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Climate change impacts on water resources: An overview

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4.1 Introduction

4.1.1 Background and significance

The repercussions of climate change on water resources are so prominent to be ignored and require significant reviews of recent developments in this domain (Borges et al., 2020). The Intergovernmental Panel on Climate Change (IPCC) fourth assessment report forecasts that freshwater resources will be reduced by 10–30% in many arid central tropical parts of the world, and that rising sea levels expected to rise by 2080 as a result of climate change (IPCC, 2007). Developing countries are especially vulnerable to the effects of climate change (Amoo and Fagbenle, 2020). It is estimated that they will bear the brunt of the changing climate, with South Asia and Africa experiencing a 4–5% decline in GDP (McMahon and Gray, 2021). Developing countries in Asia and the Pacific are especially sensitive to climate change because of the presence of deltas for example, Asian megadeltas, coral reefs (Bleuel et al., 2021), and vulnerability to cyclones (Walsh et al., 2016; Cha et al., 2020), and increasing the risks of economic growth (Tezuka et al., 2014).

Water resources are important in supporting biodiversity and providing social and economic benefits to people (Grizzetti et al., 2016; Lu et al., 2019). Rising temperatures are seen as some evidence of environmental change, and this has begun to lead to significant effects on water resources and will have serious growing consequences over time (Lu et al., 2019; Srivastav et al., 2021). Adding to these effects are an increase in demand for water and energy, a shift in economic activity, an increase in industrial activity, and an increase in pollution (Grizzetti et al., 2016; Borowski, 2020). Srivastav et al. (2021) provided a detailed account on the various strategies for tackling the climate change triggered challenges posed on water resources.

According to the prediction by IPCC's AR5 report (IPCC, 2014), atmospheric temperatures could rise globally by 4°C by 2100, which in turn will significantly affect global water supply and water demand. The combined impact of water supply and demand is expected to increase the gaps in demand for water supply, which exacerbates current water management challenges (Lu et al., 2019).

Climate change may affect groundwater resources due to the expected changes in rainfall and evapotranspiration and spatio-temporal distribution of these important components of

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water balance (Taylor et al., 2013; Loo et al., 2015; Guevara-Ochoa et al., 2020; Lam et al., 2021). Increased rainfall will lead to higher levels of water flow, increased risk of flooding and reduced levels of groundwater runoff (Şen, 2021). Rising temperatures result in higher respiration evapotranspiration, and, in turn, increase the demand for irrigation water, which is already a major consumer of water under current conditions (Wang et al., 2016). For water management to be able to meet future challenges, the impact of climate change on water levels needs to be calculated from the regional scale to the area (basins). Research activities over the past few decades are increasingly tackling this problem (Goyal, 2004; Wang et al., 2016; Li et al., 2020).

General cycle models (GCMs) are often used to understand climate change and project future climate scenario (Tan et al., 2014; Chokkavarapu and Mandla, 2019). This decision, however, is the most critical of any impact studies on regional or local scale estimates. In order to obtain climate change on a regional scale, climate change estimates require a reduction in GCM decision, using variable or statistical methods (Joseph et al., 2018; Worku et al., 2020). A dynamic descent using a regional climate model (RCM) brings about a virtually stable climate change (usually 5–50 km horizontal rotation). However, even RCM with high resolution output is still prone to systematic errors (bias) compared to point recognition (Kumar et al., 2017). Therefore, bias correction is often used in RCM simulations to study regional/local scale climate impacts hydrology and water resources. GCMs are employed in representative concentration pathways (RCPs), a series of scenarios used by climate scientists to provide probable future scenarios for the evaluation of various environmental variables (IPCC, 2013). As climate scenarios, four RCPs have been developed: RCP 2.6 as the lowest range, RCP 4.5 and RCP 6.0 as the middle range, and RCP 8.5 as the maximum range (IPCC, 2013).

