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# Water, Soil and Air Pollutants' Interaction on Mangrove Ecosystem and Corresponding Artificial Intelligence Techniques Used in Decision Support Systems - A Review

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**ABSTRACT** The feasibility of artificial intelligence (AI) as a predictive model for thorough efficacy analysis on environmental pollution applied on mangrove forests are discussed. Mangrove forests are among the most productive and biological diverse ecosystems on the planet. However, due to environmental pollution and climate change, mangrove forests are in serious decline. Despite crucial issues pertaining mangrove forests, the law enforcement on the ecosystem is still dubious due to the lack of evidence and data that could provide accurate analysis and prediction. The main highlight of this review elaborates on pollutant markers in soil, water, and air, by correlating these three aspects to the sustainability of mangrove ecosystem. The research gap identified from this review suggests the application of an integrated environmental prediction system for practical environmental insights. A predictive model for environmental decision-making could be developed by integrating meteorological, climatological, hydrological, atmospheric, and heavy metal concentration to understand the interaction between each factor for an efficient solution of pollutant reduction scheme involving mangrove ecosystems.

**INDEX TERMS** Mangrove estuarine, pollutant interaction, environmental quality modeling, integrated environmental decision system.

## I. INTRODUCTION

The adoption of artificial intelligence (AI) to study the occurrence of pollution in mangrove forests should be given an increase in demand and attention. Present application of artificial intelligence in monitoring water quality, and heavy metal pollution exists but have yet to be associated with mangrove forests.

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Mangrove forests exist between the intertidal zone of sea and land, they are the most vital and productive ecosystem for the coastal community, supplying ecological functions to numerous flora and fauna such as niche bacteria, macroalgae, fungus, zooplankton, prawns, shrimps, crabs, mollusks and insects [1]. Mangrove forests are important carbon sinks which could mitigate climate change as they can store carbon dioxide (CO<sub>2</sub>) approximately 2.5 times more than the amount of CO<sub>2</sub> produced by humans annually [2]–[4]. Other than this capability, mangrove forests significantly contribute to

the rural livelihood especially that involve aquaculture and fisheries, timber, fuel, or shelter to wildlife. The mangrove ecosystem covers a total of approximately 152,000 square kilometers of the world's surface, and 42% of mangrove forests are largely found in Asia [5], [6]. The economic value of mangroves per hectare per year is approximately in the range of USD2000 to USD9000 [7].

Despite their ability to thrive in harsh conditions, mangrove forests suffered deleterious effects from climate change, notably rising sea levels and environmental pollution. The global loss of mangroves is greatly driven by anthropogenic threats [8] and direct conversion of mangrove forests for export to support economic development [3], [6], [9], [10] which includes large-scale agriculture and aquaculture development for commodities such as rice, shrimp, oil palm cultivation, local exploitation and human settlement [11]. Extreme weather events, rising sea levels due to climate change, pollution and environmental degradation also largely contribute to the loss of mangrove forests. Several mangrove species were declared as endangered or critically endangered [12]. Trend analyses by FAO [7] has shown a drastic decline of mangrove area by 20% from 18.8 million hectares to 15.2 million hectares, with an annual average change of 0.7% from 1980 to 2005. The degradation of mangrove forests caused a total CO<sub>2</sub> emission rate of 14 million Mg CO<sub>2</sub> capped at annual emission rate of 0.5 Mg CO<sub>2</sub>. The impact of this scenario is worsen when only 6.9% of mangroves in the world is recognized as a protected area network [5].

The mangrove ecosystem consists of a few major components including the soil quality, the forest, marine and hydrology system. Pollution of soil and water degradation could directly affect the productivity of mangrove forests. In this manuscript, we present the possibility of using AI to study the integration of contaminant parameters found in air, water, and soil to aid the pollution monitoring of mangrove forests.

The objectives of this paper are as follow (i) to review on the impact of air contaminants, water quality parameters and heavy metal components (ii) to discuss existing environmental prediction tools used for heavy metal study and water quality analysis that can aid as a holistic pollution assessment for mangrove ecosystem (iii) to identify gaps on how predictive nature of AI can solve environmental related challenges impacted on mangrove ecosystem.

The dire effects of water and heavy metal pollution on the mangrove ecosystem are hardly irreversible [13]–[16]. Several reviews covered the topic of environmental pollution simulation over the past few years to evaluate past researches and future concepts for pollution modelling. Thorough reviews of water quality modelling from 2000-2020 are provided by Tung and Yaseen [17], while the feasibility of machine learning models for heavy metal prediction from 2019-2020 is further reviewed by Yaseen [18]. In addition, a number of air, water, and solid waste pollution modellings have been reviewed and summarized focusing on AI applications for both single and hybrid methods [19].

Although AI based predictive models can provide enormous capability and flexibility in forecasting complex environmental problems, we consider that the predictive models covered in this study are only targeting individual solution in addressing either water, or heavy metal pollution issues that do not concern the wellbeing of mangroves. Moreover, there is no integrated solution that considers the relation of air, water, and heavy metals contaminant on the mangrove ecosystem. Thus, focus must be given to study possible degradation factors due to pollution of the highly declining mangrove ecosystem. The direction of this study aims to bridge the gap of understanding relevant parameters required for predicting environmental pollution associated with mangrove ecosystem using the intelligent approach of AI.

The paper is structured as follows: in section two, the degradation of mangroves caused by environmental pollution are elaborated based on published literature; section three introduces the correlation between environmental pollutants from water, air and soil pollution that could cause imbalance in the mangrove ecosystem; section four discusses the existing use of artificial intelligence for pollution monitoring of mangrove forests that are lacking in studies; section five provides guiding opinions to the development of integrated environmental decision system in mangrove forest; while section six concludes the review.

## II. MANGROVE FOREST DEGRADATION DUE TO ENVIRONMENTAL POLLUTION

Environmental pollution is defined as the disturbance of human activities to the physical and chemical cycle of living and non-living organisms with harmful perturbation effects. The impacts of pollution provoke the ecological system wildly and to humans as well.

Although mangrove forests are high in economical values than other ecosystems [20], mangrove forests suffer from accumulated marine litter pollution [21] and still perceived as the most convenient dumping sites. Some mangrove estuaries are suppressed by the impact of leachate and overflow garbage from the nearby illegal landfills [22]. In addition, oil spills [23], and chemical waste are also affecting the mangroves and other coastal marine habitats. The mangrove ecosystem is increasingly threatened by anthropogenic human activities such as land use conversion for agriculture and aquaculture, deforestation, greenhouse gas emission, waste dumping and overpopulation. This problem worsens with the increasing of industrial, plantation and mining activities carried out along estuary rivers. These activities not only affect the mangrove ecosystem but also alter soil quality by releasing harmful contaminants such as organic compounds, oils and heavy metals which eventually leach into the aquifer and thus affecting the water quality [24], [25]. Stressors such as land, water and air pollution are straining the ecosystem as these resources are the necessities for all living things. The disturbances of water, soil and air pollution defined for the mangrove ecosystem are evident.

**TABLE 1.** Heavy metals in  $\mu\text{g/g}$  or ppm in the collected samples of mangrove sediments.

Location	Concentration of heavy metals in mangrove sediments ( $\mu\text{g/g}$ )											References
	Cd	Cr	Cu	Zn	Pb	Ni	Mn	Hg	As	Co	Fe	
Nansha, China	0.78	155.0	113.0	159.0	55.3	48.4	880.0	-	-	-	-	[35]
Futian, China	2.3	55.4	31.7	296.3	47.8	-	-	-	-	-	-	[34]
Zhangjiangkou, China	0.03-0.19	9.67-134.51	10.79-26.66	119.69-157.84	36.71-59.86	-	-	0.00-0.08	15.6-31.6	-	-	[37]
Dongbao, China	1.08	612	1886	539	67.6	313	-	-	-	-	-	[38]
Rufiji, Tanzania	1.7	20.4	131.0	146.0	122.0	7.3	-	-	-	-	-	[40]
Muthupet, India	0.07-0.85	-	2.88-14.87	7.8-38.37	0.43-17.49	-	-	-	-	-	-	[41]
Kuala Selangor, Malaysia	-	-	1.00-10.60	215.40-259.00	18.83-28.59	-	-	-	-	-	-	[42]
Rabingh Lagoon, Saudi Arabia	20.06	15.00	218.5	134.23	288.5	102.13	-	-	-	-	8939.38	[43]
Can Gio, Vietnam	0.01-0.20	27.10-71.50	7.10-27.00	25.70-108.10	8.00-20.40	11.7-56.3	52.0-220.0	-	-	5.2-28.4	12.3-65.3	[44]

### A. IMPACT OF HEAVY METAL POLLUTION IN MANGROVE SEDIMENTS

The mangrove ecosystems is known as a natural wastewater treatment due to its high capability in retaining heavy metals such as Chromium (Cr), Copper (Cu), Zinc (Zn), Manganese (Mn) and Cadmium (Cd). Heavy metals are metallic elements that are relatively denser as compared to water. Improper discharge of heavy metals into the environment is often through the sewage runoff of manufacturing factories in metallurgy, paints, electroplating, papers, pigments etc [26]. Metal elements are high in solubility hence they are hazardous to the aquatic ecosystem as they are easily consumed and absorbed by living organisms [27].

In the mangrove ecosystem, the accumulation of heavy metals in the roots poses deleterious effects on the leaf number, stem basal diameter, biomass production and is also toxic to soil microbial communities. The interactive effects of trace metals even decrease the photosynthetic rate, and create osmotic stress toxicity to the mangrove seedlings [28]. Moreover, studies covered by Sobhanardakani, *et al.* [29] have discovered the presence of heavy metals in the gills, internal organs and tissues of fishes in polluted environment. The concentration of trace elements in marine biota such as crabs, puffer fish and seaweeds are higher than the World Health Organization (WHO) recommended standards and the exposure of metals has moderate hazard risks to human consumption [30]–[32]. Occurrence of radionuclides along with heavy metals in mangrove sediment also poses radiological hazards [33]. The combination of trace metals has a 21% probability of being toxic, with raising concerns of adverse biological effects due to Cd pollution [34], [35].

Heavy metals are reported as the highest main anthropogenic toxic elements present in mangrove ecosystems in Asia, ascending from the growth of urban and industrial development around coastal areas [13]. This condition is

accelerated with the lack of natural elimination processes for heavy metals. As such, the accumulation of heavy metal within the ecosystem creates ecological disturbance that causes risks to human health, and the aquatic biota, stressing the need for bioremediation of heavy metals [36].

Major heavy metal pollutants found in the mangrove ecosystem are Cadmium (Cd), Chromium (Cr), Copper (Cu), Zinc (Zn), Lead (Pb), Nickel (Ni), Manganese (Mn), Mercury (Hg), Arsenic (As), Cobalt (Co) and Iron (Fe) [34], [35], [37]–[44]. The pollution sources of trace metals are due to anthropogenic inputs such as metal processing, domestic sewage, agricultural and industrial activities [34], [37], [39], [43], [45]. The collection of data that studies heavy metal concentration in mangrove estuaries is shown in Table 1. Severe contamination of heavy metals that occurred in these study areas is likely due to rapid socioeconomic development, especially the disposal of industrial waste and domestic sewage. Presence of trace metals in the roots of the mangrove, although in small amounts could trigger toxic effects to the plant tissues and root epidermis [35], [38].

Among all heavy metals, Cu, Zn, Pb are the main heavy metals with high variations in each area studied, giving highest contamination levels in China. Despite having a small coverage area of mangroves about 0.04% of the total mangrove coverage in the world [46], heavy metal pollution in China is very serious owing to the discharge of industrial sewage waste and high industrialization development activities in the country.

Deforestation activities carried out since the late-1980s for land conversion industrial areas and shrimp ponds increased the rate of erosion of mangroves, which may have contributed to the high sedimentation rate and the influx of heavy metals [44]. The contamination of heavy metal is apparent and serious across the Asian region, heavy metal pollution not only causes mangrove degradation, the detrimental

impacts on adjacent coastal systems and human mankind is also irreversible. Bioaccumulation of heavy metals such as Pb, Zn, Cd and Cr are toxic to the ecological system as these metals can only get accumulated with time and not degraded naturally [47]. Hence, it is necessary to monitor the changes of heavy metal dissipation as a means of mangrove conservation.

## B. IMPACT OF WATER AND MARINE POLLUTION TO MANGROVE ECOSYSTEM

This section reviews the negligence on water pollution management which contribute to the destruction of mangrove forests. Water pollution especially oil pollution and herbicide exposure negatively affect mangrove ecosystem and other living organisms.

Discharges of wastewater and storm runoff can also cause problems to economic activities such as shrimp farming and fish cage culture Schaffelke, *et al.* [48] summarized 16 incidents that impact the quality of mangroves in the Great Barrier Reef region in Australia where 50% of damage is related to water quality contamination due to oil spills, deposition of sediments, and herbicide exposure, 31% of which are direct damage due to planned and permitted activities, giving it a total of 81% of mangrove impact are from the aftermath of human activities.

### 1) OIL SPILL POLLUTION

There is historical evidence of oil spill pollution on mangrove forests. The severe dieback of *Rhizophora Stylosa* and *Avicennia Marina* in Australia has shown that full recovery takes approximately 36 years or more [49]. The sub-lethal impacts of oil spill incidents could cause reduction of forest canopies and partial loss of habitat. Oils spills tend to coat breathing surfaces of mangrove roots, seedlings, stems, surrounding sediments and fauna [23]. A massive oil spill could smother the leaves and aerial root system of mangroves leading to death of mangroves within weeks. Lighter oil spills do not cause mortality, however it leads to initial defoliation [50].

