. Therefore, the model output must be analysed within the model inputs' uncertainty, data constraints and regularly essential application of accepted standards from the literature.

Conflict of interest

The authors proclaim that no conflicting interest is associated with this review article.

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