# CHAPTER: 06

# ARTIFICIAL INTELLIGENCE-BASED ASSESSMENT OF WATER RESOURCES IN VIEW OF CLIMATE CHANGE & POPULATION GROWTH: A CASE STUDY OF THE YAMUNA RIVER IN AGRA, U.P., INDIA


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## *ABSTRACT*

*Artificial intelligence (AI) has been broadly used in various disciplines, including engineering, medicine, computer science, robotics, economics, business, psychology etc. According to the literature of several studies have shown the application of artificial intelligence in modelling approaches yields results that are comparable to those produced from real-world data when solving linear, nonlinear, or other systems. As specified in the local master plan, the Yamuna River water basin in North India will be evaluated for quality and quantity in terms of several future scenarios, such as increased population, industrial growth, various construction activities including construction of new wastewater treatment facilities, by 2030. The results of the study are then compared to the impact of climate change on the quality and amount of water available for consumption. To measure river pollution, the three essential aquatic ecosystem health indices of Dissolved oxygen (DO), chemical oxygen demand (COD) and biochemical oxygen demand (BOD) were simulated. The present state-of-the-art and advancements in artificial intelligence modelling of water variables, including rainfall-runoff, evaporation and evapotranspiration, streamflow, sediment, and water quality factors, will be discussed. Furthermore, the study has suggested several potential future research avenues as well as some modelling recommendations for the variables affecting the water. Compared to the climatic change impact, the impact of human population growth is significantly greater. Because untreated pollutants from upstream were conveyed in the water, the environment downstream of the study region was generally poorer than the environment above (plus those from nearby). This discovery will be useful to policymakers and stakeholders in the water business as they develop long-term, adaptive strategies for the water industry. Developing a nationwide sewerage and septage management programme, and ensuring that it is practicable, should be a top priority for any prospective governmental action. Thus, the Sustainable Development Goals will have a better chance of being achieved.*


***Keywords: Artificial intelligence methods, modelling, DO, COD, BOD, water quality modeling***

## 1. INTRODUCTION

Climate change causes a significant threat for water supply, food security and overall well-being of India's 1.38 billion inhabitants in the twenty-first century. A disparity exists in water resources at geographical distribution in various parts of India. This is true across the nation, from the dry northwest, where rainfall is scarce, to the northeast, which receives the greatest rainfall. Numerous disastrous extremes of climatic have struck India in recent decades, causing widespread devastation. For example, the 2016 drought affected over 330 million people across around 10 states and resulted in an estimated $100 billion in economic damage (ASSOCHAM Report 2016). Agriculture in India provides food for around 17.2 percent of world's population while having just about 9 percent of the world's arable land. Rainfed agriculture accounts for more than 56 percent of the total agricultural area in India (Singh et al. 2014; Rathore et al. 2014).

Groundwater table in north India decreased 2 cm per year between 2002 & 2013 (according to Gravity Recovery Climate Experiment, GRACE), whereas groundwater table in southern India raised at a rate of 1–2 cm per year between 2002 and 2013. This is due to changes in underground water pumping as well as in precipitation patterns, as data measured by GRACE (Asoka et al. 2017). According to the Planning Commission (2011), flood catastrophes affect around 13.78% of geographical area of India, and over 33 million people were influenced by floods between 1953 and 2000 (Kumar et al. 2005). On July 26, 2005 in Mumbai (India's financial hub) got a record-breaking 944 mm of rain, inflicting widespread devastation and multiple fatalities (Kumar et al. 2008). In India, the impacts of climate change on water resources vary significantly between various areas and river basins, making it impossible to draw broad conclusions about them. The multidisciplinary integration of information about climate change implications on resources of water in India is still lacking, as evidenced by a recent gap in the literature. It will no longer be possible to prepare for the future based on previous climatic circumstances because climate change will produce situations that are far outside of the bounds that were used in the past. So far, only a few studies have looked at the current state of water resources and the management measures that will be implemented in the near future.

This study evaluates the status for year 2020 and predicted future perspective for year 2030 in the River Yamuna in terms of water demand and water quality drop by basic indicators such as dissolved oxygen (DO), chemical oxygen demand (COD), and biochemical oxygen demand (BOD). The study findings will be utilised for developing solutions for sustainability of water resource management in the future.

## 2. STUDY AREA

### 2.1 COUNTRY BACKGROUND

India is a country with official name Republic of India in South Asia. According to the United Nations, India is 7th-largest country in land area, the second-most populous country and the world's most populated democratic country in the world. The boundary of south in India is formed by the Indian Ocean, its western border by the Arabian Sea, and its southern border with Bangladesh is formed by the Bay of Bengal. Its land borders with Nepal to the east, Pakistan to the west, China to the north, and Bangladesh to the west are shared with these countries. It is bordered on the east by Myanmar and Bangladesh. While Andaman and Nicobar Islands share a maritime border with the countries of Indonesia, Thailand, and Myanmar on the country's eastern beaches. The country's western shores are bordered by Sri Lanka and the Maldives. There are three major geological zones in India : the Himalayas, the Indo-Gangetic Plain and the Peninsula. Both of these and other parts of India may be divided into different physiological zones, which include mountains, plains, deserts and river valleys, among other things. The lowest point in the nation is 0 metres above sea level at the Indian Ocean, while the highest point is 8,598 metres above sea level at Kanchenjunga, the third tallest peak in the world and the highest point in the country, which is located in the Himalayas. The Himalayas (together with the neighbouring countries of Bhutan and Nepal) serve as northern border of India with China. Pakistan is bordered on the west by India and on the east by Bangladesh (previously East Pakistan) and Afghanistan. On Account of regional ethnic and political issues, the frontiers of the Indian polity are not completely defined, and this is a source of occasional tensions inside the country.