### 2) HERBICIDE POLLUTION

Another source of water contamination is herbicide deposition from surface runoff. Photosystem II inhibiting herbicides are atrazine, diuron and ametryn that are commonly used for general weed control of commercial and industrial areas. Herbicides are strong in photosynthetic inhibition properties, causing chlorosis and wilting of leaves [51]. The presence of herbicides reduces canopy condition and declines the growth of seedlings. Herbicide poisoning is associated with the cause of severe dieback of 30 km<sup>2</sup> of mangroves at Mackay region, Australia in 2000. Further consequences from the dieback involve deteriorated water quality, increase in sediment and nutrients deposition and the dispersal of toxins [52].

### 3) SALINITY INTRUSION

Climate change causes the rising of sea levels giving impact on the increase of water salinity, posing a threat to the survival

and growth of mangrove forests. Such phenomena is evident in the Sundarbans, Bangladesh, where an increasing salinity trend was observed over a period of 27 years [53]. Increasing concentration of salinity has significant effects on mangrove seedlings, it delays root initiation and deters the rate of seedling establishment [54]. Seedlings at higher salinity failed to establish and died due to low survival rate [55]. For older mangrove trees, different species have different salinity tolerance limit, characteristics such as smaller height and grith of main stem, shallower roots are observed for mangroves at high saline zones [56]. Moreover, del Refugio Cabañas-Mendoza, *et al.* [57] studied the influence of salt concentration concluded that the increment in salinity inflicts changes in pH and the translocation of lead uptake to the mangrove leaves. This will then increase the heavy metal contamination risk.

### 4) OVERLOADING OF NUTRIENT

In South Australia, six years after the establishment of the sewage outfall, 250 ha of the mangrove species *Avicennia marina* have died since 1956. This is associated with excessive nutrients caused by algae bloom as an indirect human related cause [58]. Overloading of nutrients content in nitrogen, phosphorus, and silicate triggers the growth of algae. The long-term eutrophic condition in the Sundarban estuary showed declining of species and diversity resulted from abiotic stress [59]. Eutrophication disturbs the balance of the water ecosystem, as it introduces instability to the mangrove forests by lowering the mangrove resilience. Nutrient enrichment of coastal areas stimulates the growth of shoots yet increases the mangrove's vulnerability to water stressors such as high salinity and low humidity [60].

In another part of Asia, the discharge of sewage waste and in Navi Mumbai, India has impacted the water quality of mangroves in Uran [16], resulting in high levels of Orthophosphate (O-PO<sub>4</sub>), Nitrate-nitrogen (NO<sub>3</sub>-N), and silicates acting as an anthropogenic stress to the mangrove ecosystem. Almost similar pattern can be seen in the Merbok River, Malaysia where there is a significant declined in fish catches due to anthropogenic stress from large amount of ammonia and nitrate concentration in the estuary [61]. The high level of sediment and nutrient loadings might pose further threats in the future coastal and estuarine fisheries.

### 5) SEDIMENTATION RATE

Sedimentation is the sinking process of suspended particles by gravity. The rate of sedimentation has a negative correlation on mangrove density. According to Halim *et al.* [62], the higher the sedimentation rate, the lower the mangrove density. Mangroves roots are capable to retain sediment and slow down the rate of water flow hence accumulate deposition and sedimentation. Sediments are the source of nutrients to the mangrove ecology. Based on Okello *et al.* [63], mangroves at partial burial showed leaf emergence due to influx of nutrients, nevertheless, large sedimentation events may still result in negative tree development if nutrient thresholds are



not maintained. There are 26 cases of mangrove mortality in 1999 caused by root smothering due to excess input sedimentation [64]. Although mangroves flourish under sedimentary shorelines, an aerial root burial of 10 cm could cause significant death of mangrove species.

Other than that, majority of heavy metals from industrial discharge are deposited as sediment, the accumulation of sediment that contains heavy metal could further increase metal toxicity in water. These sediments release heavy metals in aqueous state leading to heavy metal pollution of water sources [65].

In short, it is apparent that the water pollution disrupts the hydrology of the river and sea causing mangroves and surrounding plants to die as well as marine fauna to be suffocated due to stagnant, anoxic, and toxic polluted water. The main driver to water pollution as elaborated in this study is due to industrial and residential sewage waste runoff. Due to the catastrophes reported worldwide, controlling and monitoring water pollution is needed either in upstream or downstream ecosystems.

### C. INTERACTION OF AIR POLLUTANTS ON TREE PHYSIOLOGY

Albeit direct impacts of air pollution to the health of mangrove ecosystem are lightly reported, the indirect impact of air pollution due to factors such as transportation, industrial and domestic activities could deter the water and soil quality existing nearby the trees. The most common air pollution phenomenon that could significantly influence water and soil are soil acidification and the increase of ozone concentration. The former scenario can affect the overall mangrove ecosystem through water and soil quality temperament resulting from acid rain that has higher concentration of Carbon Dioxide (CO<sub>2</sub>), Sulphur Dioxide (SO<sub>2</sub>) and Nitrogen Dioxide (NO<sub>x</sub>) than the allowable standard. Meanwhile, the later intensification of ozone concentration could deter the soil quality of mangrove forests from the chemical reaction by NO<sub>x</sub> and Volatile Organic Compound (VOC) under daily meteorological conditions.

In addition, there are increasing reported cases on the impact of the air pollution associated with tree health [66]–[70]. Findings from Takahashi *et al.* [71] concluded that acid deposition due to air pollution is a possible stressor for tree health in the changing climate. The effects of air pollution and climate change to forests as described by de Vries *et al.* [72] affects the soil processes, tree health and change in biodiversity.

#### 1) ACID DEPOSITION

In China, acid deposition is suspected as the main driver to the decline of the sub-alpine Faber's fir (*Abies fabir*) forest in Mt. Emei and forests at the Jiuzhaigou Valley World Heritage site [68]. According to [68], [69], high levels of sulphur and nitrogen depositions from industrial and agricultural air pollutants and acid rain during the wet season are thought to be the primary cause of forest damage in Jiuzhaigou Valley,

leading to tree dieback, tufa degradation and increased algal production. Soils in tropical areas have a high adsorption capability of SO<sub>4</sub><sup>2-</sup> hence there poses a major risk of soil acidification by nitrogen deposition specifically in East Asia as reviewed by Duan *et al.* [66].

The industrialization and urbanization over the past few decades is one of the main reasons to the acidification of river waters due to cumulative acid loading from the atmosphere to the soil [73]. The water pH trend study conducted by Qiao *et al.* [74] at river basins in China concluded that the increasing water pH trends from 2004 to 2014 are possibly caused by the reaction of water with SO<sub>2</sub> and NO<sub>x</sub> compounds from acid rain and anthropogenic pollutions. The change in pH may affect the association and distribution of Cu organic matter with the mangrove sedimentary [75].

A preliminary research performed by R. M., *et al.* [76] simulated acid rain on coastal zone tree species that included white mangrove, red mangrove and button mangrove commonly found in Mexico. The authors suggested that low pH exposure will lead to stress development in mangrove trees. Increased exposure of mangroves to acid significantly increases sulphur content increase, while chlorophyll a/b ratio decreases. Nutrient levels were also highly sensitive to low pH values. The publication suggested that the mangrove tree species could act as bioindicators for atmospheric pollution.

#### 2) OZONE POLLUTION

Moreover, extremely high concentrations of O<sub>3</sub> in the atmosphere as a result of climate change is likely to exacerbate effects on tree physiology [71]. Forest decline symptoms is observed in China and Japan at urban, mountain and subboreal forests [77], [78]. The phytotoxic air pollutant, O<sub>3</sub> has adverse effects to the tree vitality by impeding plant growth, reduce leaf biomass productivity, lower photosynthesis rates, and accelerate the process of tree deterioration [79], [80].

Griselda *et al.* [81] studied the effects of high ozone concentration on three mangrove species of which the research found visible damage on mangrove leaves that is caused by photo-oxidation. The mangrove species studied are sensitive to ozone exposure levels, showing a decrease in carotenoids.

As of now, the serious risks of ozone pollution are highly distinct in China [82]–[86] which not only reduce crop and yield productivity, but also threatens the health of human wellbeing and accounts for economic loss in food and wood production.

#### 3) HAZE EVENTS

Although severe tree decline due to haze events have not extensively reported, there are evident impacts of haze in Southeast Asia that may imply the inhibition of plant physiology, for instance Yoneda and Nishimura [87] reported the tree growth deceleration in the West Sumatra is prolonged by the Indonesian haze event by 23% that occurred in 1997. Effects of air pollution and forest fires causes a sunlight shielding effect due to particulate matter (PM), hence a reduction of stomatal conductance therefore directly impacts the

photosynthesis rate of plants [88], [89]. Philip [90] compared the photosynthesis rate and stomatal responsiveness of urban trees in Malaysia during non-haze periods with haze episodes and concluded the rates of photosynthesis and photosynthetic photon flux density declined between 20%–50% and 40%–75% respectively. Other than that, toxic metals such as Cr, Pb, As and Antimony (Sb) that are present in particulate matters may contaminate the plant tissues [91].

#### 4) DROUGHT EVENTS

Drought events and extreme heat waves are the impacts of climatic global warming resulting in the drying of vegetation, agriculture, and water resources [92], [93]. An occurrence of extreme drought event between late 2015 and early 2016 recorded a severe massive dieback of mangroves along Australia's shoreline [94]. During that time, there was an unusually lengthy period of severe drought conditions, unusually high temperatures and a receding of sea levels were observed. Furthermore, drought change brought about a clear reduction trend of mangrove canopy of the Persian Gulf and Oman Sea [95]. This was associated with the onset of sudden decrease of precipitation rate and rainfall.

The effects of climate change on mangrove ecosystems as analysed by Mafi-Gholami *et al.* [96] concluded that the changes in rainfall pattern from drought could lead to a rapid decline of mangrove establishment and growth. The conclusion was made from over 32-year observation period where adverse effects on the biomass production potential of mangroves are remarked. Reduction of rainfall makes the coastal quality less favourable due to changes in soil salinity and nutrients. Further impacts of drought bring about the deterioration of water supply, intrusion of saline water and increased pollution of waters from undiluted pollutant discharges. Sediment metal contaminants (Cu and Pb) were found to present higher levels when riverine flow was slow during drought periods [97].

Presently, the number of potential environmental distress due to climate change and air quality affecting the tree growth, forest ecosystem and agricultural vegetations are evident. If the concerns are not addressed, the environment could be in significant risks under large scale containment especially on mangrove forest since its growth is associated with water and soil qualities. As of now, the severe effects of air pollution towards the growth of mangrove forests have yet to be reported. Nevertheless, as impacts of air pollution on tree physiology are apparent in other parts of the world, the effects of ambient air pollution on mangrove forests cannot be disregarded.

### III. CORRELATION OF AIR, WATER AND HEAVY METAL POLLUTANTS IN MANGROVE ECOSYSTEM

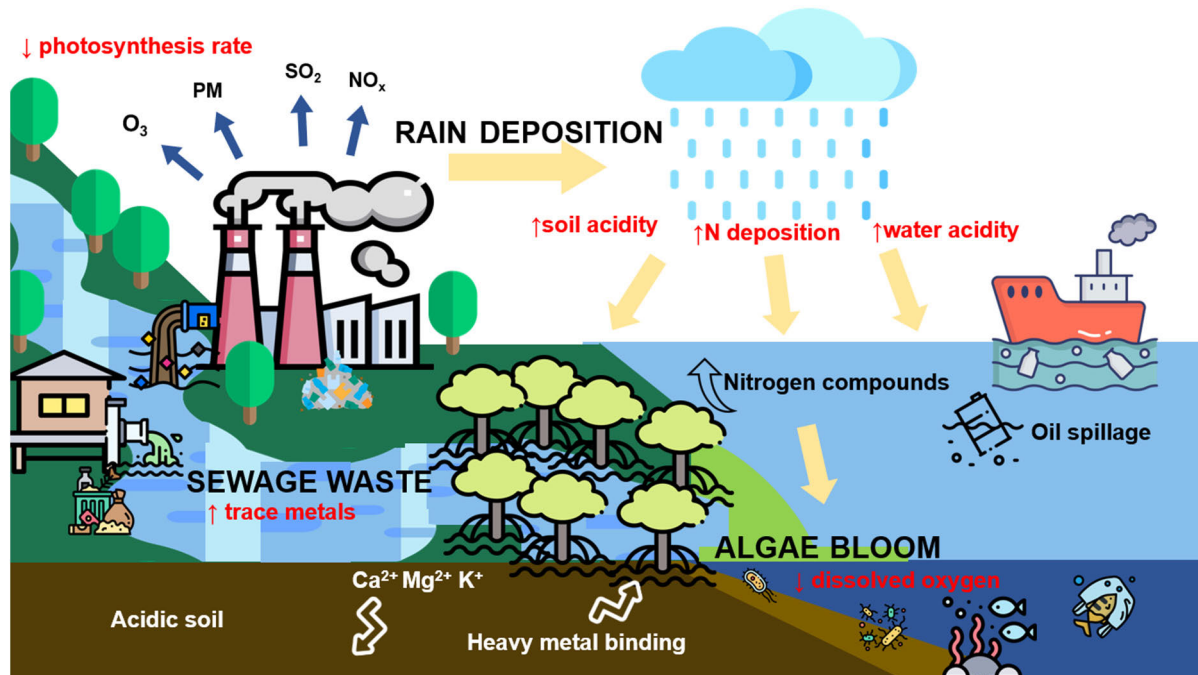
Reviews on the impacts of each pollution (*i.e.*, water, air, and heavy metal) to the mangrove ecosystems have been presented in Section 2. Even though the effects of air pollution towards the growth of mangroves do not show clear signs of deterioration, air pollutants could significantly deter the soil

and water quality of the ecosystem through acid deposition. This is due to acidifying compounds in the air particles that could leach into the hydrological cycle, increasing the acidity of the water or soil, the interaction effects are not always visible on water. According to Driscoll *et al.* [98], rivers or lakes may seem clean, yet they might be polluted due to acid precipitation that is caused by rain, snow and particulate matter. Water quality may also indirectly be contaminated by nutrients and heavy metals that leach from soils. Although acidification might be short term that varies with seasonal and stream flow, the sudden acid shock could be toxic to the aquatic biology, moreover, long term exposure of acid deposition could also alter the pH levels of water bodies.