Numerous studies have examined the impact of climate change speculation on the hydrology of various regions around the world (e.g., Huntington, 2006; IPCC, 2007; Labat et al., 2012; Dragoni et al., 2015; Jose and Dwarakish, 2020). However, systematic studies of Asian catchments are scarce; physical process based hydrological or ecohydrological models have been often used (e.g., Gosain et al., 2017; Bajracharya et al., 2018; Sahoo et al., 2018). More recently, climate change phenomenon is evidently reflected in the Indian mainland (Kumar et al., 2017; Ali et al., 2019; Vijaykumar et al., 2021). Numerous studies have predicted a growing trend at higher temperatures (Singh and Kumar, 2019; Vishwakarma and Goswami, 2021; Yaduvanshi et al., 2021) and a significant rainfall anomalies in different geographical regions in India (Singh and Kumar, 2019; Vijaykumar et al., 2021; Singh and Singh, 2021; Vishwakarma and Goswami, 2021).

In order to upgrade expertise on climate change, Coupled Model Intercomparison Project (CMIP) was initiated by the World Organization Research Program in 1995 as a representative climate model project whose results are used in IPCC assessment reports (Taylor et al., 2012). Different modeling groups around the world are constantly updating climate models to include higher spatial resolution, new physical processes, and biogeochemical cycles (Bader et al., 2008). These concerted efforts are part of CMIP, among which CMIP5 and CMIP6 models are gaining attention among researchers. Earlier, the fifth assessment report (AR5) formulated in 2013 featured climate models from CMIP5, while the latest IPCC sixth assessment report (AR6) featured CMIP6 models with around 100 distinct climate models (IPCC, 2013).

Predicting the fate of global water resources based on future climate scenario is crucial for developing adaptation strategies. More scientific understanding is needed to address the physical, chemical, biological, and economic impacts of the current and anticipated global climate change on water resources (Borowski, 2020). Henceforth, the present chapter attempts to give a brief outline on climate change impacts on water resources and applications of different types of models in this aspect.

4.2 Observed climate change impacts

4.2.1 Precipitation

Precipitation plays a crucial role in sustaining life on Earth. Considering the population dependence on precipitation, the monsoon dynamics response to increased GHG concentration in space is a problem for both scientific and social relevance (Kishore et al., 2016). India's freshwater resources are mainly dependent on the southwest monsoon. As a result, meeting the water needs of agriculture, industry, domestic objectives, energy sectors and the environment depends on the monsoonal system. More than 80% of the annual rainfall occurs during monsoon season that is, mid-June-September (Kumar et al., 2010). Therefore, any change in climate, especially during the monsoon season in India, could have a profound effect on agricultural production, which is now under pressure due to high population growth and problems related to water resource management (Mall et al., 2006).

Air temperature is directly proportional to the evaporation rate and atmospheric moisture content (Boulet et al., 2020). Theoretically, high levels of atmospheric water vapor content due to global warming gives rise to acceleration/intensification of hydrological cycle. The aforesaid theory is summarized in thermodynamic Clausius-Clapyeron relationship that implies that specific humidity would increase almost exponentially with temperature (Alduchov and Eskridge, 1996).

Intensification of global water cycle ultimately results in two major hydrological extreme events as outcome- droughts and floods (Huntington, 2006). Drought is a prolonged period of anomalous dry weather interrupting the hydrological balance driven due to enhanced potential evapotranspiration (Rind et al., 1990; Wang et al., 2018). Localized convective instabilities, large-scale organized monsoon activity, and anomalous extratropical circulation, as well as their interactions with the monsoon circulation across the Himalayas have all been identified as synoptic-scale signatures in connection with these extreme rain situations (Shrestha, 2016). Earlier, several lines of research reported extreme precipitation over the central Indian region (Rao, 1976; Rajeevan et al., 2010). However, later research revealed a decrease in heavy precipitation events in north and central parts of India (Guhathakurta et al., 2015). Heavy down-pouring cloudburst (rainfall rate $>$100 mm/h) and mini cloudburst (rainfall $>$50 mm in consecutive 2 h) events which lead to landslides and flashfloods are strongly associated with global warming (Deshpande et al., 2018).