According to its topography, India can be categorised as: the northern Himalayan mountains, the Indo-Gangetic Plain, the Central Highlands, the Deccan (Peninsular) Plateau, East & West Coasts (including the Kankara, Konkan, & Malabar coasts), the Great Indian Desert (Thar Desert in Pakistan), the Rann of Kutch, the Brahmaputra valley etc. Brahmaputra and Indus rivers, both of which are 2,896 kilometres in length, are India's longest rivers, however neither is wholly contained inside the country. There are several more significant rivers, including the Ganges (Ganga, the longest India-originating river at 2,525 kilometres), Godavari (1,465), Kaveri (Cauvery, 800 kilometres), Krishna (1,401 kilometres), Mahanandi (851 kilometres), Narmada (1,3112 kilometres), and Yamuna (1,370). Flood plains are found in India around the north-western, southern, central and northern-eastern parts. These locations are subjected to both frequent floods and seasonal droughts on a regular basis. The coastal plains of the southern hemisphere are vulnerable to cyclones and storm surges, as well as saline intrusion and coastal flooding.

### 2.2 INDIA'S CLIMATE CHANGE AND WATER RESERVOIRS

Because of its geographic and climatic separation from the rest of the Eurasian landmass, India exists as a distinct geo-hydrological and climatic entity. As a result, while investigating global climate and water regimes, the problems of floods and droughts in India are treated as a separate unit of investigation. However, in the modern day, the anthropological aspect has risen to the top of the priority list in disaster debates. Hazards related to Climate Change in India include temperature & rainfall changes, droughts, cyclone & storm surges, floods, salt intrusion and sea level rise. During the monsoon, temperatures are expected to rise between 0.7°C and 1.3°C. In the foreseeable future, a research predicts more droughts in Northern and Northwest India. Droughts would certainly become more severe across India by the end of the century (Climate Risk Index 2021). The frequency of severe landslides and floods is expected to rise in areas like Assam. A recent study found that rising temperatures, especially during pre-monsoon (March-April-May), are a big issue in coastal areas. According to a World Bank report, India's yearly rainfall has risen, however many areas/locations are experiencing irregular weather patterns, such as decreased rainfall, early or late rain, and sudden bursts of heavy For example, the northern areas have dry weather. Coastal communities and consequently many others across the country, have lately suffered from cyclones and storm surges. With regard to frequency, this contradicts the IPCC's fourth assessment report's prognosis. Lack of seasonal rainfall, cyclones, tidal surges, and rising sea level continue to be major issues for coastal populations. In the months of March-April-May, the north-western parts of the nation are frequently hit by drought. Every year, the nation is hit by floods and water logging caused by river overflow or extreme rainfall.

A significant role in the causes of large-scale floods in central part of India, particularly Mumbai floods of 2006 & 2017, has been attributed to climate change. The frequency of widespread severe rainfall events has increased threefold around northern and central India – Chhattisgarh , Gujarat, Madhya Pradesh, Maharashtra, and Jharkhand, Odisha, Telangana, and Assam – as well as portions of the Western Ghats – North Karnataka, South Kerala and Goa. It is thought that the rise in the number of intense rain events is linked to changes in the monsoon westerly winds, which are happening as a result of rising heat in the Arabian Sea. This causes periodic flow of humidity transfer from the Arabian Sea to subcontinent, resulting in intense rains for 2–3 days and covering a enough region to cause flooding in some locations. Farmers in the impacted areas were forced to deal with major difficulties since they were unprepared for such a disaster. The Kosi-Ganga plains of Bihar, the Brahmaputra lowlands in Assam & West Bengal, flooding in urban area of Chennai, and irregular flooding during the monsoon season in central part of India have all seen severe floods in the last two years. Tamil Nadu, southern Karnataka, and parts of Kerala have been experiencing severe drought conditions for four consecutive seasons as a result of the failure of the monsoons (both south-west and north-east). Flooding will continue to be a major problem for the country's biggest community and its livelihoods in the face of a changing climate system, which will intensify in the future. It is possible that sea level rise, driven by the rapid melting of glaciers and ice caps, as well as other reasons, may alter the country's geographic and topographic history in the future.

## 2.3 CASE STUDY

In North India, the Yamuna River (tributary of the river Ganga), originates from the Yamunotri glacier, which is located next to the Banderpunch peaks of lower parts of Himalayas at 6320 metres above sea level height in the Uttaranchal State. The river's overall length, from its source in Saptrishi Kund in confluence with the Ganga at Allahabad, is approx. 1376 kilometres, and it passes through five states on its journey. In terms of importance and significance, this river is on a pace with the magnificent River Ganga itself. A holy river Yamuna, which is home to numerous hindu pilgrimage sites, including Yamunotri, Paonta Sahib, Delhi, Mathura, Vrindavan, Bateshwar and Allahabad (all in Uttar Pradesh), all the cities are located on or near its banks. On its banks are also large urban areas like Yamuna Nagar, Sonepat, Delhi, Faridabad, Gautam Budh Nagar, Mathura, Agra, and Etawah. Furthermore, the Yamuna basin is one of the most fertile and high-yielding agricultural basins in the world, particularly in the districts of Haryana and the Western district of Uttar Pradesh, where food grain yields are very high. In light of all of this, it is clear that the Yamuna river not only runs through the hearts of Indians, but it plays a significant part in the country's economy.

About 25 KM of the River Yamuna in Agra, flowing between the Keetham Lake and downstream of the Taj Mahal, is included in the scope of the investigation. This stretch of the river is the most polluted as compared to any part in India, and it having no perennial flow of its own virtually. The river continuously receives partially treated & untreated wastewater effluents from the Mathura refinery to the downstream of the Taj Mahal in Agra, and it is the most polluted stretch of any river in the country as a whole. The studied stretch starts at Keetham lake and ends at downstream of Taj Mahal as shown in Fig. 1 (a & b) is considered as highly polluted stretch in the country.