The correlation between these pollutant markers in air, water and soil are not well defined. Existing research focused on individual impact of these pollutions on mangrove ecosystem. Therefore, we propose to analyze the correlation of air pollution to the water and soil quality along with their effects on mangrove ecosystem as shown in Fig. 1. Fig. 1 depicts the relation and impacts of each pollutant that exists in the mangrove habitat. Harmful air pollutants are released from industrial emission, burning of fossil fuels, vehicle pollution, and agricultural activities. Toxic air pollutants such as O<sub>3</sub>, PM, SO<sub>2</sub>, NO<sub>x</sub> have adverse effects to the ecosystem. This will eventually expose the plants to high ozone concentration levels and will contribute to potential risks in tree degradation and slower forest growth. This unideal condition will hinder the maturity of the mangrove and will affect mangrove rehabilitation efforts.

On the other hand, particulate matter that floats in air particles would act as a physical barrier for optimal photosynthesis, as the particle matter clogs the stomata openings and shields the leaves from receiving maximum sunlight. This is evident in the research conducted by Takahashi *et al.* [71] where they concluded that the tree and forest deterioration is due to SO<sub>2</sub> and NO<sub>x</sub>. Even though ecosystems thrive in optimal levels of nitrogen, excess nitrogen (N) results in biodiversity loss and increased stress on tree vitality. As illustrated in Fig. 1, acid rain is formed when SO<sub>2</sub> and NO<sub>x</sub> reacts with water and oxygen in air particles to form sulfuric and nitric acid. These acids are then carried to the ground when rain falls, resulting in an increase of soil and water acidic as well as elevated N deposition levels.

Furthermore, the mangrove environment is saturated with metals that are accumulated from sewage waste from industrial and agricultural runoff, boating activities, domestic garbage dumps leachate, leaching from domestic garbage dumps and mining activities [99]. Acid precipitation that occurs might further alter the soil chemistry [100] which in turns affect the physiology growth of plants. The relation of the increase in soil acidity increases the mobility of heavy metals in soil do exists. Higher concentrations of Al compound are observed in water sheds containing higher level of strong acids, suggesting the evident relationship of metal mobility with soil acidity. Research on mining areas in China carried out by Li *et al.* [101] defined that soil organic matter



**FIGURE 1.** Correlation of environmental pollution in air, water, and soil to the mangrove ecosystem.

and pH are significant contributors to the heavy metal content found in soil Liao *et al.* [102] ranked Zn, Cd and Cu as metals of most sensitivity towards acid deposition. Moreover, soil with higher acidity also has lower ability to retain essential plant nutrients such as calcium, magnesium, and potassium. From a study carried out by [103] in tropical forests, long term elevated N deposition in the plant ecosystem accelerates soil acidification and depletes the available Ca and Mg ions exchange in soil content.

In addition, nitrogen compounds might be accumulated in soils from rainfall even though the amount might be insignificant [104]. Nitrogenous atmospheric compounds are mostly attributed to air pollution, while rainwater contains mostly dissolved inorganic nitrogen. Cape *et al.* [105] reported that 24-40% of total dissolved nitrogen in rain and snow in the UK are made up of the organic nitrogen from air pollution. The amount of nitrogen from rainfall that flows into the soil and water bodies is dependent on location and seasonal influence, [106] highlighted that location that has impacts of excessive fertilizer use as well as air and water pollution poses higher chance of nitrogen compound accumulation as summarized in Fig. 1 [104]. Case study on the flow of fertilizer into rivers should be made around mangrove forests to further understand this potential risk. Other harmful sources that causes high N and phosphorus (P) levels which might lead to eutrophication are from agricultural activities due to the use of inorganic fertilizers [107].

Ecosystem with over saturated amount of nutrients especially nitrogen and phosphorus would trigger the growth of algae resulting in algae bloom. The eutrophication process

then further deters the water quality due to toxic algal, leading to anoxic or hypoxic conditions in rivers or estuaries that deprives the dissolved oxygen levels [108]. The impairment of the coastal marine ecosystem due to eutrophication threatens the fish community, causing die-offs of plants, creating a dead zone environment which is unable to support most organisms [109]. The toxicity of ammonia due to untreated human sewage discharge poses potential ecological impacts on aquatic species and ecosystem, particularly at high pH [110] Reef *et al.* [111] reviewed that despite the potential of mangroves as natural treatment systems for purification, the negative consequences of eutrophication could stunt the mortality rate of mangroves.

Substantially, particulate matter contamination and the spike of ozone concentration could weaken the mangrove trees by slowing down photosynthesis. Temperature change and rainfall patterns could alter the salinity content of water bodies, and therefore retain more heavy metal sediments. Moreover, water quality in mangrove ecosystem is also affected by human activities from agricultural, industrial, and residential development, causing further imbalance to the ecosystem. All these factors decrease the ability of mangrove forests to function effectively.

As a conclusion, despite the possible harm and interrelation of each pollutant factors towards plants or mangrove forests, there are no correlation studies that compile the interaction between environmental quality, specifically towards the most important mangrove ecosystem. We hope that this review gains insight for readers to explore on the pollution issue surrounding mangrove forests for an improved conservation.

We urge the correlation of the pollutant markers suggested in this study to be explored particularly in mangrove forests, as the ecological system is one of the few ecosystems that exists intertidal and heavily dependent on estuarine quality in terms of water and soil factors. The next subtopic shall discuss on an integrated solution based on artificial intelligence to uncover complex behavior between each pollutant markers.

#### IV. ENVIRONMENTAL POLLUTION SIMULATION USING ARTIFICIAL INTELLIGENCE

Over the years, environmental quality management has urged the development of various models for predicting and monitoring of resources. Mathematically expressed models including process-based (mechanistic) models and data-based (statistical) models are proven capable of encapsulating water quality drivers [112]. An example of simulation model is the Delwaq-Bloom-Switch eutrophication model which defines nutrient cycling, algae modelling, and oxygen-related processes [113].

The limitations of mathematical models are the complexity to represent every physical, chemical, and biological processes of terrestrial and aquatic ecosystem. This brings about uncertainty and complex developing process as mathematical models tend to oversimplify data analysis. In addition, highly detailed mathematical models are costly, and time consuming to develop and apply [112].

The application of AI techniques operates on a knowledge base which enables separation of data for prototyping and model re-usability, its advantage in handling numerous spatial data can be used for effective diagnosis, optimization, planning and management of the mangrove forests. While the advancement in the AI provides the edge of early prediction, this section presents the capability of AI in environmental pollution prediction by evaluating existing works on heavy metal and water quality prediction.

This section of review (i) provides supplementary information of research works based on AI models, and the advancement of their applications in water quality and heavy metal modelling; (ii) highlights the relevance of different input variables in different targeted area, give suggestions for data collection, discuss model advantages and performance comparison; (iii) lastly, give emphasis on the lack of studies in predicting pollution at mangrove ecosystem. Nevertheless, in-depth description of each AI models, the mathematical theory and architecture given in this review have not been detailed. The review has cited appropriate literatures for readers to further their knowledge.

##### A. HEAVY METAL SIMULATION

Heavy metal modelling using AI architecture such as neural network, fuzzy logic, regression and hybrid models have been extensively established to apprehend the irregular patterns of heavy metal simulation in soil sediment and water bodies [18]. The field on predicting the heavy metal

concentrations is yet to be ventured extensively particularly in mangrove sites. Recent studies compiled and reviewed are heavy metal samplings in water bodies originating from acid main drainage in Table 2 and heavy metal soil modelling in Table 3.

Publications reviewed in this section aims (i) to understand characteristics of heavy metal with other parameters in existing water bodies and soil; (ii) to decipher the trends of earlier simulation models and the later development of hybrid models that are well suited for the prediction of heavy metals.

##### 1) HEAVY METAL INPUT-OUTPUT CONSIDERATION

The common input parameters listed for heavy metal concentration prediction in water bodies are power of hydrogen (pH), sulphate ( $\text{SO}_4^{-2}$ ), Magnesium (Mg), electrical conductivity (EC), total dissolved solids (TDS), total suspended solids (TSS), nitrate ( $\text{NO}_3$ ), phosphate ( $\text{PO}_4$ ), dissolved oxygen (DO), chloride (Cl), turbidity (TUR), total nitrogen (TN), ammonia nitrogen ( $\text{NH}_3\text{-N}$ ), nitrate nitrogen ( $\text{NO}_3\text{-N}$ ), total phosphorus (TP), orthophosphate ( $\text{PO}_4\text{-P}$ ), permanganate index ( $\text{COD}_{\text{Mn}}$ ), water temperature (WT), clay, organic carbon (OC), air temperature, rainfall, humidity, flow rate, hydraulic gradient, lifetime, water level, and abstraction.

Fig. 2a shows the percentage of common input parameters used by researchers in heavy metal simulation. pH,  $\text{SO}_4$ , Cl, EC, TDS, TSS and water temperature are the non-metal variables preferred in heavy metal modelling studies, specifically in water bodies.

pH or hydrogen ion concentration is one of the most important environmental aspects that influences the survival and physiology of the aquatic ecosystem. The pH level is dependent on the biological activities and acidity of the bottom sediment. A high pH value could signify a high photosynthesis rate from dense phytoplankton blooms, whereas a low  $\text{pH} < 4$  could threaten the aquatic life. The ideal range for biological productivity is  $\text{pH} 7.0\text{-}8.5$  [126]. Heavy metal discharged in water bodies from urbanization and industrialization activities could leach into the sediments from adsorption and flocculation [127]. However, when the dynamic equilibrium of the water sediment interface is broken due to the change in environmental conditions, the heavy metals in the sediment will be transferred back into the overlaying water, and therefore pollute the water quality. This process of transferring or migration of heavy metals is known as ion exchange where the main influencing factor is pH concentration [128]. Appel and Ma [129] concluded that pH affects the adsorption characteristics of heavy metals since the hydrolysis of heavy metals and formation of ion pairs are controlled by the solubility of hydroxides phosphates and carbonates. Low pH is likely the main factor of the dissolution and leaching of heavy metals into the aqueous system particularly at acid mine drainages [114], [115], [117], [130].

Temperature is a major limiting factor to the solubility of gases and the rate of metabolic activities and distribution of



**TABLE 2.** Heavy metal simulation in water bodies.

Refere nces	Data timescale / Sample size	Sampling site / Location	Input/output variables	Performan ce metrics	Prediction model	Research conclusions
Rooki, et al. [114]	February 2006 (Not given)	Acid mine drainage (Sarcheshmeh, Iran)	pH, SO <sub>4</sub> <sup>2-</sup> , Mg // Cu, Fe, Mn, Zn	R, RMSE	BPNN, GRNN, MLR	In this study, ANN is regarded as the most cost-effective method. The study suggested to apply back propagation neural network (BPNN) and generalized regression neural network (GRNN) approaches for heavy metal prediction.
Aryafar , et al. [115]	February 2006 (Not given)	Acid mine drainage (Sarcheshmeh, Iran)	pH, SO <sub>4</sub> <sup>2-</sup> , Mg // Cu, Fe, Mn, Zn	R, RMSE	SVM, GRNN	The study concluded the SVM method resulted in a better accuracy with an RMSE reduction relative compared to the GRNN model. The SVM is much more reliable as it has an optimal running time as compared to the GRNN technique.
Elzway ie, et al. [116]	Seasonal  Wet and dry season (Malaysia), winter and summer season (Libya)  (Not given)	Lake water (Malaysia and Libya)	pH, EC, TDS, TSS, NO <sub>3</sub> , PO <sub>4</sub> , DO, Cl, SO <sub>4</sub> , WT, air temperature, rainfall, humidity // Ni, Co, Fe, Zn, Cu, Pb, Cd	R <sup>2</sup> , RMSE, NRMSE, MAE	RBFNN	This study analyzes the influence of temperature, rain and humidity on heavy metal concentration using radial basis function neural network (RBFNN). The RBFNN model justified performs well in recognizing input parameters accurately at a correlation coefficient of 0.99. Rainfall is regarded as the parameter of greatest sensitivity specifically in tropical climates.
Lu, et al. [117]	Monthly  March 2016 - April 2016 and Nov 2016 to April 2017  (Not given)	Lake and river water (Taipu, China)	WT, pH, SS, TUR, TN, NH <sub>3</sub> -N, NO <sub>3</sub> - N, TP, PO <sub>4</sub> -P, COD <sub>Mn</sub> // Ti, V, Cr, Mn, Co, Ni, Cu, As, Se, Cd, Sb, Pb	R, MSE, NSE	ANN, SVM	The support vector machine (SVM) model is better suited to model heavy metal concentrations as it is much more stable compared to the ANN model. Sensitivity analysis concluded the input parameters that are significant in descending order are pH > SS > TUR > COD <sub>Mn</sub> > TP.
Ozel, et al. [118]	Dec 2012-2013 (Not given)	River water (Bartın, Turkey)	WT, pH, EC, COD, BOD, and SS // Cu, Fe, Zn, Mn, Ni, Pb	R <sup>2</sup> , RMSE, MAE	MLP, RBN, ANFIS	The MLP model is successful for Ni modelling, the RBN is best suited in estimating Cu, Zn and Mn, while Fe and Pb is best predicted using the ANFIS model.
Sonme z, et al. [119]	Bi-monthly  Dec 2014- Dec 2015	River water (Filyos, Turkey)	Fe, Cu, Mn, Zn, Ni, Cr // Cd	R <sup>2</sup> , RMSE, MSE, NSE, MAPE, MAD	ANFIS	The ANFIS model is accurate for modelling Cd concentrations in this study, the correlation between the observed and modelled output concentration is relatively high at coefficient of determination R <sup>2</sup> =0.91.