4.2.2 Cryospheric water resources

The cryosphere, an intrinsic part of the climate system includes glaciers, ice sheets, ice shelves, ocean, lake or river ice, ice cover, permafrost, and occasional glaciers. These vulnerable reservoirs of water respond rapidly to the on-going climate changes (WMO, 2021). Global warming induced impacts on cryospheric water resources have been documented worldwide (Shrestha and Aryal, 2011; Wu et al., 2015; Taloor et al., 2021; Hock and Huss, 2021). As a consequence, increased runoff and discharge peaks are observed in cryospheric river basins (Wu et al., 2015; Escanilla-Minchel et al., 2020). Stored glacial water in the High Mountain Asia (HMA) region controls the water dependent economies sustaining the livelihood of millions of people (Immerzeel et al., 2020). Mishra et al. (2020) evaluated the impacts of climate change on hydropower based energy security in HMA. Similar works were carried out in North Western Greece (Skoulikaris et al., 2021), Brazil (Mendes et al., 2017), Sub-Saharan Africa (Falchetta et al., 2019), etc. Glacial melt is accompanied by lake expansion and intensification of the water cycle over the Tibetan Plateau better known as "Third Pole," one of the major water towers in the world (Mao et al., 2018; Yao et al., 2019).

4.2.3 Surface water resources

Surface water resources are subjected to significant alterations as a result of changes in climate variables viz., temperature, precipitation, evapotranspiration, etc. Discharge regime of rivers is affected as these changes impact runoff and water availability (Jahandideh-Tehrani et al., 2019). Streamflow, one of the integral components of hydrological cycle, is very sensitive to the varying climate and this could become even more important in the future. Several studies have demonstrated the possible hydrological impacts of climate change on future streamflow of various rivers worldwide (Jahandideh-Tehrani et al., 2019).

Although some parts of the world are predicted to have an increase in streamflow, for example, Ethiopia (Fentaw et al., 2018); Indonesia (Santikayasa et al., 2015), Pakistan (Hassan et al., 2019), certain other regions are predicted to have decreased streamflow in future for example, Australian tropics (Usman et al., 2021), NW Greece (López-Ballesteros et al., 2020), Nepal (Maharjan et al., 2021), Qinghai–Tibetan Plateau (Tian et al., 2020), etc. Vanderhoof et al. (2018) opined that the effects of variables viz., precipitation and evaporative demand on surface water quantity with respect to different climate extremes are often varying.

As discussed earlier, shifts in precipitation could interrupt river flow regimes, consequently affecting the dilution and mobility of pollutants (Rehana and Mujumdar, 2011). Another possible factor resulting in surface water quality deterioration is elevated temperature by means of altering chemical reaction kinetics. Numerous researchers have discussed on surface water quality vis-à-vis climate change (Whitehead et al., 2009; Rehana and Mujumdar, 2011; Vanderhoof et al., 2018).

There are umpteen pieces of evidence in literature confirming the role of humic acids in accelerating global warming (Kirschbaum, 2006; Tranvik et al., 2009; Raymond et al., 2013). Conversely, Lipczynska-Kochany (2018) scrutinized the climate induced impacts on structure and reactivity of humic substances present in surface waters, a research area which remained less explored until then. The breakdown of Soil Organic Matter (SOM) due to global warming increases the production of Dissolved Organic Matter (DOM) in water and induces microbial growth promoting biodegradation of contaminants. However, there may be negative consequences like disruption of solar disinfection process attributed to the elevated levels of DOM.

Table 4.1 Climate change impacts on water resources in different parts of the world.

Region/location	Impact	Reference
Tekeze Basin, Ethiopia	Increase in precipitation and annual runoff	Fentaw et al. (2018)
Azerbaijan, Middle East	Decline in water storage, water equivalent depletion of $\sim 3.5 \times 10^{-3}$ cm/year.	Bozorg-Haddad et al. (2020)
Ganges Basin , India	Groundwater storage depletion at the rate of 1.25–2.1 cm yr^{-1}	Panda et al. (2016)
Lhasa River Basin, China	Decrease in sediment load and streamflow	Tian et al. (2020)
Citarum River Basin, Indonesia	Increase in precipitation and run-off potential evapotranspiration losses	Santikayasa et al. (2015)
Global	Highly variable precipitation (irregular patterns)	Konapala et al. (2020)

Unlike many previous studies, Islam et al. (2018) incorporated socio-economic variables to predict the future river microbial water quality in a changing climate scenario.