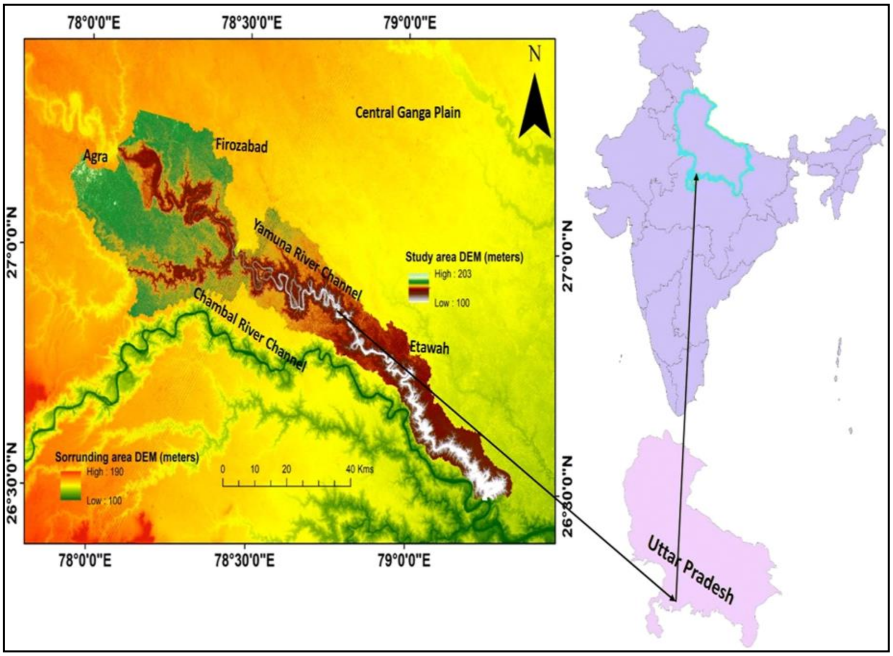



**FIGURE 1 (a). Yamuna River Basin Location on Map of India**

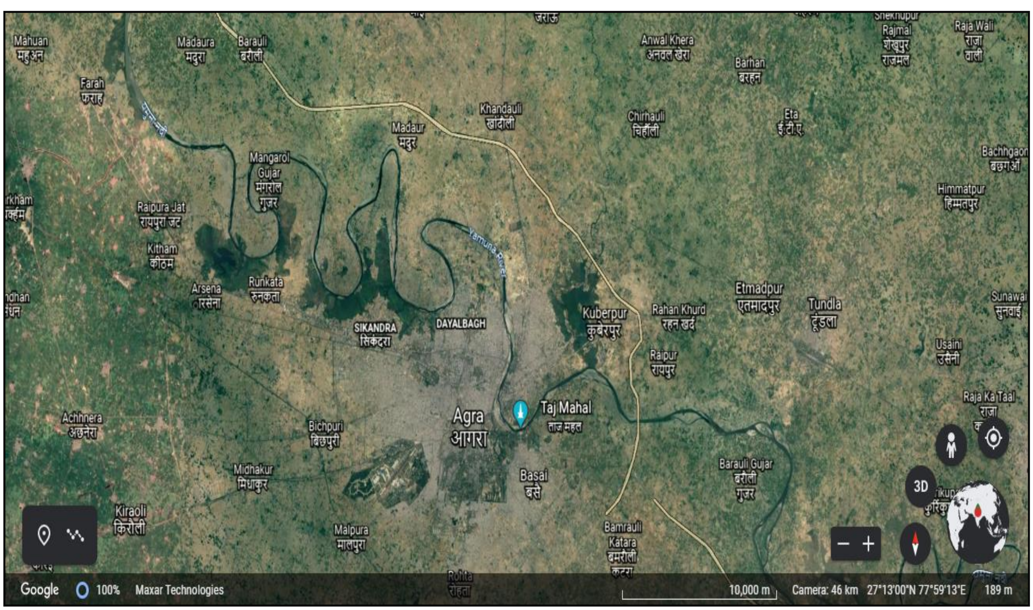



**FIGURE 1 (b). Giant satellite view of the Yamuna River at Agra, U.P.**

**Table 1. River Yamuna water characteristics at various sites in its massive flow from Yamunotri to Allahabad**

| Station Name | State Name | Dissolved Oxygen (mg/L) | | pH | | Bio-chemical Oxygen Demand (mg/L) | | Total Coliform (MPN/100ML) | |
|---|---|---|---|---|---|---|---|---|---|
| | | Min | Max | Min | Max | Min | Max | Min | Max |
| | | >5 mg/l | | 6.5-8.5 | | < 3 mg/l | | - | |
| River Yamuna At Yamunotri | Uttarakhand | 10.8 | 10.8 | 7.4 | 7.4 | BDL | BDL | 4 | 4 |
| River Yamuna At Hanumanchatti | Uttarakhand | 11.6 | 11.6 | 7.9 | 7.9 | BDL | BDL | 140 | 140 |
| River Yamuna At U/S Lakhwar Dam | Uttarakhand | 8.6 | 10.8 | 7.7 | 8.4 | BDL | BDL | BDL | 30 |
| River Yamuna At U/S Dak Patthar | Uttarakhand | 8.2 | 10.2 | 8.0 | 8.2 | BDL | 1.2 | 40 | 70 |
| River Yamuna At Hathnikund, Yamunanagar | Haryana | 7.1 | 8.5 | 7.3 | 8.3 | 2.4 | 6.6 | 110 | 21200 |
| River Yamuna At Sonepat, Haryana | Haryana | 7.1 | 10.6 | 6.5 | 8.6 | 1.8 | 5.5 | 330 | 1600000 |
| River Yamuna At Nizamuddin, Delhi | Delhi | BDL | 2.4 | 7.1 | 7.9 | 5.6 | 57.0 | 700000 | 28000000 |
| River Yamuna At Okhla Bridge (Inlet Of Agra Canal), Delhi | Delhi | BDL | 2.6 | 7.1 | 7.9 | 5.6 | 27.0 | 350000 | 16000000 |
| River Yamuna At Mazawali, U.P | Uttar Pradesh | BDL | 2.3 | 6.4 | 8.1 | 8.7 | 59.0 | 3300 | 9200000 |
| River Yamuna At Shahpur | Uttar Pradesh | 4.6 | 6.9 | 7.1 | 7.5 | 5.8 | 10.0 | 53000 | 110000 |
| River Yamuna At Kesighat, Vrindavan | Uttar Pradesh | 4.0 | 7.6 | 7.1 | 7.6 | 6.0 | 10.4 | 46000 | 88000 |
| River Yamuna At Mathura U/S , U.P. | Uttar Pradesh | BDL | 4.6 | 6.5 | 8.5 | 7.3 | 30.0 | 1100 | 9200000 |
| River Yamuna At Vishramghat, Mathura | Uttar Pradesh | 4.1 | 7.4 | 6.9 | 7.6 | 6.8 | 12.0 | 54000 | 140000 |
| River Yamuna At Mathura D/S , U.P. | Uttar Pradesh | 1.6 | 6.8 | 6.5 | 8.3 | 6.9 | 21.0 | 2200 | 1400000 |
| River Yamuna At Agra U/S, U.P. | Uttar Pradesh | 1.4 | 9.6 | 6.5 | 8.5 | 4.7 | 25.0 | 2200 | 7900000 |
| River Yamuna At D/S Of Agra, U.P. | Uttar Pradesh | 3.8 | 16.2 | 6.5 | 8.7 | 9.1 | 25.0 | 2200 | 32000000 |
| River Yamuna At Juhika B/C With Chambal, Etawah, U.P | Uttar Pradesh | 8.1 | 11.3 | 7.7 | 8.2 | 8.7 | 13.0 | 1700 | 220000 |
| River Yamuna At Allahabad D/S (Balua Ghat), U.P | Uttar Pradesh | 7.3 | 11.5 | 7.8 | 8.4 | 1.8 | 2.4 | 1700 | 3900 |