**TABLE 2. (Continued.) Heavy metal simulation in water bodies.**

Bayatzadeh, et al. [120]	February 2008 (52 samples)	Groundwater (Lakan, Iran)	SO <sub>4</sub> <sup>2-</sup> , Cl, TDS // Fe, Mn, Pb, Zn	R <sup>2</sup> , MSE	ANN, ANN-BBP, MANFIS- SCM	This study optimized the connections weights of ANN by incorporating ANN with biogeography-based optimization (BBO) and demonstrated multi-output adaptive neural fuzzy inference system (MANFIS) paired with subtractive clustering method (SCM). The hybrid MANFIS-SCM model is a reliable technique to estimate heavy metal distribution in groundwater given its high degree of accuracy and robustness.
Boudaghpour and Malek mohamadi [121]	Seasonal 2012–2013 (168 samples)	Groundwater (Qazvin, Iran)	pH, EC, flow rate, hydraulic gradient, lifetime, water level, and abstraction // As, Pb, Zn	R <sup>2</sup>	ANN	Dispersal of heavy metals in groundwater is modelled in this study using ANN. Well depth, well water level, and hydraulic gradient are effective input parameters to forecast concentration of metals in future situations.

aquatic organisms. The influence of temperature to heavy metal concentration is established based on the temperature changes and climate that are affected by rainfall. Rainfall intensity and volume are important factors to the export of TSS from agricultural areas into the watershed [131]. The rainy environment could carry various pollutant from the surface runoff into water bodies. Therefore, heavy metal concentration is highly related to the content of TDS and TDS. Moreover, TDS and temperature also affect the depletion level of DO in the water [132].

Electrical conductivity on the other hand could increase the inorganic substance concentration according to the amount of evaporation in the environment. Generally, sulphates and chlorides are anions responsible for salinization, these anions when react with available cation metals will increase the salinity of the soil solution. Salinity is the contributing factor to the ionic strength of a soil solution [133]. An increase in ionic strength increases the mobility and concentration of heavy metals released [134].

The use of pH, water temperature, TDS, TSS, EC, SO<sub>4</sub> and Cl as input parameters show close relation to the distribution and concentration of heavy metals, future work in heavy metal prediction should heavily consider these input data for an accurate and reliable predictive performance.

The output metal types illustrated in Fig. 2b represented the number of publications that have used these output variables in their studies for heavy metal concentration analysis. Among the 14 outputs studied, Pb and Zn are mainly considered for simulation as lead and zinc are the common contaminants found in water bodies and sediment. Toxicity

of Pb, Cd, and As are regarded as the major public concern by the WHO.

## 2) TIME SCALE OF DATA

From the review of the above heavy metal simulation, fluctuations of heavy metal concentrations vary according to the season and region of study. Areas of high humidity and rainfall rates tend to carry more TSS and TDS into the aqueous environment, hence showing higher correlativity to the concentration of heavy metals. Seasonal samplings of heavy metals should be encouraged to understand the climatological factors on prediction output. In addition, smaller time increments are well suited for analyzing heavy metal parameters as heavy metals are particularly sensitive to the slight changes in climatic conditions. Larger sampling size could prevent the overfitting models which are common in ANN.

## 3) PERFORMANCE METRICS

There are 10 performance metrics used in this namely modified index of agreement (md), mean absolute deviation (MAD), NashSutcliffe efficiency (NSE), mean absolute percentage error (MAPE), mean absolute error (MAE), normalized root mean square error (NRMSE), root mean square error (RMSE), mean squared error (MSE), coefficient of determination (R<sup>2</sup>) and correlation coefficient (R). The most common performance metrics applied were R<sup>2</sup> and RMSE. Generally, higher value of R<sup>2</sup> and lower value of RMSE represent better fitness and smaller discrepancy of predicted and actual values. The acceptable range of R<sup>2</sup> is greater than 0.6 and an RMSE less than 10%.

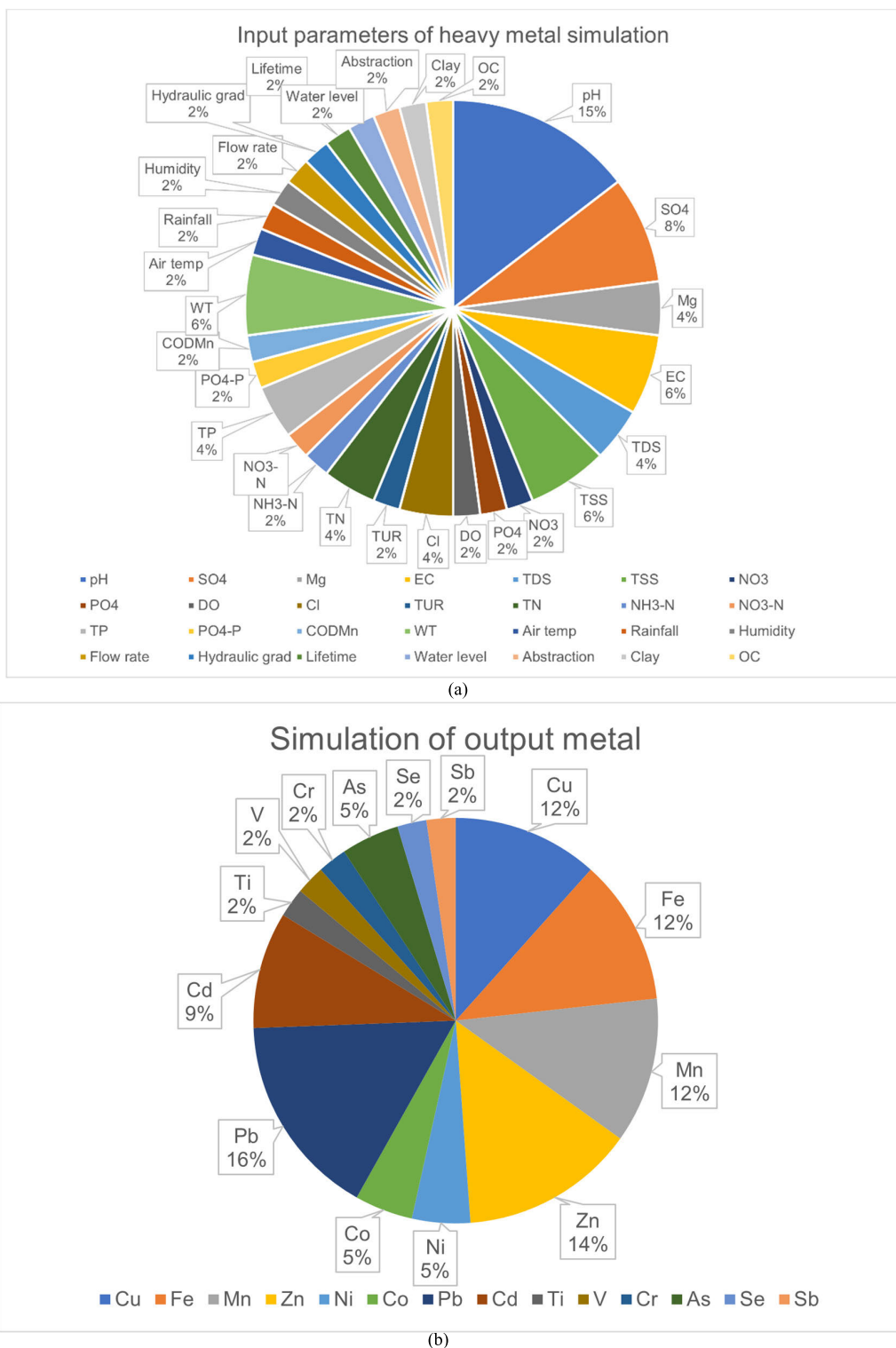
**TABLE 3. Heavy metal modelling in soil sediment.**

References	Data timescale / Sample size	Location	Input/output variables	Performance metrics	Prediction model	Research conclusions
Bazoobandi, et al. [122]	Not given (250 samples)	Gilan, Iran	Clay, OC, pH, P, and TN // Pb, Cd	R <sup>2</sup> , RMSE, MAE	ANN, MLR, ANFIS	The study demonstrated the reliability of ANN models (RMSE 1.04, 0.23) compared to ANFIS (RMSE 2.56, 1.27) and MLR models with organic carbon (correlation coefficient, R = 0.55) regarded as the best input parameter for prediction of Pb and Cd in soil.
Bhagat, et al. [123]	Bi-monthly February, April, June, and Nov 2012 at Bramble Bay (48 samples), April, June, and Nov 2012 at Deception Bay (78 samples)	Bramble and Deception Bay, Australia	Zn, Ni, Co, Fe, Cu, Gallium (Ga), Cerium (Ce), Aluminium (Al), Vanadium (V), Tl, Uranium (U), Thorium (Th), and Titanium (Ti) // Pb	R <sup>2</sup> , RMSE, MAE, NSE, MAPE, md	ANN, SVM, RF, XGB	This study utilizes explores the potential of the extreme gradient boosting (XGBoost) model using SuperLearning (SL) algorithm as an effective method for Pb prediction. Hyperparameter tuning of the XGBoost model was able to overcome the overfitting problem. Zn was determined as the most effective predictor for Pb.
Li, et al. [124]	Weekly 1998-2017 (Not given)	Elbe River, Europe	pH, EC, WT, river flow, NO <sub>3</sub> -N, and DO, and Fe // As, Pb, Zn	R <sup>2</sup> , RMSE	BPNN, NARX, WNN, WNARX	Hybrid models were incorporated in this research using concepts of wavelet transform into ANN and nonlinear autoregressive exogenous (NARX) model. Although hybrid wavelet methods enhanced the prediction performance of heavy metals, different input combinations coupled with different models were required to ensure optimum results
Cao and Zhang [125]	(Not given)	Ningxia, and Wuhan, China	Cr, Cs, Mg, Pb, Ti // Co (Ningxia) As, Cd, Ni, Pb, Zn // Cr (Wuhan)	RMSE, MAE, MAPE	SVM, RBFNN, WNN, BSA-WNN	This study integrated wavelet neural network (WNN), to form a collaborative compound neural network model (CCNN). The parallel bird swarm algorithm (PBSA) enhances the searching algorithm and optimizes the WNN parameters. Future work can be put forward to minimize the computation time of the CCNN.

#### 4) HEAVY METAL PREDICTION MODELS

Common heavy metal modelling techniques such as ANN, SVM and ANFIS have proven their effectiveness to simulate heavy metal concentration based on data collected. Nevertheless, these techniques possess drawbacks that prevent or limit the model from being widely adapted. Subsequent improvements using ensemble and hybrid methodology could overcome the limitations albeit the drawback of complexity and large computational time. Table 4 below summarizes these advantages and disadvantages.

Artificial neural network (ANN) is frequently implemented as a reliable predictive model for most of the studies. ANN is made of at least an input and output layers that which consist of neurons connected with weights, other than the two input and output layers, several hidden layers could exist depending on the number of parameters used for prediction. Earlier studies in 2011 by Rooki *et al.* [114] at acid mine drainage (AMD) utilized ANN to capture the complex relationship of input data. The ANN techniques have demonstrated high coefficient of determination and lower error rate compared to multilayer regression (MLR)



**FIGURE 2. (a) Pie chart of number of researches applied against input parameters of heavy metal simulation of water bodies. (b) Pie chart of number of researches against output metal type in heavy metal simulation.**

and adaptive neural fuzzy interference system (ANFIS) models. The ANFIS is a structure composed of a five layered feed-forward network that adopts fuzzy logic and neural network to map the input space to the output space.

However, one of the most common disadvantages of ANNs is the overfitting phenomenon during the training phase. In large networks of less available data, the error of training set is driven to small error values, yet when new data is introduced, the network returns a large error.



TABLE 4. Summary of heavy metal modelling techniques.