4.2.4 Groundwater resources

Understanding the interaction of climate variables with groundwater is more intricate compared to that with surface water (Lipczynska-Kochany, 2018). Climate change affects groundwater systems in terms of both quantity as well as quality. With regard to quantity, climate forcing could influence rates of soil infiltration, percolation, and subsequently groundwater recharge. Additionally, elevated temperature aggravates evaporative demand in a region, further restricting the replenishment rate of groundwater. In an unsaturated aquifer system, the vadose zone provides significant information about climate change in a scale of decades to millennia. Several solute (e.g., chloride) based (Ma et al., 2004; 2012; Manna et al., 2019; Lu et al., 2020) and isotopic (e.g., $\delta^{18}O$, δD, ^{3}H, ^{14}C) tracer studies have been successfully applied in extracting this information (Cook et al., 1992; Aquilina et al., 2015; Abiye, and Leketa, 2021). Climate change poses threat to groundwater quality as a result of alterations in hydrological processes (Kløve et al., 2014). Also, increased temperature modifies biological, chemical, and physical properties of groundwater, hence affecting its quality (Hähnlein et al., 2013). Alteration in timing and magnitude of groundwater recharge, fluctuation in groundwater levels are other negative impacts of global warming (Scibek et al., 2007; Taylor et al., 2013). These fluctuations in groundwater levels eventually affect the surface water-groundwater connectivity in the region (Scibek et al., 2007).

Few of the important observed impacts of climate change on water resources worldwide are summarized in Table 4.1.

4.3 Modeling approaches

Forecasting the effects of climate change, especially the long-term impacts on water resources using integrated hydrological and climate models remains a daunting task. To overcome this challenge, modeling techniques are applied to conceptualize the interactions between climate and water resources. General circulation models (GCMs) are the most extensively used tools in climate change research at global/regional scales through the generation of climate scenarios for present and future time frames (Tan et al., 2014; Chokkavarapu and Mandla, 2019). On coarse horizontal scales (100–300 km grid), GCMs perform well and impart data for climate studies (Fung et al., 2011). However, GCMs do not account for any regional or local scale research, and henceforth, the projections of variables must be downscaled. This downscaling can be achieved using dynamical/statistical/hybrid dynamical-statistical approaches and hydrological models (Mejia et al., 2012).

Statistical downscaling approach analyzes the statistical relationship between coarse scale climate variables (i.e., GCMs) and high resolution local scale observations. Some of the most frequently used statistical downscaling methods are weather typing (Vrac et al., 2007; Bermúdez et al., 2020), stochastic weather generators (Jeong et al., 2012; Kreienkamp et al., 2013), resampling (Thorndahl et al., 2017; Vrac, 2018), regression, etc. among which regression method is preferred due to its ease of applicability (Chen et al., 2010). Though statistical approach is user friendly, it is not suitable in conditions where large scale-local scale variable relationship is insignificant. On the other hand, dynamical downscaling approach incorporates a RCM within GCM framework to provide fine resolution climate information.

Formulated based on physical principles, downscaling by a dynamical approach using a RCM delivers physically reliable climate variable (usually horizontal resolutions of 5–50 km). This approach is more efficient than statistical downscaling, but highly time consuming (Kumar et al., 2017). Henceforth, some researchers apply dynamical-statistical method to nullify the demerits of both techniques. However, even high-resolution RCM output is still prone to systematic errors (biases), and hence, bias corrections are often applied to RCM simulations (Teutschbein and Seibert, 2012) to study the impact of climate change on water resources (e.g., to study hydrological aspects of a basin by hydrological models).

In the literature, several bias correction methodologies have been developed (e.g., Muerth et al., 2013; Ahmed et al., 2013; Turco et al., 2017; Macias et al., 2018; Worku et al., 2020). They all get a transfer function between the weather information on a large scale GCM or RCM scale and local scales (Wilby et al., 2002; Teutschbein and Seibert, 2010, 2012). These transfer functions are then used in future weather forecasts under static conditions. Current methods of correcting bias are based on simple line methods (e.g., Teutschbein and Seibert, 2010; Shrestha et al., 2017) and algorithms based on mathematical distribution (e.g., Teutschbein and Seibert, 2012; Hosseinzadehtalaei et al., 2021).