As shown in Table 1, a detailed water quality characteristics investigation of the Yamuna river from its source to its fusion with the Ganga river (near Allahabad) was reported (according to the Report of Central Pollution Control Board (CPCB), 2020) (Status report in the matter of original application no. 06 of 2012 Titled as Manoj Mishra vs Union of India & ORS in compliance of Hon'ble NGT Directions (date of hearing: 18.02.2020 and date of uploading on website: 05.03.2020) in the matter of OA no. 06 of 2012).

During the monsoon and non-monsoon seasons, the flow of the Yamuna River changes dramatically. Throughout the monsoon season, the river has the highest flow, accounting for approx 80% of annual flow; nonetheless, the condition of the river during the non-monsoon season is crucial. A total of 20 percent of the yearly remaining flow in the river is diverted and distracted in an indiscriminate manner for drinking water, agricultural, and industrial uses (CPCB 2006). In dry season, there is little or no flow in the river, the situation becomes catastrophic. Furthermore, the participation of partially treated/untreated wastewater effluents from 26 different sewage treatment plants (Khairatitola, Rajwah, Balkeshwar, Waterworks, Bhaironnala, Khojanala, Sanjay place, Shaheed Nagar, Dhanddupura, and others) enhances the pollution intensity of the stretch. Thus, it is vital to sure that the water quality criteria for drinking & other household uses are met with these areas.

The average annual rainfall is approximately 724.8 mm. Known as both one of the hottest and coldest cities in India, Agra is a popular tourist destination. It is common for temperatures to spike unexpectedly in summer, with temperatures occasionally exceeding 46°C and extremely high humidity levels prevalent. A typical daytime temperature in July is between 46 and 50 degrees Celsius. The temperature drops to a moderate 30°C at night, which is a pleasant change from the daytime. Even though winters in Agra are a little cool, they provide the ideal climatic conditions. However, the minimum temperature can occasionally dip into the negative 2 and negative 2.5°C, with the average temp. hovering between 6 and 8°C. The average yearly temperature is roughly 25.3 degrees Celsius. According to the land use or land cover map, the entire area is classified into the following classes: farmland, buildings, woods, trees, grass, freshwater, river, paddy field, open land, and urban areas. As a result of rapid urbanisation and exponential population increase in Agra, the environment has deteriorated, particularly in the area of water resources.

## 3. NEED TO INTEGRATE WITH ARTIfiCIAL INTELLIGENCE

The fast growth of numerical models has resulted in a huge variety of models that may be used to solve engineering challenges or environmental problems in an efficient manner. A successful numerical model for a real-world water quality problem demands a thorough knowledge of its applicability and limits. Ragas et al. (1997) conducted a comparison of eleven models for water quality used in discharge permits in the United Kingdom and the United States and revealed that selection of model is a challenging process including matching model elements with the specific circumstance. However, traditionally, the focus has been put on mathematical approaches to tackle specific coastal issues, rather than on the actual solutions. Because these numerical models are not sufficiently user-friendly, there are no knowledge transfers in the process of model interpretation. As a consequence, there are significant restrictions on the usage of models, as well as significant gaps with model creators and practitioners. It is a challenging task for beginner programme users to choose an acceptable numerical model since there are so many variables to consider, such as the depth of the water, the velocity of the water, the grid spacing, and so on. In most cases, the time of model manipulation operations is determined mostly by the user's prior experience, which is particularly true for unexpert users. As a consequence, it is require to create a link between model creators and consumers of application software. As a result, in order to serve as a design assistance or training tool for engineers or students, it is vital to incorporate certain elements that will assist them in making model selection decisions. AI is becoming increasingly important in the selection and manipulation of numerical models of flow and/or water quality. Furthermore, due to advancement in numerical modelling systems, it promotes the trend toward the incorporation of ever-increasing features that are based on modern computer technology.

AI has generated a great deal of attention during the last ten years (Chau, 1992; Chau and Yang, 1993; Chau and Zhang, 1995; Chau and Ng, 1996; Ay and Ozyildirim, 2008). By merging procedural knowledge, descriptive information, and reasoning knowledge, AI approaches have made it possible to imitate human competence in a tightly defined area throughout the problem-solving phase of the process. The advancement of AI methods allows the construction of these systems of intelligent management via the shells usage under the existing developed platforms such as C++, Visual Basic, MathLab etc. The development and present advancements of the incorporation of AI in water quality modelling discussed in research. This section discussed the AI integration necessity AI with modelling of water quality in terms of the current challenges and hydrodynamic, the causes for these problems, and the inclination toward this integration.

### 3.1 Numerical model's problems

Mathematics can be defined as the transformation of physical knowledge into digital formats, simulations of behaviour, and the translation of numerical results back into an understandable knowledge format as part of numeric modelling (Abbott, 1993). It is difficult to avoid model manipulation when building models, because even a small change in a parameter can have dramatic effects on the model's output. Water flow and quality modelling, discretization of equations for physical & chemical processes, methodologies for solving discretized equations effectively and correctly, and analysis of output are all examples of model knowledge that may be put to practical use.. It is possible that this information will be used without the user's awareness. A large number of model users, on the other hand, lack the essential knowledge to collect its input data, develop algorithmic models, and evaluate the outcomes of its models. These models may be underutilised or fail completely as a result of poor design.