Techniques	Prediction Capability		Advantages	Disadvantages
ANN [114, 116, 118, 121, 122]	[114]	BPNN/GRNN	- Cost effective	- Large input sensitivity such as noise
	R	BPNN 0.22-0.97	- High accuracy and performance	- sensitivity which could cause
		GRNN 0.37-0.99	- Close correlation between predicted	- changes in simulation results
	RMSE	BPNN 1.31-7.68	- and measure concentrations	- Instable outputs due to randomized
		GRNN 1.31-9.89	- Good at handling non-linear data	- weightages
			- using hidden layers	- Local minima problem
	[116]	RBFNN		
	R <sup>2</sup>	0.6046-0.9968		
	RMSE	0.0020-0.2129		
	[118]	RBN		
R <sup>2</sup>	0.764-0.989			
RMSE	0.0008-0.1281			
[121]	ANN			
R <sup>2</sup>	0.76-0.88			
[122]	ANN			
R <sup>2</sup>	0.54-0.89			
RMSE	0.23-1.83			
SVM [115, 117]	[115]		- Effective in distinguishing marginal spaces	- Same output from same training data
	R	0.86-0.99	- Memory efficient	- Not suitable for large training datasets
	RMSE	1.22-3.21	- Optimal running time	- Lack of probabilistic explanation
	[117] R	0.63-0.99		
ANFIS [119]	R <sup>2</sup>	0.87-0.98	- Rapid learning capacity	- High computational cost
	RMSE	0.00019-0.00076	- Takes the advantages of ANN to capture nonlinear process	- Dimensionality constraints
			- Highly adaptable	
			- More transparent, less memorization errors.	
Ensemble [123]	R <sup>2</sup>	XGB 0.87-0.99	- Tuning of hyperparameters of AI predictive models	- Large scale of dataset needed to optimize the global minima
	RMSE	XGB 0.58-2.39	- Able to overcome overfitting	- Predicting capability and complexity leads to different prediction results
			- Optimal learning process	
Hybrid [120, 124]	[120]	R <sup>2</sup>	- Higher accuracy degree and robustness	- Different and specific input combination required for optimum prediction results
	ANN	0.52-0.79		
	ANN-BBP	0.69-0.85	- Enhances long term concentration prediction	
	MANFIS-SCM	0.60-0.99		
	[124]	R <sup>2</sup>		
	WNN	0.101-0.768		
	WNARX	0.006-0.637		
		RMSE		
	WNN	0.026-3.428		
	WNARX	0.278-13.727		

**TABLE 4.** (Continued.) Summary of heavy metal modelling techniques.

CNN [125]		RMSE	-	Efficient in ANN hyperparameters tuning and optimization	-	High computation time
	BSA-WNN	7.758-17.469				Large training data needed
	CCNN	7.246-17.391				

Stopping criteria, Bayesian regularization methods, fixing the number of epochs and dividing the datasets into training and testing sets are one of the few ways to avoid this occurrence.

A continuation study of AMD heavy metal prediction conducted by Aryafar *et al.* [115] found that support vector machines (SVM) technique contributes to lesser processing time and higher accuracy under the small number of samples. SVM is a type of classification and regression technique that is able to construct nonlinear decision functions to improve generalization performance in pattern recognition.

The drawbacks of ANN compared to SVM are the sensitivities of input parameter. ANN is sensitive to noise and a small 10% relative error could lead to large changes. Moreover, the weightage of each ANN models are initialized randomly for every simulation, hence the output of ANN is not as stable as SVM when applying the same input data [117]. Nevertheless, ANN techniques are still prominent in heavy metal modelling. Hybrid techniques such as bio-geography based optimization in Bayatzadeh Fard *et al.* [120] to regulate the weight and biases in ANN.

Complexity in heavy metal modelling tends to perform better using hybrid methods such as Convolutional Neural Networks (CNN) [125] and ensemble algorithms. Bhagat, *et al.* [123] demonstrated the use of the XGBoost model gives higher predictability with less declination. Another popular element of hybridization is wavelet neural networks (WNN). WNN is a breakthrough in wavelet analysis and research, the proposed network combines traditional methods of neural networks giving the advantage of faster convergence speed and strong nonlinear approximation ability [125]. WNN can achieve convergence despite the divergence effect of multiple inputs. In such, the activation function retains its sensitivity to predict extreme values and display better adjustments [124]. Subsequently, wavelet decomposition poses extraction properties of the input's division signals bringing positive effect for heavy metal content prediction.

To conclude this section, other than pH, EC, TSS, SO<sub>4</sub>, Cl and the input parameters mentioned above, the levels of heavy metals are also highly reliant on the content of clay and slit specifically in mangrove sediments [135]. Estimation of heavy metals remains a challenge for researchers due to adsorption of metal ions in fine clay, hence increasing the complex behavior. Despite the complex behavior of heavy metals, the estimation of heavy metals remains an ongoing research to understand the pattern of contamination as the effects of metal toxicity to the environment. The common

issues experienced by AI modelling of heavy metals are the adequacy of the selected input data and the model topology in which both are key factors to the efficiency of AI models [136].

Global average values of heavy metals in water bodies have critically exceeded the WHO and United States Environmental Protection Agency (USEPA) guidelines, according to the global heavy metal evaluation conducted by (Kumar *et al.*, 2019) from 1994 to 2019. Measuring and sampling of heavy metal pollution level requires a largescale of labor, cost and time, therefore modelling of prediction levels offers an effective alternative to monitor the pollution level for the sustainability of resources and for prevention of further contamination. Artificial intelligence tools in predicting the pattern of heavy metal pollution reviewed in this study can be served as a baseline to explore the ecosystem that can be affected from heavy metal contamination. Thus, the research gap presented in this section suggested further heavy metal prediction techniques should be applied in monitoring the heavy metal contamination of mangrove forests that is at risk for contamination and deterioration.

## B. WATER QUALITY SIMULATION

The employment of artificial intelligence has long been applied into water quality monitoring since 2000s as concluded by Tung and Yaseen [17]. AI models are reliable as they could overcome the problem of missing or unavailable data. The easy implementation of AI model also allows cost-effectiveness and eases the decision-making process. Table 5 below depicts several studies that performed water quality related modelling and optimization understanding by means of artificial intelligence for water quality index prediction. Table 6 summarized several AI works on the simulation of a single water quality parameter.

The review of publications in this section aims (i) to provide a brief overview of common input parameters used to describe water quality; (ii) to gain understanding of the advancement of water quality modelling; (ii) to cite variation of input used in effective water quality simulation through potential synergistic interactions or nonlinear meteorological attributes.

### 1) WATER QUALITY INPUT CONSIDERATION

There are about 33 water quality variables in terms of physicochemical and biological parameters such as pH, Water Temperature (WT), Conductivity (COND), Salinity (SAL), Turbidity (TUR), Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen

**TABLE 5. Artificial intelligence in water quality index modelling.**

Refere nces	Data timescale / Sample size	Sampling site / Location	Input / Output data	Performan ce metrics	Prediction model	Research conclusions
Samsu din, et al. [137]	2011-2015 (Not given)	Estuaries (Peninsular Malaysia)	DO, TSS, FC, AN, NO <sub>3</sub> , PO <sub>4</sub> , OG, As, Cr, Cd, Cu, Pb, Zn // MWQI	R <sup>2</sup> , RMSE	SDA-ANN, SDA-MLR	The study concluded the robustness of ANN models for effective computation of WQI. The use of spatial discriminant analysis (SDA) was performed to identify significant variables for the mangrove water quality index (MWQI). It was found that DO, TSS, O&G, PO <sub>4</sub> , Cd, Cr and Zn are important predictors.
Tiwari, et al. [138]	1996-2012 (Not given)	Satlju River, India	pH, COND, Cl, DO, BOD, TDS, TSS, AN, NO <sub>3</sub> , TP, FC // WQI	R <sup>2</sup> , RMSE, MSE	SC-ANFIS, FCM- ANFIS	Clustering algorithms used in this study to develop fuzzy logic ANFIS model proved to have reduced the lengthy computations of WQI. The study suggested that subtractive clustering (SC) approach is proved to have better predictive ability than the Fuzzy C-Means (FCM) model for characterization of WQ.
Dezfoo li, et al. [139]	2007-2012 (172 samples)	Karoon River, Iran	pH, TUR, TP, WT, BOD, DO, NO <sub>3</sub> , FC, TS // WQI	Accuracy, Error value (EV), Error rate (ER)	PNN, kNN, SVM	In this study, the authors revealed that the Probabilistic Neural Network (PNN) is competent in classifying water quality with the only three water quality parameters on fecal coliform, total solids and turbidity with an accuracy rate of 90.70% and only 9.30% of error.
Kamya b- Talesh, et al. [140]	Monthly Dec 2007 – Nov 2008 (Not given)	Sefidrud River, Iran	pH, WT, TUR, TDS, BOD, DO, NO <sub>3</sub> , PO <sub>4</sub> , FC // WQI	R <sup>2</sup> , RMSE	SVM	This study modelled the use of SVM in WQI simulation returns an R <sup>2</sup> of 0.87 and RMSE of 0.061. The most important input parameter identified is nitrate concentration.
Li, et al. [141]	Monthly 2004-2013 (Not given)	Euphrates River, Iraq	TDS, BOD, Cl, K, DO, COND, Na, Mg, Alkalinity, pH, Ca, PO <sub>4</sub> , NO <sub>3</sub> , TH, SO <sub>4</sub> // WQI	R <sup>2</sup> , RMSE, MAE, d	SVR, SVR- FFA	The authors proposed a robust hybrid SVR model with the firefly Algorithm (FFA) to predict WQI. The SVR-FFA model enhanced the standalone SVR model of RMSE and MAE by 42% and 58% respectively.
Asadol lah, et al. [142]	Monthly 1998-2017 (Not given)	Lam Tsuen River, Hong Kong	BOD, COD, DO, EC, NO <sub>3</sub> -N, NO <sub>2</sub> - N, PO <sub>4</sub> , pH, WT, TUR // WQI	R <sup>2</sup> , RMSE, NSE, MAE	DTR SVR ETR	The study employed the novel ensemble extra tree regression (ETR) algorithm to predict WQI. The ETR model showed improvement than the traditional decision tree regression (DTR) and support vector regression (SVR) models,

**TABLE 5. (Continued.) Artificial intelligence in water quality index modelling.**

<p>Demand (COD), Ammoniacal Nitrogen (AN) or <math>\text{NH}_3\text{-N}</math>, Ammonium Nitrate (<math>\text{NH}_4</math>), Total Suspended Solids (TSS), Total Dissolved Solid (TDS), Total solid (TS), Nitrate (<math>\text{NO}_3</math>), Chloride (Cl), Phosphate (<math>\text{PO}_4</math>), Sulphate (<math>\text{SO}_4</math>), total phosphorous (TP), total hardness (TH), Alkalinity, Arsenic (As), Mercury (Hg), Cadmium (Cd), Chromium (Cr), Lead (Pb), Zinc (Zn), Calcium (Ca), Iron (Fe), Potassium (K), Magnesium (Mg), Sodium (Na), Oil and Grease (OG), MBAS (Methylene Blue Active Substance), Escherichia coli (E-coli) and Fecal Coliform (FC) used for water quality index (WQI) formulation.</p>	<p>in terms of performance and minimal input parameters. With only BOD, TUR and phosphate concentration, the system could achieve a high accuracy of <math>R^2 = 0.97</math> and <math>\text{RMSE} = 3.74</math>.</p>
<p>From Fig. 3 below, it can be identified that DO, BOD, pH and <math>\text{NO}_3</math> are regarded as the significant input parameters for accurate representation of WQ, further concluded from [151]–[153] that the parameters with the highest significance are dissolved oxygen and ammoniacal nitrogen. Kamyab-Taresh <i>et al.</i> [140] identified <math>\text{NO}_3</math> as the most important attribute for WQI with subsequent importance in BOD and TDS. Nonetheless, the study in Bayatzadeh Fard <i>et al.</i> [120] regarded fecal coliform the most significant parameter for water quality classification, as the study has proven that a great error might occur if FC is omitted.</p>	<p>For the prediction of dissolved oxygen, pH and water temperature are regarded as the most reliable parameters [143], [144], [160], [161]. The fluctuation of pH affects the photosynthesis rate of aquatic life, higher photosynthesis results in higher oxygen released. Moreover, solubility of oxygen is affected by temperature, at warmer temperature, levels of dissolved oxygen decreases; while other possible influencing parameters to the solubility of dissolved oxygen is salinity and pressure [162].</p>
<p>The relative importance of each variable differs slightly for every region since land use and socioeconomic development of every river is not the same. For example, at Kinta River, Perak [153] the major use of land near the river basin are extensive mining, logging, urban development, oil palm and rubber planting. Even though Gazzaz <i>et al.</i> [153] rated the relative importance of water quality parameters in Perak as <math>\text{DO} &gt; \text{BOD} &gt; \text{AN} &gt; \text{pH} &gt; \text{COD} &gt; \text{turbidity}</math> in 2012, Isiyaka <i>et al.</i> [154] further the study in 2018 to conclude the significant parameters contributing to water pollution are <math>\text{DO} &gt; \text{AN} &gt; \text{COD} &gt; \text{BOD}</math>. This suggests that the increase in AN significance is attributed to the rise of improper waste management of industrial and agricultural activities carried out near the basin.</p>	<p>Hydrological and climatological data were used by Kumar <i>et al.</i> [145] and Song and Zhang [150] to predict nitrogen and turbidity values respectively. The model built in both studies were effective and reliable, suggesting the importance of environmental factors to predict water quality. Furthermore, Iglesias <i>et al.</i> [149] improved the ANN model behavior when a synergistic variable was included as input. The interaction of two input parameters forms a synergy that characterizes the joint action of two or more inputs, resulting in a greater accuracy from the sum of these causes. Environmental systems often react in nonlinearity, thus the outcome from synergistic responses is an advancement to represent the complicating factors in environmental modelling.</p>
<p>The high number of dependent variables requires higher computing power to process the large dataset. Several researches have carried out input sensitivity for the determination of the relative importance of each parameter in the specific area of study [151]–[159]. The analysis is conducted through the leave in one out approach by excluding one parameter to determine the percentage of contribution to the calculation of water quality index [151], [152]. Sensitivity analysis is one of the most essential steps for modelling the characteristics of water quality index as different rivers portrays different dependent input parameters.</p>	<p><b>2) TIME SCALE OF DATA</b></p> <p>According to the above reviews, monthly and daily sampling are sufficient to produce a capable prediction system. To improve robustness and efficacy of prediction models, daily values of water quality parameters scaled on hourly averages are more reliable. The variations of water quality are highly volatile to the surrounding weather events, therefore, to capture accurate patterns of water quality for prediction modelling, smaller time step of data is recommended. Nevertheless, due to the large amount of available water quality instances, feature selection of input parameters has to be site specific to prevent lengthy computation time.</p>
	<p><b>3) PERFORMANCE METRICS</b></p> <p>Dominating performance metrics in water quality modelling are <math>R^2</math>, RMSE and NSE among other performance indices of accuracy, EV, ER, MSE, MAE, degree of agreement (d), and relative error. RMSE is regarded as the most reliable performance metric as it is able to display several deviations whereas <math>R^2</math> is a good form of performance measurement for predictive models that evaluates the model with respect to the actual value. Moreover, the NSE indicator is sensitive to extreme values and is coherent for datasets with large outliers.</p>