Climate models have seen continuous improvement in recent decades (Tan et al., 2014; Kumar et al., 2017; Chokkavarapu and Mandla, 2019). Recent advances have seen the integration of biogeochemical cycles - the chemical transfer between living organisms and their environment - and their interaction with climate (Zaehle and Dalmonech, 2011; Friedlingstein, 2015). Like their predecessors, these “Earth System Models” (ESMs) are used to predict the future climate in terms of different emissions of GHGs. But while the addition of new processes and more details has led to more complex comparisons of the Earth’s climate, it comes at the expense of growing and sophisticated models (Liu et al., 2017; Ongoma et al., 2018).

4.3.1 Applications in water resources: A commentary

Many of the evidence incorporating the IPCC report includes observations collected from around the world and numerous simulations from the latest generation of climate models (Song et al., 2015; Misra et al., 2019; Gholami et al., 2021).

Past several years witnessed the use of efficiency of GCMs and RCMs in rainfall and streamflow predictions. Prediction of long-term precipitation patterns is indispensable for effective water resources management (Chokkavarapu and Mandla, 2019). Hydrological systems in high elevations are extremely sensitive to increasing global temperatures (IPCC, 2013). In several climate related studies, a significant loss of glacial masses is projected, sustaining their role as one of the major drivers accelerating sea-level rise in the coming decades (Zekollari et al., 2019; Hanna et al., 2020). As discussed in Section 2.2, the cryosphere plays a major role in storing water and maintaining runoff in rivers. Glacier mass loss due to climate change has serious consequences on river runoff and water quality. Laurent et al. (2020) computed runoff in the Arve river of Mont-Blanc massif region using CMIP5 simulated climate under RCP4.5 (lower warming scenario) and RCP 8.5 (high emission scenario), and predicted a decline in river discharge by the end of 21st century.

Groundwater recharge is strongly influenced by precipitation and soil properties (De Vries and Simmers, 2002). Numerous works have focused on groundwater recharge with emphasis on land use/land cover change (LULC) (Zomlot et al., 2017; Purandara et al., 2018; Lamichhane and Shakya, 2019). However, studies on groundwater potential under climate change scenarios are vital for sustainable water resources management. Nyenje and Batelaan (2009) incorporated statistically downscaled climate data in WetSpa rainfall-runoff model to simulate climate change effects on groundwater recharge and base flow in Sezibwa watershed, Uganda. The results predicted intensification of hydrological cycle and a corresponding increase in recharge upto 100% in the 2080. Similar technique using WetSpa model was applied to simulate future groundwater availability in Tekeze basin, Ethiopia, and projected results suggested significant decrease in groundwater recharge rates in future (Kahsay et al., 2018).

Physical models using Richards' equations have been employed by several researchers to study groundwater dynamics including saturated and unsaturated flows (Clement et al., 2020). However, models like soil water assessment tool (SWAT) need to be integrated for considering other important land surface variables including vegetation cover (Kin and Jackson, 2012; Awan and Ismaeel, 2014). Recently, modular finite difference groundwater flow (MODFLOW) coupled with SWAT (SWAT-MODFLOW) model is used to investigate subsurface flow processes, water availability, surface-groundwater interactions, etc. where both LULC and climate change effects are considered (Bailey et al., 2016; Guevara-Ochoa et al., 2020; Yifru et al., 2021).

In addition to availability issues, groundwater resources are vulnerable to climate forcing in terms of quality. DRASTIC (D– depth to groundwater, R– rate of recharge, A- aquifer media, S- soil media, T- topography, I- impact of vadose zone, C- hydraulic conductivity of aquifer) is one of the widely used models suitable for analyzing groundwater vulnerability (Li and Merchant, 2013; Persaud and Levison, 2021). In order to elucidate the climate change and urban land use pattern driven effects on groundwater, Huang et al. (2017), considered land-use pattern (L) as an additional parameter in DRASTIC. Climate change would directly impact R and D, whereas L accelerates the groundwater pollution risk. Milner et al. (2020) developed climate change vulnerability assessment tool by integrating statistical methods with a multi-model ensemble generated from different scenarios, RCPs 2.6, 4.5, 6.0 and 8.5. One of the drawbacks of groundwater vulnerability models is that climate change factors are combined in a linear model for prediction. However, physical processes influencing groundwater pollution is not linear and there is a high possibility for over or under estimation of future pollution risk (Li and Merchant, 2013). As the nonlinear complex relationships of hydrogeological variables and subjective weights are not considered, it results in uncertainty. Henceforth, other tools like AI and ML should be implemented to improve traditional models. Applications of these techniques are discussed in the next section.