### 3.2 Relevant studies in the literature

In light of these valuable studies, the various relevant papers and books, as well as projects using established research methodologies and AI philosophy, have been studied for a number of years now and continue to be discussed. Recently, a number of studies on rainfall-runoff, evaporation-evapotranspiration, streamflow-sediment, dam/lake levels, and water quality parameters have been undertaken using artificial intelligence methodologies (Maier et. al. 2010; Khan and See 2016; Goyal et. al. 2018; Lin et. al. 2018; Wang et. al. 2021). In programming languages like as MATLAB and FORTRAN, many of the mathematical functions that are required to employ these methods are already included. For water variables such as rainfall-runoff, evaporation-evapotranspiration, streamflow-sediment, dam or lake water levels, and water quality variables, artificial neural networks (ANNs), fuzzy-based models, and their hybrids are the most widely used among all types of AI. As shown in Table 2, AI approaches have been successfully applied to estimate silt in a river's breadth section.

### 3.3 Reasons for integration with AI

Because of the limited resources of a computer (memory and speed), an appropriate balance must be struck with accuracy and speed. During the manipulation process, modellers tend to keep certain fundamental parameters constant. Using two-dimensional coastal modelling as an example, the researchers simply modified the coefficient of bottom friction (Chau and Jin, 1995). Baird and Whitelaw (1992) reported that the behaviour of algae was strongly related to the temperature of the water and the pace at which they respired in water quality modelling. When simulating eutrophication, modellers will take into account the water column's variation in sunlight intensity (Chau and Jin, 1998). Examples like these show how human intelligence makes use of pre-existing knowledge to narrow the field of options and thus improve the efficacy of model manipulation. They tend to only change a couple of parameters each time. That's because if they change too many parameters at once, they could easily get off track. This lack of competence can be replicated and supplemented by AI approaches. The algorithms exploration with the Knowledge-based system, the Genetic algorithm, the Artificial neural network, and the Fuzzy inference system, are categorised and applied (Table 3). A variety of tactics can each serve differently to the incoporated model, and they aren't always mutually incompatible.

**Table 2. Table of recent AI research sorted by variables**

| Parameters | References |
|---|---|
| Dam/ lake water level | Hipni et al., 2013; Unes et al., 2015; Li et al., 2016 |
| Evaporation-evapotranspiration | Goyal et al., 2014; Karimi et al., 2016; Guclu et al., 2017 |
| Rainfall-runoff | Talei et al., 2013; Darras et al., 2015; Londhe et al., 2015; Chithra and Thampi, 2016 |
| Sediment | Demirci and Baltaci, 2013; Güner and Yumuk, 2014; Demirci et al., 2015; Droppo & Krishnappan, 2016; Talebi et al., 2016 |
| Streamflow | Cigizoglu, 2003; Huang et al., 2004; Nourani et al., 2012; Ashrafi et al., 2017 |
| Water quality variables | Kwok-wing Chau (2006); Akkoyunlu et al., 2011; Ay & Kisi, 2012; Ay & Kisi, 2013a; Ay & Kisi, 2013b; Kisi & Ay, 2013; Ay, 2014; Chang et al., 2014; Alizadeh & Kavianpour, 2015; Khan & Valeo, 2015; Ahmad et. al., 2016; Ay & Kisi, 2017; Aldhyani et. al., 2020; |

## 4. MODEL EVALUATION

### 4.1 Rainfall Trends and Projections

The southwestern monsoon, which occurs between June and September in India, is responsible for around 80 percent of the country's yearly precipitation (Lacombe and McCartney 2014). Using data from 306 stations across India over a period of 135 years (1871–2005), researchers reported that significant trend is found in average yearly rainfall across the country. An overall declining trend in yearly rainfall was recorded across India, however an overall rising trend was reported in northern and western India (Kumar et al. 2010) and in peninsular India (Mondal et al. 2015). During 1871–2008, no discernible trend in rainfall was seen in northeastern India, which is the world's highest rainfall-receiving region (Jain et al. 2013). Across India, a rise in heavy rainfall events was found, while a decline in low & medium rainfall observed (Goswami et al. 2006).

**Table 3 Artificial Intelligence techniques**

| Technique | Algorithm | Domain | Applications in water quality/hydrodynamics |
|---|---|---|---|
| Knowledge-based systems | Logical & symbolicl reasoning | Automate human specialists' decision-making and reasoning processes to solve problems | Numerical hydrodynamic/ water quality model selection and manipulation |
| Genetic algorithms | Algorithm using selection, reproduction, crossover, and mutation | Develop computer-based problem-solving systems using computational models of natural evolutionary processes. | Optimisation of numerical model parameters for hydrodynamics/water quality |
| Artificial neural networks | Interconnected processing elements in data driven modelling | Develop an information-processing paradigm inspired by biological nervous systems for the purpose of mimicking yet-to-be-understood fundamental linkages. | 1. Identification of unknown physical/ biological links<br>2. Calibration of numerical hydrodynamic/water quality models' parameters |

During the period 1951–2010, a statistically significant declining trend (10 percent) in the mean July and August rainfall was recorded in central part of India (Singh et al. 2014b). Several major river basins have seen a decrease in the number of monsoon rainfall, but the frequency of critical events increased (Jain et al. 2017).

Rainfall patterns have been altered as a result of climate change, which has been demonstrated in this study. For the years 2000, 2010, 2020, and 2030, graphical representation as comparable monthly rainfall pattern is shown. It is evident that the patterns are changing with the average lowest and greatest values of rainfall in 2030 are shown side by side. Less precipitation occurs on dry days and more precipitation occurs over a shorter time period is plainly seen (Figure 2). The frequency of adverse events of weather such as flooding and droughts, as previously noted, is anticipated to rise in the future as a result of this trend.