**TABLE 6. Artificial intelligence in modelling water quality parameters.**

References	Data timescale / Sample size	Sampling site / Location	Input / Output data	Performance metrics	Prediction model	Research conclusions
Abba, et al. [143]	Monthly 1995-2005 (Not given)	Yamanu River, India	pH, BOD, WT // DO	R <sup>2</sup> , RMSE	MLR, ANN, ANFIS	The ANN model in dissolved oxygen (DO) modelling outperforms both ANFIS and MLR models. The performance of ANNs is higher in accuracy as it overcomes the overestimation or underestimation from ANFIS and MLR models.
Kisi, et al. [144]	Hourly 1997-2004 and 2015-2017 (Not given)	Link River, USA	pH, WT, EC // DO	R <sup>2</sup> , RMSE, NSE	BMA, ELM, ANN, CART, MLR	An emerging ensemble method, the Bayesian model average (BMA) is compared with extreme learning machine (ELM), ANN, classification, and regression tree (CART) and MLR model. The proposed method shows accuracy superiority to the other models.
Kumar, et al. [145]	Monthly 1981-2017 (Not given)	Langat River, Malaysia	Rainfall, water level, discharge // nitrate-N or ammonia-N	R, MSE, MAE, relative error	GRNN, RBFNN, MLR	This study presents the training and selection procedures of ammonia and nitrate compounds using hydrological data. The multilayer performed very well compared to the general regression neural network (GRNN) and RBFNN.
Bagherzadeh, et al. [146]	Daily 2015-2017 (800 samples)	North Torbat Wastewater Treatment Plant (WWTP), Iran	pH, DO, COD, BOD, mixed liquor suspended solids (MLSS), mixed liquor volatile suspended solid (MLVSS) // NH <sub>3</sub> -N, TN	R <sup>2</sup> , RMSE, MAE	ANN, RF, GBM,	Feature selection methods are applied in this study to enhance the prediction capability of TN in WWTPs. The study concluded the effectiveness of random forest (RF) and gradient boosting machine (GBM) compared to ANN methods.
Montasiri, et al. [147]	1993-2012 (Not given)	River basins, (Nazlu Chay, Tajan, Zayandeh Rud and Helleh), Iran	Flow rate, EC, bicarbonate, sulphate, Cl, Na, Ca, Mg, sodium adsorption ratio (SAR), soluble sodium percentage (SSP) // TDS	R, RMSE	ANN, ANFIS, ANFIS-GP/SC, GEP, wavelet-ANFIS/GE P	Single and hybrid models were constructed on ANN, ANFIS, gene expression programming (GEP), coupled with grid partition (GP) or sub clustering (SC) and wavelet techniques to analyse the TDS content of four basins in various climatic conditions. Results concluded that EC, Na and Cl is highly correlated to TDS whereas negative correlation is identified with flow rate. All hybrid techniques outperform all single computing techniques especially the WGEP model.

**TABLE 6. (Continued.) Artificial intelligence in modelling water quality parameters.**

Jamei, et al. [148]	Monthly 1985-2005	Sefid Rud River, Iran	Discharge (Q) // TDS	R, RMSE, NSE	MGGP, W- MGGP, GEP, W- GEP	In this study, standalone models of multigene genetic programming (MGGP) and GEP models are applied with hybrid wavelet methods. The proposed hybrid W-MGGP and W-GEP models are more efficient than standalone models with the W-MGGP model showing the best prediction accuracy for TDS.
Iglesias, et al. [149]	Hourly averages 2010 (Not given)	Nalon River, Spain	pH, WT, DO, EC, NH <sub>3</sub> -N // TUR	R <sup>2</sup>	ANN	The novelty in this study demonstrated the influence of several water quality parameters for prediction of turbidity. The use of synergistic variable improves the results substantially. The most influential water quality parameter in turbidity identified is temperature.
Song and Zhang [150]	Every 3 hour March-October 2017, March- October 2018 (Not given)	Qingcaosha reservoir, China	Water level, wind direction and wind speed // TUR	RMSE, NSE	LSTM	This study presented the efficiency of long short-term memory (LSTM) neural network in the computation of turbidity using environmental factors. The model showed fast convergence, accurate prediction, and high stability. The study suggested the inclusion of wind field data could effectively forecast turbidity.

#### 4) WATER QUALITY MODELLING

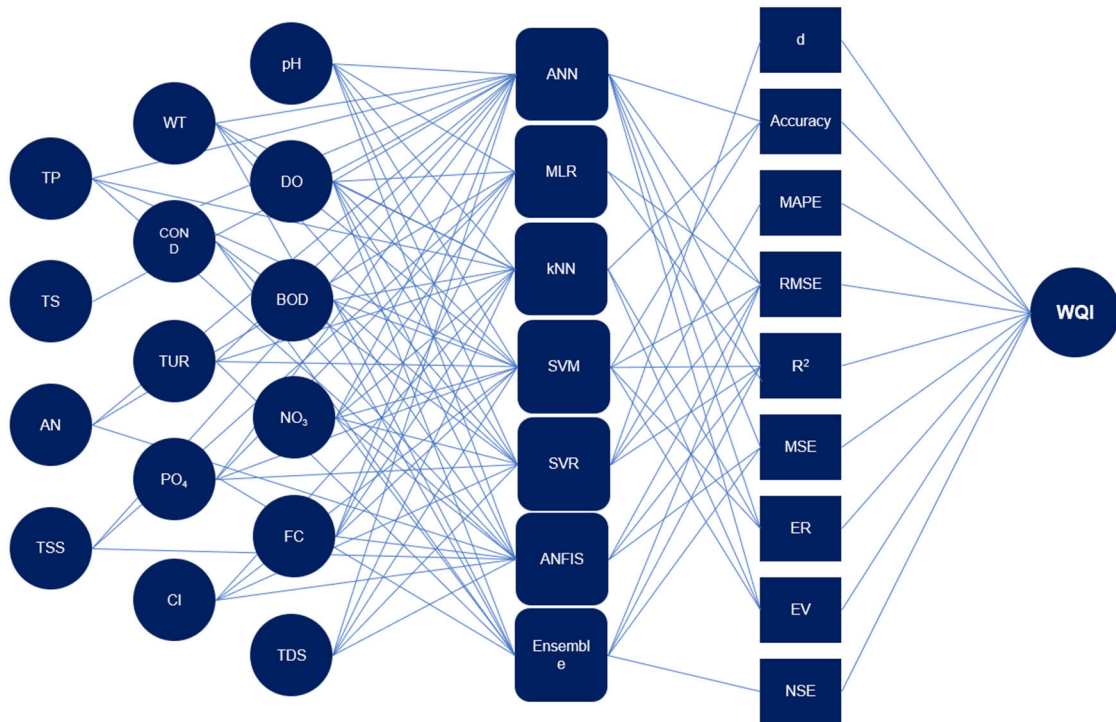
The advancement of water quality modelling is able to simulate the concentration of water quality parameters using history data or sampling data collected during the duration of study. Table 7 compiles the benefits and limitations of the water quality models highlighted in this review paper.

The conventional multiple linear regressions (MLR) method is a multivariate statistical technique that models linear statistical relationship between explanatory and response variables without considering causation. The model performance is only restricted to independent variables that are linear and continuous. Therefore, studies incorporated ANN [137] models are capable to learn non-linear relationships and map the complex patterns in dataset. ANFIS models were also commonly applied to produce nonlinear time series mapping [138].

Other than ANN and ANFIS models, Kamyab-Talesh *et al.* [140] proposed the stability of SVM model that results to 87% of total variability and lower bias. However, the training process of SVM is rather laborious as all classes require optimization. Li *et al.* [141] characterized the uncertainties

and randomness of support vector regression (SVR) models using firefly optimization algorithm (FFA) to tune the internal parameters of the SVR kernel functions. The hybrid SVR-FFA algorithm is well suited for semiarid riverine environments as it simplifies computation time and effort. The use of gradient boosting machines (GBM) from Bagherzadeh *et al.* [146] produced good generalization of dataset patterns specifically for unseen datasets. The GBM models are less sensitive to the number of input parameters, hence providing better accuracy than ANN models, which tend to be inaccurate when redundant features are included.

Advancement of water quality modelling is demonstrated by Asadollah *et al.* [142] using ensemble learning model. The study combined decision tree (DT) weak learners with classic standalone SVR techniques to improve prediction performance. The extra tree regression (ETR) method introduced in this study optimizes the whole training dataset to nominate the best features in the node splitting process. The feature selection process makes the ETR less prone to overfitting. The ensemble model proposed by Asadollah *et al.* [142] shortens lengthy computation and provides accurate prediction of water quality.



**FIGURE 3.** Relation of input attributes, modelling techniques and performance metrics of water quality simulation reviewed in this study.

Generally, hybrid soft computing techniques such as WANN, WANFIS, WGEP [147] were proven to reduce the errors of soft computing calculation. Hybrid models are highly potential in speeding up water quality modelling processes. Other methods such as the long short-term memory (LSTM) neural network is capable to solve long term dependency and timing problems [150].

In this study, it is suggested that water quality simulation shall not be limited in determining the water quality of rivers but to also assess the surrounding habitat and ecosystem to which the river supplies to such as the mangrove ecosystem [163]. The study on marine water quality and estuary health status has yet to be explored since complex environmental variables are required for the accurate modelling of the prediction system. Other than biological, hydrological, meteorological, sedimental factors suggested from this study, Tung and Yaseen [17] elaborated that in future research directions, additional variables such as seasonal run-off, industrial influence and population change should also be taken into consideration for a robust estimation of water quality analysis. More hydrological or climatological inputs should be employed into the predictive models to attribute all aspects of the environmental irregularities such as sediment load, dead zones and irregular flow of the riverbed for suspended sediment prediction [164].

In short, modelling of water quality variables is important for identifying the pollution sources especially in mangroves and estuarine zones to identify the marine pollution trend [137]. The assurance of clean water quality is part and

parcel to the overall wellbeing of mangrove forests as well as the marine ecosystem.

## V. IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE TO MONITOR WATER AND SOIL POLLUTION OF THE MANGROVE ECOSYSTEM

Despite worldwide efforts in conserving and promoting ocean and marine sustainability, our coastal ecosystem especially mangrove forests are still suffering from anthropogenic stress. For that reason, time to time monitoring and assessment of mangrove estuary is significant to avoid deterioration of this important ecosystem that sustains global biodiversity.

Concurrently, there is no predictive model formulated for ecological patterns monitoring of air, water, and soil indexes. Majority of researches carried out predictive analysis based on a single pollution factor which have not included mangrove forests. Studies that relate to the influence of physical, biological, socioeconomic, and meteorological factors of the mangrove estuaries are also quite limited. Prediction methods solely based on the linear relationship of pollution factors to the degradation of mangroves are not enough in predicting the possibilities of future outbreaks, but rather a solution that comprises the arbitrary relationship of each environmental pollution aspects might be the key for long term monitoring.

Fig. 4 represents the conceptual framework of implementing artificial intelligence in addressing correlation between air, water, and soil attributes to the well-being of mangrove ecosystem. The framework summarizes the architecture and ideas projected from this review.