4.4 Sustainable water resources management using AI/ML under changing climate

With the effective use of data, learning algorithms, and sensing devices, AI is a disruptive paradigm that has increased ability to analyze, anticipate, and mitigate the climate change risk (Levy and Prizzia, 2018). It carries out calculations, forecasts, and makes decisions to help reduce the effects of climate change (Huntingford et al., 2019; Cowls et al., 2021). AI helps us better comprehend the effects of climate change across different geographical places by generating effective models for weather forecasting and environmental monitoring (Bublitz et al., 2019). It analyzes climatic data and forecasts weather events, extreme weather conditions, and other socio-economic consequences of climate change and precipitation.

A comprehensive overview of the literature pertaining to the application of AI-based methods, viz., artificial neural networks (ANN) inferred that there are contradictory issues regarding their performance. While most of the studies vouch for the efficiency and superiority of ANNs over traditional statistical tools viz., multiple regression (MLR) based models, there are few studies with contrasting findings (Abdellatif et al., 2013). The discrepancy of results obtained as a result of modeling largely depends on the quantity and quality of the input data. For instance, the existence of noise in the data set make AI-based modeling more difficult for larger data sets, especially in nonlinear models (e.g., ANN, adaptive neuro fuzzy inference system/ANFIS, etc.).

Bowden et al. (2005) pointed out that ANN-based hydro-climatic process modeling may end up with less accurate results due to: (1) irrelevant input variables increasing the difficulty in training; (2) low precision and lack of convergence; (3) time-consuming process; (4) requirement of large computational memory; (5) difficulty in understanding complex models with large data sets compared to simple models. As a result, input feature extraction methods as a preprocessing strategy can greatly improve the efficiency of AI-based downscaling models. More advanced research in this domain is required to achieve the best results from AI for climate change mitigation.

Groundwater availability prediction is an integral part of water sustainability. Such predictions provide important real data based insights, for example, the influence of declined stream and river flows (Hussein et al., 2020). Also, researchers and planners can actually get a picture on the water supply shortage factors which led to drought in a region. By assisting in the forecast of groundwater availability, methods viz., AI, ML have the potential to drive groundwater knowledge and management. This can be accomplished by enabling the collection, storage of large water datasets, and processing them to obtain useful insights that can be used by water resource managers to: (1) predict water quality in unsampled areas thus filling the gap where there is missing primary data (Hussein et al., 2020; Jha et al., 2020); (2) design targeted monitoring programs; (3) inform groundwater protection strategies; and (4) assess the sustainability of groundwater resources (Hussein et al., 2020).

ANN models are proven to be useful in simulating groundwater level fluctuations in response to climate change (Jeihouni et al., 2019; Ghazi et al., 2021). Chang et al. (2015) assessed the sensitivity of suprapermafrost groundwater level to climate change using two ANN models: the former with three input variables including previous groundwater level, temperature, precipitation data; the later one using two variables viz., temperature and precipitation. This method proved to be effective in modeling and forecasting, as mathematical methods are not applicable in permafrost groundwater.

In recent years, climate scientists have found another tool available to them due to the rapid advances in AI and, in particular, ML (Kadow et al., 2020; Luccioni et al., 2021). Unlike models that follow a clear and predetermined set of rules, ML is aimed at building systems that can read and consider such rules based on data patterns (O'Gorman and Dwyer, 2018). As a result, a new line of climate research is emerging aimed at completing and maximizing the use of observations and models (O'Gorman et al., 2018; Huntingford et al., 2019). The overall aim of ML application is to address the ongoing challenges of climate research and to improve future forecasts.