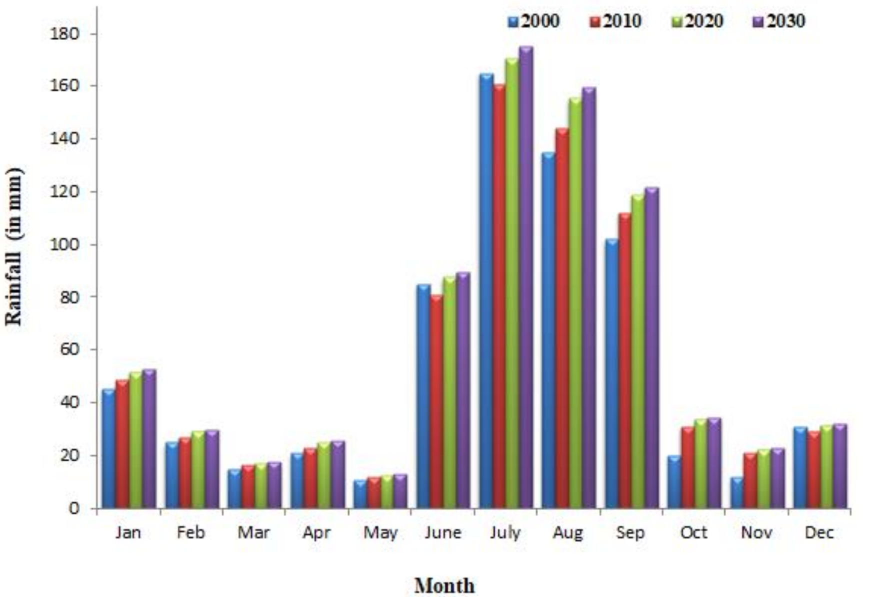



**FIGURE 2. A comparison between observed and predicted rainfall in 2000, 2010, 2020 and 2030.**

### 4.2 Water quality: Key parameters

Water quality data monitoring is being taken by the CPCB on a consistent basis led to the selection of these three stations for DO, COD and BOD.

**COD:** The COD value was used to evaluate the simulation performance of the water quality module. for different months as well as minumum, maximum and average in the simulation at three locations, namely Upstream (Ketham), Midstream (Poiya Ghat) and downstream (Bank of Taj Mahal) as shown in (Figure 3-5).

**DO & BOD:** Figure 6 (a), (b) & (c) are depicting the deteriorating impact of DO and BOD due to climate changes and population growth. The deterioration of DO is showing as decrease in DO level consistently from upstream to downstream. It dropped to zero in downstream since 2005. Water quality deterioration in terms of BOD is showing as rising its value continuously from upstream to downstream.