**TABLE 7. Summary of water quality modelling techniques.**

Techniques	Prediction Capability	Advantages	Disadvantages		
ANN [137, 139, 143, 145, 149]	[137] ANN R <sup>2</sup> 0.7113-0.9044 RMSE 5.224-8.5134	- Ability to predict complex input variables	- Loss of generalization due to many hidden neurons known as the grand-mothering effect where the model is capable of memorizing input patterns - Unable to detect important features when the model is unable to generalize - Time consuming in determining the optimal number of hidden neurons and hyperparameters - Accuracy drops if redundant features are introduced		
	[139] PNN Accuracy 76.74-94.57 Error value 4-25 Error rate 5.43-23.26	- Higher accuracy - Able to overcome overestimation or underestimation			
	[143] ANN R <sup>2</sup> 0.70-0.94 RMSE 0.70-1.72				
	[145] ANN MAE 0.017-0.771 MSE 0.0013-7.09 NSE 0.9457-0.9715				
	[149] ANN R <sup>2</sup> 0.50-0.81				
	SVM [140]	R <sup>2</sup> 0.87		- Capable of minimizing upper bound on generalization error - Able to avoid local optimums - Good in solving nonlinear problems due to the initial dimensional feature space	- High influence of kernel parameters to the model accuracy - Long training time
	ANFIS [138]	R <sup>2</sup>			- Complex structure of ANFIS and gradient learning
		SC-ANFIS 0.983-0.992 FCM-ANFIS 0.9025-0.985 RMSE		- Draws the benefits of both ANN and fuzzy techniques	
		SC-ANFIS 0.870-1.609 FCM-ANFIS 1.159-2.774		- Can achieve high nonlinear mapping in producing nonlinear time series	
Decision Trees [146]	R <sup>2</sup>		- Higher training time and complexity - Decision trees are sensitive to slight changes of data		
	ANN 0.42-0.81 GBM 0.51-0.88 RF 0.46-0.88 RMSE	- Able to generalize dataset patterns - Capable of shrinking estimation errors with the addition of new trees			
	ANN 0.073-0.104 GBM 0.068-0.096 RF 0.055-0.100	- The Gradient Boosting Machine (GBM) is less sensitive to the addition or removal of input features			
Ensemble [142, 144]	[142] R <sup>2</sup>		- Produces inaccurate results in the presence of nonlinearity or noisy datasets that is inappropriate for time series problem		
	DTR 0.582-0.911 SVR 0.615-0.967 ETR 0.710-0.996 RMSE	- Decision trees contains straight forward rules to describe the format of data pattern			
	DTR 5.794-11.7704 SVR 3.414-12.537	- Ensemble model is more accurate and less prone to overfitting			



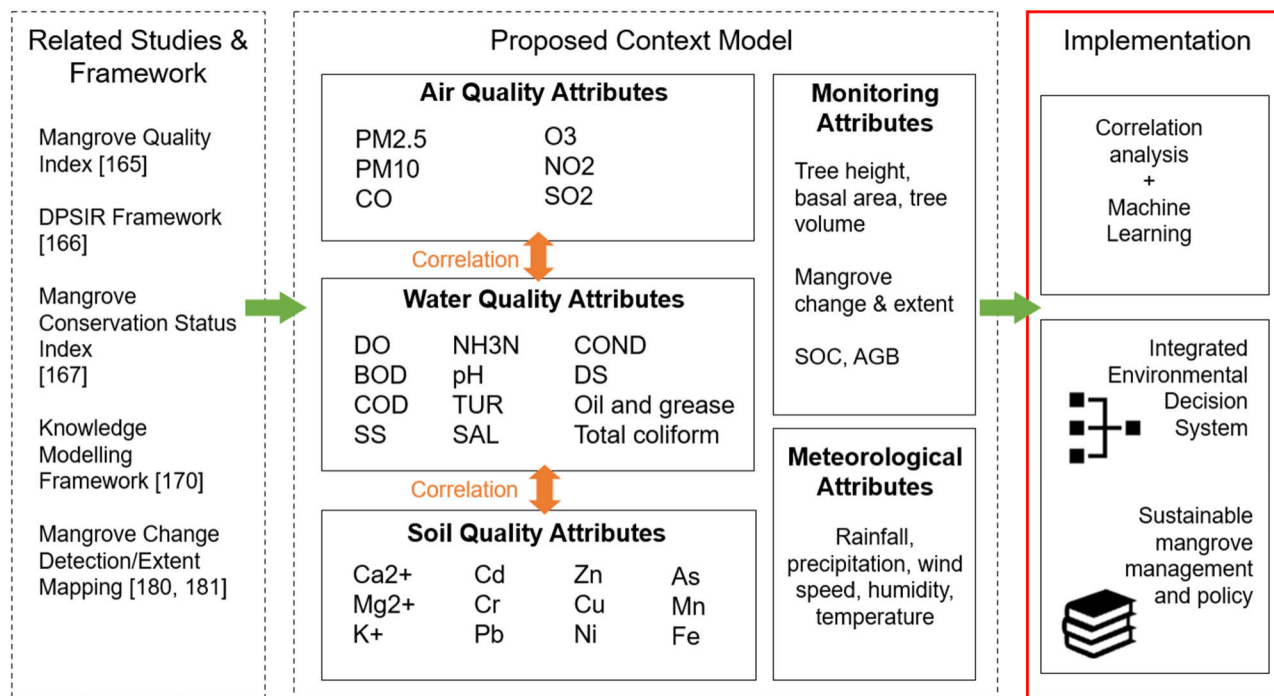
**TABLE 7. (Continued.) Summary of water quality modelling techniques.**

	ETR	1.371-10.377		
	[144]	R <sup>2</sup>	-	Has less scattered estimates
	ANN	0.001-0.95	-	Considerably less over or under estimation of output values hence higher accuracy
	ANFIS	0.009-0.949		
	ELM	0.005-0.956		
	CART	0.010-0.986		
	MLR	0.007-0.909		
		RMSE		
	ANN	0.369-1.733		
	ANFIS	0.310-1.907		
	ELM	0.347-1.658		
	CART	0.195-1.920		
	MLR	0.354-1.909		
Hybrid [141, 147, 148]	[141]	R <sup>2</sup>	-	Good and robust compared to single computing techniques
	SVR	0.82	-	Able to optimize internal parameters
	SVR-FFA	0.9	-	Reduces the computation time substantially
		RMSE		
	SVR	4.91		
	SVR-FFA	2.81		
	[147]	WGEP	-	Wavelet analysis presents data via superposition of scaled and translated versions using minimal input, fast simulation
	R <sup>2</sup>	0.399-0.99	-	Provides explicit relation between input-output dataset
	RMSE	2.66-303.04		
	[148]		-	Best performance for decomposition of environmental, hydrological, and ecological time series data
	MGGP (R = 0.396, RMSE = 239.72)		-	Accurate prediction even with limited input data using time-frequency domain analysis of signal
	GEP (R = 0.433, RMSE = 263.41)		-	Increases computational accuracy
	W-MGGP (R = 0.942, RMSE = 90.38)			
	W-GEP (R=0.927, RMSE = 993.28)			
LSTM [150]	RMSE	<0.05	-	Fast convergence
			-	High stability
			-	Accurate prediction
			-	Effectively solve timing and long-term dependency problem
			-	Less error with small fluctuations thus better stability

**A. RELATED STUDIES TO DEVELOP A MANGROVE ASSESSMENT INDEX OR FRAMEWORK**

Several researches have abundantly performed the assessment of mangrove health status [165] and trend loss of

mangrove forests [166], or to categorize the conservation index of mangrove forests [167] Faridah-Hanum *et al.* [165] classified the status of mangrove forests comprehensively in an ecological-socioeconomic approach using biotic integrity,



**FIGURE 4.** Proposed conceptual model and the implementation of the study of environmental pollution assessment of mangrove forests.

soil, marine, hydrology, and socio-economic factors. The novelty of this study incorporated key indices of aquatic life abundancy and fishery activities as a measure of mangrove health. The mangrove quality index developed can be used as a basis for future potential automated monitoring system with the use of artificial intelligence or Internet of Things (IoT) [168].

On the other hand, Turschwell *et al.* [166] captured the multi-scale interactions of mangrove losses at different impacts for different nations through landscape differences and state changes by the application of an Bayesian hierarchical model within a Drivers, Pressures, State changes, Impact, and Response (DPSIR) framework. The Pressure–State–Response framework is a useful tool to understand the changes in environment caused by human activities [169]. The correlative relationships of the DPSIR variables defined by Turschwell *et al.* [166] are weak and contains uncertainty since complex political and socio-ecological perspectives are involved. The gap in this study is the lack of predictors for human related activities such as the likelihood of land conversion for agriculture, aquaculture and plantation, or the effects of pollution and ecosystem threats.

The Mangrove Conservation Status Index (MCSI) is a simple scoring system based on the Delphi Method Survey, Rapid Assessment Questionnaire, and the Remaining Vegetation index to provide adequate information for policy makers to classify the conservation status of mangroves. Nevertheless, the use of this indicator lacks the assessment of change in environmental quality and ecological indicators since the index is mainly composed from expert’s and local opinions.

A holistic view of the knowledge modelling framework, presented by Oprea [170] covers three aspects of environmental domains such as water pollution analysis for river resource management, prediction of ozone levels due to air pollution and soil pollution analysis. The authors suggested a solution based on an ontological approach, application of data mining and Bayesian networks for data analysis. The conceptual model generates uniformity in rules from data sets and decision tables, grouping the probabilistic and uncertainty factors into distinct rules for decision making. The knowledge modelling framework could serve as a basis to apply AI into the study of correlated environmental variables of mangrove forests.

In general, publications on the health status and conservation index of mangrove as cited in this paper could be further improved by incorporating the quality of air, soil and water. Our review paper has cited the proficiency of AI in exploiting individual pollutant markers of soil, water and air in the form of a predictive model feasible as an integrated environmental decision system. The use of artificial intelligence as cited in Section 4 above is limited to one aspect of environmental quality. Application of a simulation system on two or more environmental indicators is unavailable at the time of the study as each model either focuses on heavy metals, water quality or air. The interaction between these three factors linked to the mangrove ecosystem have been insignificantly modelled using artificial intelligence. Due to complex and non-linear behavior, the study on correlation between these three factors is still limited.

## B. DATASET AVAILABILITY

Large scale mangrove conservation and research is under rapid development in terms of big data, forthcoming and global datasets of the state of the world's mangrove will soon to be widely available [171]. Existing datasets of the distribution of mangrove extent can be found from the USGS Global Mangrove Forest Distribution, v1 2000 dataset [5], Global Database of Continuous Mangrove Forest Cover for the 21st Century (CGMFC-21) [46] and Global Mangrove Watch (GMW) 2016 [172]. Furthermore, there mangrove canopy height, basal area and biomass map dataset produced by Simard *et al.* [173]. Other available datasets are the Global Distribution of Modelled Mangrove Biomass provided by Hutchison *et al.* [174], annual mangrove carbon stock assessment from 2000 to 2012 [175], distribution of carbon density [176] and soil organic carbon (SOC) stocks [177].

Following air quality and marine water quality dataset can be retrieved from governmental or local authorities. The water quality parameters and the dataset can be made easily available through online platforms. Air quality dataset of ozone, ionic concentration and particulate matter could also be retrieved from similar application procedures. Subsequent available meteorological and climatology data is accessible from WorldClim [178] or the World Weather Records (WWR) Clearinghouse. A novel initiative among 13 countries developed the Acid Deposition Monitoring Network in East Asia (EANET) contains dataset that monitors wet deposition, dry deposition, soil and vegetation, and inland aquatic environment [179].

Nevertheless, soil quality dataset that includes the concentration of heavy metals are not widely accessible thus, it could be obtained from soil sampling analysis of targeted mangrove area. In addition, the traditional procedures for heavy metal sampling are time consuming and complicated to analyze as the parameters require laboratory chemical analyses which is expensive.

Field measurements and sampling of dataset in terms of mangrove coverage, water quality or soil content consumes time and effort, as not all areas are accessible for collection of sampling. Therefore, several researches have demonstrated the advancement of AI using remote sensing and supervised machine learning techniques to classify the mangrove extent or to estimate biomass and soil carbon content Li *et al.* [180] improved the mangrove distribution of the USGS 2000 dataset and included the detection of submerged mangrove recognition index (SMRI) and normalized difference vegetation index (NDVI). In addition, Hsu *et al.* [181] used drones to enhance satellite imagery, and correct the GMW dataset. Other than that, aboveground biomass (AGB) could be accurately estimated using light detection and ranging (LiDAR) techniques [182]. Hyperspectral imaging of high spectral resolution using visible and infrared bands showed promising prospects of retrieving soil metal concentration and surface water quality. Random forest model is considered as a successful method to estimate distribution trends of heavy metal in soil through

air-borne images [183]–[187] while ANNs used in generating surface water quality from satellite imagery performed at  $R^2 > 0.80$  [188].

All in all, with large amounts of dataset pooled into environmental quality monitoring, the implementation of artificial intelligence to make use of these dataset into an integrated environmental decision-making system has been scarce. Thus, as discussed in this review, the need for implementing AI as the way forward to monitor the state of heavy metal contamination, and water quality modelling of the mangrove forests is highly recommended for long-term sustainability of estuaries.

## C. CONCEPTUAL MODEL

With the capability of AI in filling the gap for data limitations, and predicting future environmental outbreaks, AI can be served as an extensive model for enhancing policy making and law enforcement driven for the rehabilitation and conservation of the mangrove ecosystems. The predictive model and patterns of data related to mangrove threats of pollution can be developed in accordance with national and international environmental quality index. Publications related to air pollution, water pollution and heavy metal contamination have demonstrated the adoption of artificial intelligence could aid in real-time forecasting of future events. The monitoring of air pollution gained attention from researchers worldwide for pollution prediction [189], [190], and understanding of health impacts [191]. Yet the effects of air pollutants to the quality of water or soil have yet to be investigated.

Monitoring variables suggested in this paper to construct the linkage of environmental pollution effects on mangrove forests for air pollutants are PM, O<sub>3</sub>, SO<sub>2</sub>, NO<sub>x</sub>, which relates to pH levels in soil and water bodies, in response to heavy metals, DO and AN concentration. The proposed context model illustrated in Fig. 4 described the use of correlation analysis in machine learning in order to study the relationship between air, water, and soil quality. Occurrence of heavy metal concentrations presented a good relationship with suspended solids and turbidity for efficient prediction and long-term monitoring [192].