ML is an all-encompassing term for many different tools, those sensory networks - a set of interconnected algorithms that are freely modeled on the human brain are a widely known and used model (Hannachi, 2021). With "supervised learning" which uses data sets to "train" algorithms—these tools can be used to reveal patterns and complex relationships between variables, allowing them to perform specific tasks such as sorting or analyzing data (Shen, 2018). For example, a neural network can be trained to identify and distinguish patterns on satellite imagery - such as cloud structures (Rasp et al., 2020), ocean eddies (Li et al., 2020) or crop quality (Zhong et al., 2019) and to create predictions based on past records, model results and physical balance equations.

Unlike conventional models, ML does not require prior knowledge about governing rules and the relationship between the problems (Camps-Valls et al., 2021). Proper relationships are found entirely in the data used during the default learning process. This flexible and dynamic concept can be extended to almost any level of complexity (Reichstein et al., 2019). The availability of physical climate data and model simulations combined with ready-to-use machine learning tools have led to accurate output.

Understanding long term trends of temperature and precipitation is critical for water resource management, water supply, planning, etc. (Venkataraman et al., 2016). Climatic variability and trends are important for so many water-related sectors, hence accurate forecasting and prediction of climate variables is particularly crucial for policymakers, planners, and sustainable water resource management. Furthermore, such forecasts are vital for managing water supply and demand (Dallison et al., 2020), reducing the uncertainty by providing information on the future availability and quality of water (Bhave et al., 2018), ensuring optimal water resources allocation (Guan et al., 2021), etc.

ML methods viz., support vector machines (SVM), k-nearest neighbors (kNN), random forests (RFs), etc. are the frequently applied tools for long-term daily rainfall prediction, using atmospheric synoptic patterns from reanalysis databases. While scrutinizing the literature, it is evident that each algorithm has its own set of pros and cons; selection of the best method is a tough task.

SVM is a supervised ML algorithm used in regression problems for dimension reduction and data visualization (Maszczyk and Duch, 2008). This kernel based tool has a wide range of applications in water resources domain. Ghosh and Katkar (2012) compared the performance of three downscaling methods, linear regression (LR), artificial neural network (ANN) and SVM for simulating three rainfall conditions –low, medium, and high. SVM outperformed the other two methods, especially under high rainfall conditions. Other applications of SVM include forecasting groundwater level fluctuations (Ghazi et al., 2021), runoff projection (Sarzaeim et al., 2017), daily streamflow prediction (Niu and Feng, 2021), etc.

The kNN is a simple, nonparametric supervised algorithm used for classification which estimates the input-output relationship without any preset assumptions. To address water stress issues, Khatri et al. (2018) simulated future water demand and availability under changing emission scenarios using kNN. Despite the fact that kNN is applied in several water quality studies (Raseman et al., 2020; Azadi et al., 2021), Modaresi and Araghinejad (2014) pointed out that SVM is more efficient than kNN for water quality classification, as the latter one generated large number of errors. This was later reaffirmed by the findings of Babbar and Babbar (2017), where SVM outperformed kNN in predicting river water quality index.

More recently, data mining technique like RF algorithm has been widely employed in flood mitigation (Naghibi et al., 2020), rainfall forecasts (Ali et al., 2020), soil moisture prediction (Carranza et al., 2021), water quality investigation (Wang et al., 2021), groundwater potential mapping (Naghibi et al., 2017), landslide susceptibility modeling (Dou et al., 2019), sediment load prediction (Meshram et al., 2021), streamflow prediction (Abbasi et al., 2021), etc. RFs are made up of nonparametric decision regression trees that classify data with each node representing predictive flexibility (Breiman, 2001). RF implements "Gini index," a performance based measure to assess how varied the data is until it reaches the final point, is commonly used for data classification (Breiman et al., 2017).

In short, the vast spectrum of applications mentioned above shows the potential of AI and ML in managing water resources sustainably.