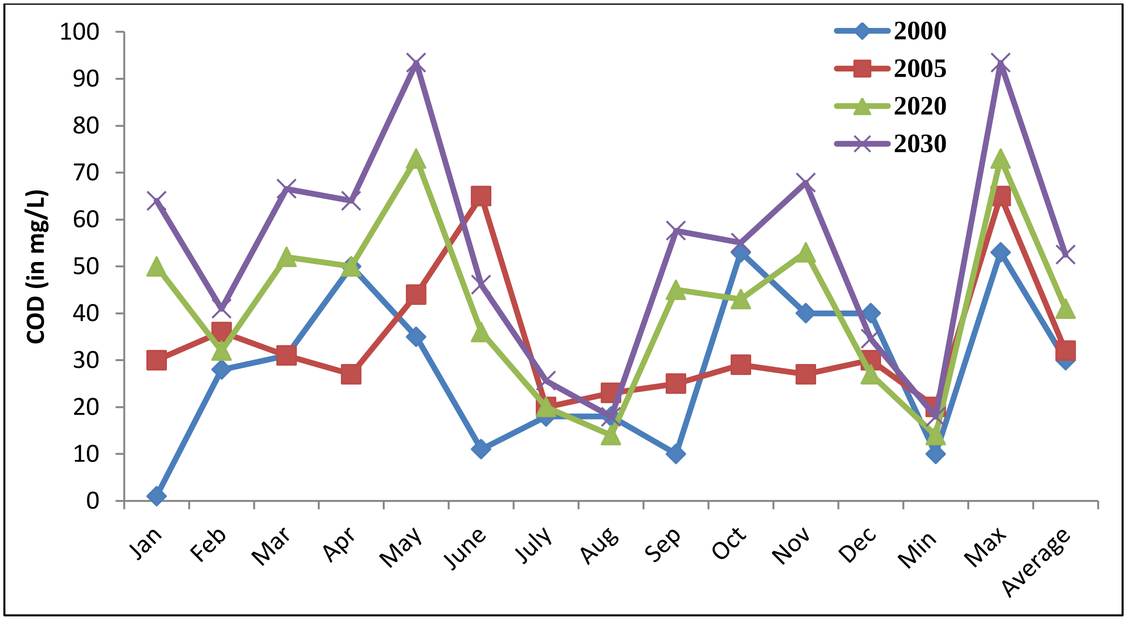



**FIGURE 3.** Upstream COD simulation versus observation

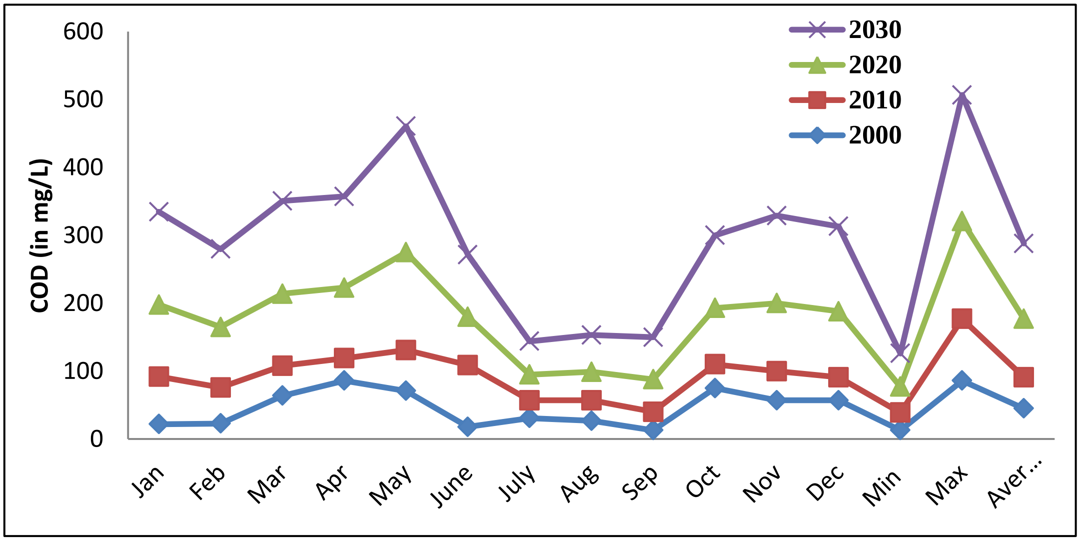



**FIGURE 4.** Midstream COD simulation versus observation

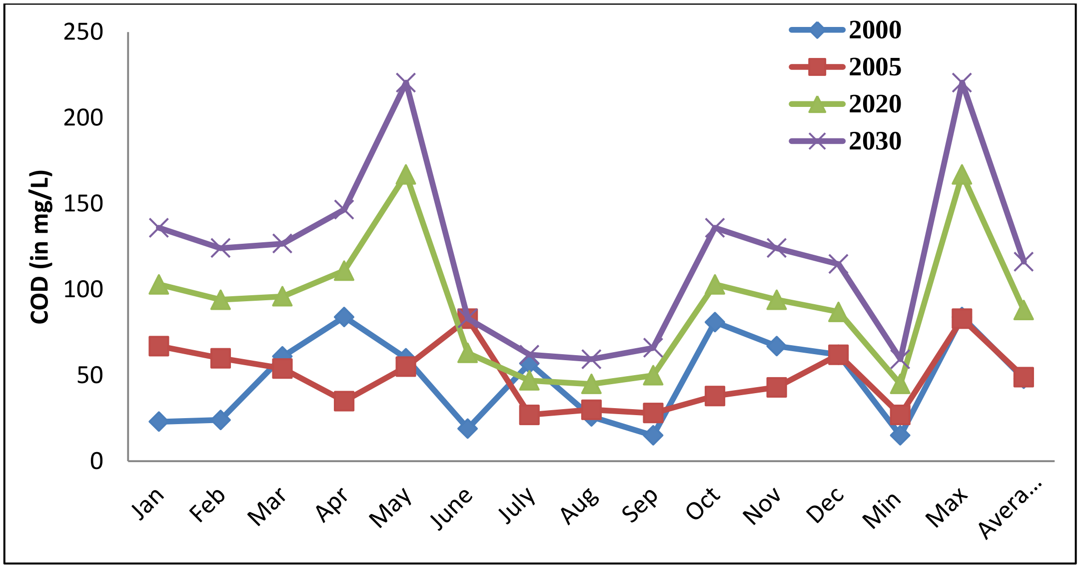
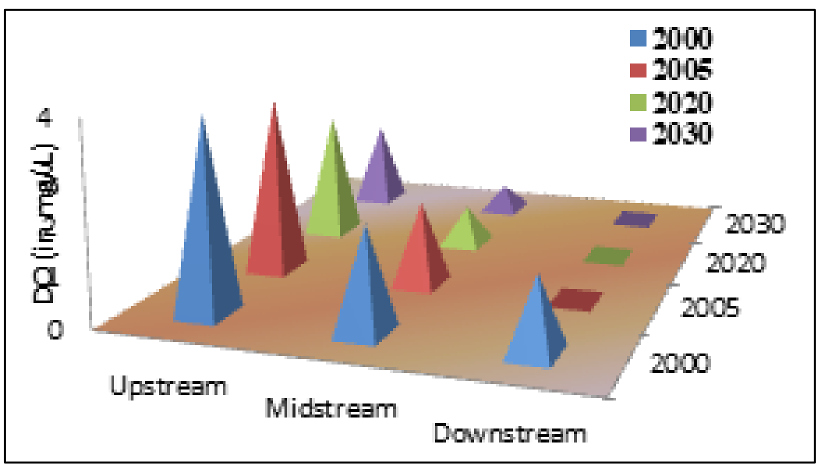
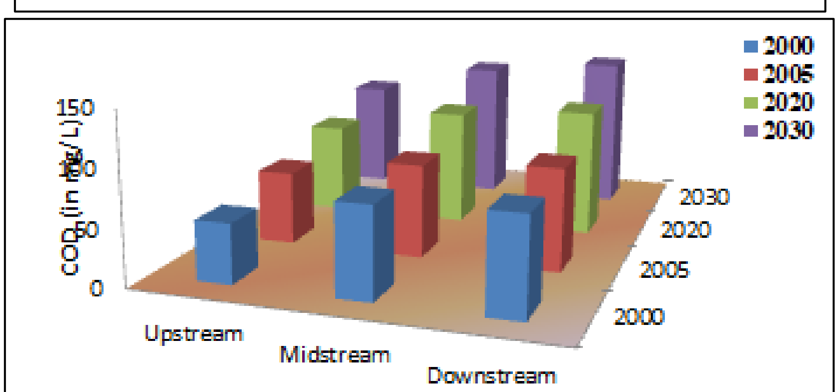
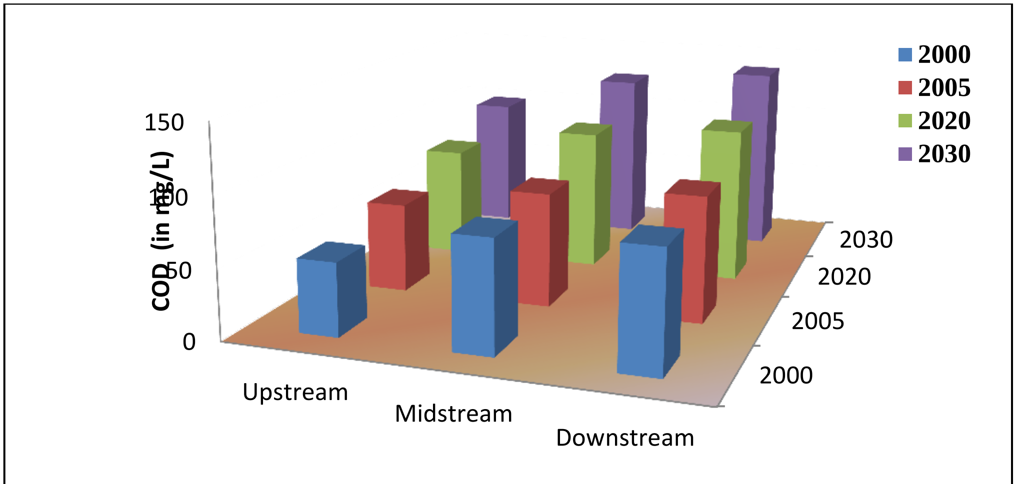