Meteorological conditions such as monsoon and precipitation rate are persistent factors for environmental change yet little to no studies have incorporated such parameters into the modelling of ecosystem quality for pollution prediction. A relation of meteorological data was identified between the prediction of heavy metals in water bodies or nitrogen and turbidity concentration [116], [145], [150]. Moreover, meteorological and climatological variables were found to have a profound impact on soil distribution, where air temperature could complement the prediction of soil temperature [193].

Alongside with available input datasets of air, water and soil indicators, the impacts of these input attributes are mapped from meteorological data based on the monitoring attributes which contains the biotic integrity, extent change, and carbon content. Examples of forest structure attributes that characterizes mangrove health are biomass, basal area,

canopy height, frequency, density, dominance, importance value which is formulated into the Complexity Index (CI) [194], (1) as shown at the bottom of the page.

The CI value computed is a good measure to indicate whether the forest is under stress, or for comparison between two different data. The measure of these mangrove monitoring attributes in coverage changes and biological variables of mangrove trees shall be validated with expert opinions and related studies of assessing mangrove health.

#### D. INTEGRATED ENVIRONMENTAL DECISION SYSTEM

Mother nature is a complex and dynamic system where various interactions could lead to the same impact, thus increasing the complexity to determine their global impact. This is due to the consequences of each variable which cannot be easily represented, and the interrelationship of each component is highly unpredictable. Integrated environmental knowledge especially for environmental data science is the way out to the complexity of environmental problems [89]. With the capability of AI in providing patterns and predictive data that can easily monitored and predicted, valuable environmental knowledge for the decision-making process can be realized. Early prediction using pattern analysis can provide the intelligence in anticipating the occurrence of the event and thus effective action can contain any environmental outbreaks to the safest margin [90].

The integrated environmental decision system (IEDS) acts as a mean for pollution simulation and control. The implementation of the IEDS covers a holistic understanding of environmental policies, biophysical, and socioeconomic processes. An example of EDS is demonstrated by Zhang *et al.* [195] for real-time water quality and pollutant reduction simulation schemes. A handful of approaches to integrate a decision system framework adapted for multiple issues and uncertainties are Bayesian networks, in systems dynamics, coupled component models, agent-based models and knowledge-based models or expert systems [196].

In this study, the construction of mangrove integrated environmental decision system is illustrated in Fig. 5 below. The IEDSS is fed with input parameters related to observational meteorological data that contains wind speed, wind direction, weather, rainfall, humidity, and precipitation rate; atmospheric pollutant data of ozone, sulphate, nitrate concentration and particulate matter; hydrological data of dissolved oxygen, biological oxygen demand, pH, turbidity, ammoniacal nitrogen concentration, total dissolved solids etc.; and heavy metal concentration identified for water bodies and soil content.

Missing values of dataset can be overcome by applying prediction models whereby other available input parameters are used to predict the missing values. The model is

developed based on correlational studies between air-water-soil attributes. Significant output indicators for favorable growth of mangrove forests will be identified with fundamental researches and experts. The air-water-soil quality model generates the measure of mangrove quality, if the threshold values are not reached, the model simulates pollutant removal processes to be applied into pollutant removal of heavy metal or wastewater. Subsequent monitoring models of mangrove change and future detection are then included at the end of the study to forecast the likelihood of pollution or degradation.

Pollutant removal techniques have been extensively applied for wastewater (WW) treatment and heavy metal (HM) removal using methods such as adsorption, solvent extraction, flocculation, coagulation, reduction, oxidation and membrane filtration [197]. Pollutant removal processes are expensive and laborious therefore, modeling and optimization of pollutant removal processes were often simulated using AI tools [198]–[200].

The framework implemented based on the emerging issues identified from correlation analysis traces each potential environmental factors could facilitate a better decision-making process for a sustainable mangrove policy. Even though the knowledge of ecological is limited, climate-conservation actions should not be discouraged. We urge the rapid research on such environmental decision or early warning systems that could supply possible solutions to future scenarios. Moreover, by understanding environmental factors that acts as drivers to the tipping point of the ecosystem, we could reduce other local pressures of the system to cope with the global stressors [201].

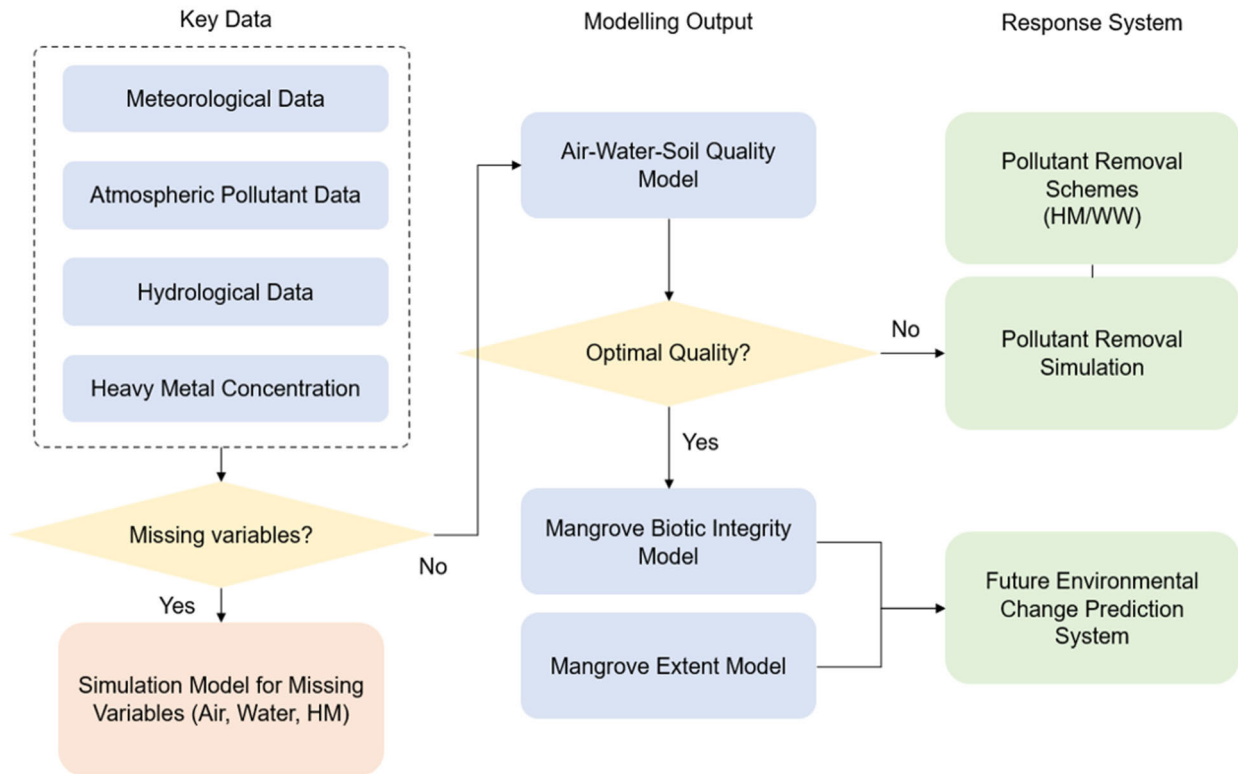
The objective of this review is to critically discuss the fundamentals and advantages of AI tools as well as combined approaches to facilitate the response of mangrove ecosystems from environmental changes. The modelled outcomes due to these pollution circumstances provide significant information for the assessment of environmental impacts by environmental management authorities to perform influential resolutions. Hence, the presence of mangrove quality models is important to identify the pollution sources and to imply possible reduction efforts of the existing pollutants in the ecosystem.

#### E. STUDY LIMITATIONS AND FUTURE CHALLENGES

Prediction models discussed above that are constructed from AI techniques have proven its high accuracy in monitoring environmental pollution and changes. Although myriad studies have reported on the efficacy of the AI models, the struggle to outstretch the data unavailability of mangrove forests are still present. These issues have hindered the comprehensive process to understand the complex correlation between soil, water and air pollutions that impacts the mangrove ecosystem. Lack of continuous data due to unforeseen

$$CI = \frac{(\text{\#of species of mangroves}) (\text{\#of stems}) (\text{basal area}) (\text{max height of mangroves})}{100} \quad (1)$$





**FIGURE 5.** The framework design of the Integrated Mangrove Environmental Decision System, and schematic linkage of input and output components.

climatic conditions or insufficient monitoring stations at unreachable areas could be overcome with the automation of AI expert system that replicates decisions based on the limited information. The conventional environmental features (i.e., pollutant markers) used to feed the AI architecture can be improved by incorporating geographical information system (GIS) and remote sensing images to improve spatial modeling of the mangrove ecosystem. The projection of the spatial patterns drawn can improve the predictive model in terms of optimum number of layers, weight, bias values, data allocation for training and testing and overcoming problems of missing data.

With current solutions focusing on the containment of environmental outbreaks, they are often resulted in high expenditures and require massive workforce. This review suggests an integrated environmental modelling solution constructed based on soil, water, and air pollution factors to simulate and predict the risks and distributions of the concentrations of pollutants in the specific mangrove ecosystem. The integrated decision system can be implemented beneficially to save cost and labor for long term experiments and monitoring, of which can be simplified with a prediction model.

Challenges concerning the overall mangrove prediction model include unpredictable meteorological conditions, synergy effects of various pollutants, such as soil acidity with heavy metal, and the possibility of excessive nitrogen oxides contamination in the air or overloading of nutrients from

sewage waste disposal. The outcome of this review sheds some light into integrating environmental factors with artificial intelligence systems that could forecast the behavioral pattern of pollutants for spatial understanding especially in predicting the likelihood of consequential pollution. However, the limitation of AI is the inability to include human activity factors that could cause the increment of pollutant levels. Moreover, awareness efforts should be granted as a priority to garner attention from locals and authorities towards an effective environmental management of anthropogenic activities to stop extended adverse effects exerted on the environment since prevention is better than cure.

Furthermore, the greatest challenge identified to realize this mangrove prediction system is the difficulty in gathering the air-water-soil quality data that are similar in time frame. Moreover, the significance of each attribute by applying different weightage requires intensive modelling efforts and expert opinions before developing an air-water-soil environmental indicator, since the previous research gap for correlation studies of the pollutant markers has yet to be explored. Socioeconomic factors and human exploitation of forest resources is another major complication to tackle in order to obtain the most accurate predictive model for preventing future outbreaks. Nevertheless, after highlighting these challenges, step by step measures and implementation of an intelligent decision-making system would serve as a useful tool for policy makers and authorities to well

manage nature's resources and prevent future environmental outbreaks.

The wetland ecosystem is unique from other landforms due to the adaptation of aquatic plants to hydric soil. Mangroves are keystone species to climate change responses and processes since the habitat supports a large ecological community. Future research to obtain site-specific information should start as key to effective conservation efforts Ragavan *et al.* [202] summarized steps to a holistic Ecosystem-Based Management (EBM) of mangrove forests starting with the mapping of shifts in species distribution. Impacts of climatic-driven change towards the physiology of ecosystem should be studied before modelling forecast tools to assess the adaptation capability of key species. Finally, a response system for conservation is developed accordingly, and site-specific information is integrated for adaptive strategy planning in the multi-stressor environment.

Therefore, this paper has provided an overview of environmental soil, water, and air pollution to understand the physiology of mangroves with climatic factors. The feasibility of artificial intelligence as the way forward to solve complex environmental solutions are also reviewed. Significant features such as soil, water and air pollutant markers could be integrated into AI models to form mechanism that correlates each attribute. Since different input and outputs are used in different AI environmental model, future research studies should include additional variables such as air quality, seasonal runoff, precipitation, population change and industrial influent and effluent to provide a good chance for healthy mangrove ecosystem and to cope with emergency environmental outbreaks and the restoration of ecological balance.

## VI. CONCLUSION

The mangrove forests are unique and vital to the aquatic wildlife and the livelihood it surrounds. Mangrove loss diminishes the water quality of estuaries, causes disruption in biodiversity, annihilates the nursery habitats, and adversely degrades the adjacent ecosystems. Key requirements for mangrove sustainability are continuous monitoring of rehabilitation efforts, coastal protection, government structure and as suggested in this paper, environmental decision system to predict future outbreaks. AI is expected to serve as an integrated environmental prediction model. The capability of AI to make assumptions and identify patterns from large datasets creates unprecedented possibilities to curb complex environmental problems. It is important to maintain the well-being of mangrove forests as the ecosystem plays a huge part in global diversity. Through this review, we have presented the following key points for future research direction:

The feasibility of analyzing correlation between pollutant markers in soil, water, and air as an effort to conserve mangrove ecosystem. Secondly, the complex interaction between these pollutant markers could be solved by implementing integrated and intelligent decision making in monitoring and managing the mangrove ecosystem.

The review has thoroughly discussed the capability of AI in predicting environmental data and act as environmental decision system especially those affected the mangrove ecosystem. However, current solution focused on understanding and proposing environmental decision-making system based on the individual pollutant markers either in soil, water, or air. The correlation between pollutant markers has not been well studied and authors have provided the possibility of further research that could be conducted to reduce possible degradation risks and future threats to the mangrove ecosystem.

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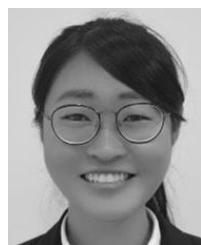
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