4.5 Hybrid models

Data driven models like AI and ML overcome the drawbacks of conventional physical models. ML models have the following benefits (i) perform well in nonlinearity (ii) knowledge underlying physical processes is not required (iii) low computation cost (iv) fast training, validation,

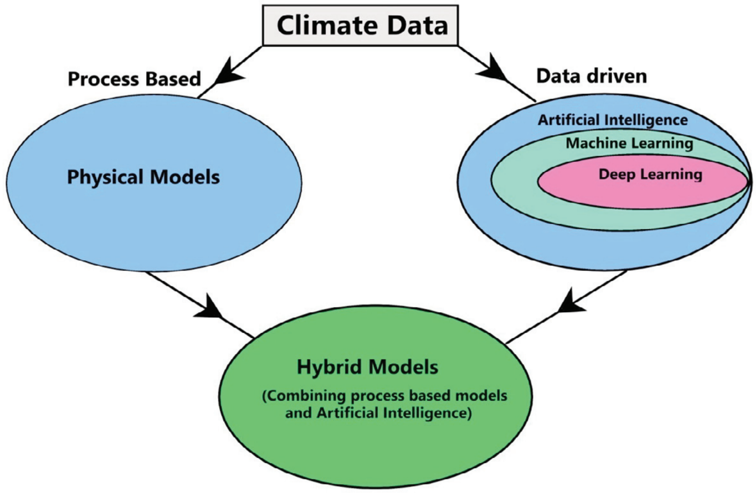

FIGURE 4.1 Conceptual diagram showing hybrid model development for climate research.

testing, and evaluation. On the other hand, it is often very difficult to verify machine learning in accordance with physical harmony, even though its produced results may seem plausible. They demand much labeled data for training, which is rarely available in real settings. Henceforth, for obtaining best results, hybrid models i.e., ML models coupled with traditional physical models should be developed (Fig. 4.1). Such approach will help improving accuracy of the output by reducing errors. For instance, Liang et al. (2018) predicted long-term streamflow using SWAT integrated with RF model. Compared to the efficient seasonal auto-regressive (SAR) model, this hybrid model performed better generating more accurate long-term streamflow simulation.

4.6 Conclusions and outlook

There is an urgent need to address the precarious condition of global water resources due to the rapid global warming. Due to the altered hydrological cycle driven by rising global temperatures, extreme hydrological events, viz., floods and droughts have been frequently observed in recent years. In order to develop appropriate adaptation strategies against climate change, planners need reliable future scenario projections. To fill the existing knowledge gaps, a multidisciplinary approach is required. Despite being potential for a wide variety of applications, the process based models tend to generate a lot of errors, consequently overestimating or underestimating the predictions. The limitations of these conventional models have paved way to the emergence of more efficient data driven AI/ML based models. ML has lot of advantages over physical process based models. ML is potential enough to find structure and patterns in nonlinear complex problems. However, ML has its own limitations as it requires lot of labeled data, which is hard to obtain in physical settings. Hence, application of hybrid models by combining ML and physical knowledge can generate more reliable output with high resolution.

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Non-Print Items

Abstract

Recent years have witnessed an upsurge of worldwide interest in potential impacts of climate change on water resources. Climate change is often entwined with alteration of water quantity as well as quality, aggravating the fast-growing water crisis. Over the past few decades, the negative effects of climate extremities are reflected in hydrological cycle, viz., pronounced shifts in global precipitation patterns and increased atmospheric water vapor content, glacier melting, floods, soil erosion, and drought etc. This situation substantially hinders the progress toward the attainment of Sustainable Development Goals (SDGs), thus jeopardizing the needs of future generations. It is therefore necessary to scientifically address the water security issues triggered by the escalating atmospheric and ocean temperatures. Water resource management has an obvious impact on a wide range of policy sectors, including energy, health, food security, and environment. As a result, practitioners need to design appropriate adaptation and mitigation strategies across diverse water-dependent sectors. However, there is a call for scrutinizing the current knowledge gaps in climate change vis-à-vis its implications on water resources. Owing to the complexities of climate system, anticipating these impacts is extremely challenging. Hence climate models related to the hydrological cycle provides a framework to conceptualize future scenario which is important for effective decision making. This chapter briefly discusses climate change impacts on water resources and process based modeling approaches combined with artificial intelligence /machine learning for tackling those issues.

Keywords

Artificial intelligence; Climate change; Machine learning; Modeling; Water resources