**FIGURE 5. Downstream COD simulation versus observation**





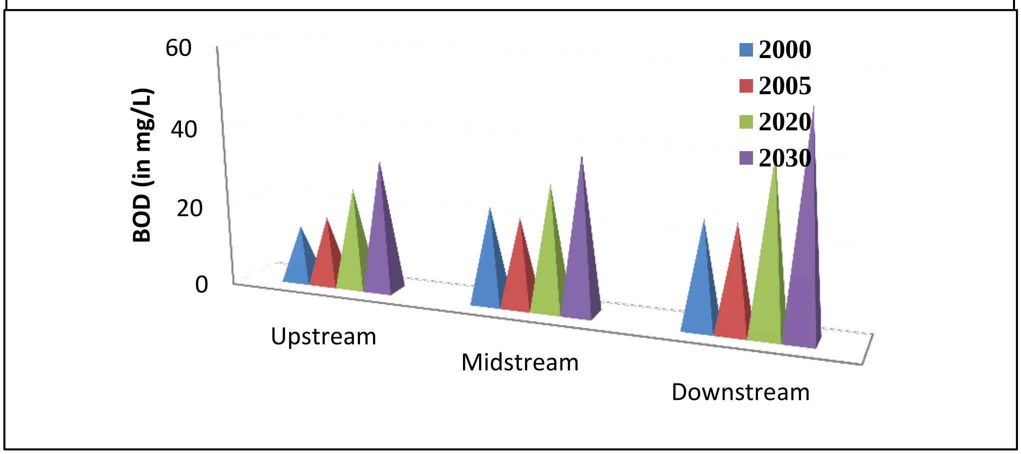




**FIGURE 6. The results of the simulation for the annual average values of (a) DO (b) BOD (c) COD for three locations (Keetham, Poiya Ghat and bank of Taj Mahal) in 2000, 2005, 2020 and 2030**

The results revealed as tabulated form in Table 4, as a statistically significant relationship between observed & simulated values, confirming that model's performance was appropriate for the study area under consideration (CPCB, 2006)

**Table 4: Correlation Coefficient (r) and Correlation Determination ($R^2$) between BOD & COD at upstream & downstream sites of Yamuna River focused for different seasons (Year 2000 – 2020)**

| Locations | All The Seasons | | | Non Monsoon Seasons | | | Monsoon Seasons | | |
|---|---|---|---|---|---|---|---|---|---|
| | No. of Paired variables | r | $R^2$ | No. of Paired variables | r | $R^2$ | No. of Paired variables | r | $R^2$ |
| Upstream | 83 | 0.737 | 0.543 | 63 | 0.701 | 0.492 | 20 | 0.749 | 0.561 |
| Downstream | 84 | 0.848 | 0.719 | 63 | 0.843 | 0.711 | 21 | 0.839 | 0.704 |

## 5. CONCLUSIONS

The existing and future quality and quantity of water resources were investigated in this study under a variety of situations. Statistically correlation for the simulated and actual values indicates that the model is capable of accurately reproducing rainfall trends as well as water quality parameters as DO, COD, and BOD concentrations. A growing global demand for water resources, coupled with an exponential increase in total demand, means that encouraging the reuse and recycling of water in industry can both have importance to the restoration and recovery of water resources while also helping to reduce water consumption by urban populations. According to the findings of the simulated water quality test, the water is moderately to significantly contaminated across the Yamuna River basin, with the majority of the water being polluted. Average deterioration rates due to rise in population as well as industrial growth for DO, COD, and BOD show a decreasing trend of 24.10 percent to 31.2 percent (for DO) and an increasing trend of 25.2 – 33.6 percent (for COD and BOD) from the base year 2000 to 2020, with the decreasing trend for DO being the most severe. In addition to this, the modeling outcome showed the pace of drop in the coming future is fairly rapid due the current construction plans of various government projects like Metro rail project, ongoing & planned flyovers, sanitation stream pipeline, new housing plans etc. upto the year 2030. Because of population growth and harsh weather conditions brought on by climate change, there is a significant rise in wastewater output that must be dealt with. Developing strategic and adaptable tactics for the future is necessary in order to achieve success. Local stakeholders involved in the water industry will benefit from the findings of this research project. This argues that policy planning should take into account both climate change and non-climate change factors in order to achieve better adaptation and long-term water resource management. Achievable improvements include improved wastewater treatment standards, sectoral water use practises depend on quality of water, efficient management of water loss, combined groundwater and surface usage with extreme weather consideration.

## 6. FUTURE DIRECTIONS

Water scarcity demand is increasing per year as a result of population growth. It is irrespective to take general sense that how severe the water scarcity problem will be by that time. Water quality measurements were monitored and the overall trend revealed as water quality fall down from upstream to downstream as a result of toxic input being introduced into the system (sewerage). A further point to note is that the extent of deterioration is greater in the second scenario than in the first scenario, which includes the influence of climate change as a factor. It is plausible that the increased frequency of extreme weather occurrences as a result of climate change is the main cause of problem. If climate change causes longer periods of dryness (and consequently lower river flow), it is possible that this is one of the variables contributing to an increase in toxin concentrations. According to the climate change scenario, this will be true regardless of where they are located. BOD concentrations vary from 14 mg/L to 53.3 mg/L, indicating that the most of the water samples are medium to extremely contaminated when compared to the BOD concentration recommended for a safe aquatic system, which is 6 mg/L. When the time period between tests is extended into the past, the COD value, which is a commonly used indicator of both organic and inorganic nutrients in water samples, rises as a result. Additional research is required to advance the present frontier of knowledge in AI.

Improvements in AI tools are now being investigated for their potential to provide improved knowledge representations schemes, alternative methodologies, and mechanisms for dealing with ambiguous or incomplete data. Enhanced application of modelling systems in real-world situations will be made possible by improved and more user-friendly interfaces to database management systems, graphical displays, and knowledge acquisition modules. Given that prototype systems are being produced in this area, the demand for better AI tools is expected to rise, which may result in improved techniques for implementing AI technology. But perhaps most significantly, the prototypic systems will be followed in the lab and into real-world use. Further research and development will improve the technology and AI's applications in water quality simulation. Further growth of numerical modelling in this manner, it is anticipated, given the ever-increasing capabilities of AI technologies.

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