Machine Learning and Deep Learning Applications in Weather and Climate Studies: A Systematic Review

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ABSTRACT

Weather forecasting has evolved as the interest of numerous scholars from diverse study areas owing to its impact on human existence. Artificial intelligence (AI) frameworks have advanced in the last decade, combined with the widespread availability of massive weather and climate datasets and the advent of computational technology. It has motivated many researchers to investigate hidden hierarchical patterns in large volumes of datasets for weather and climatological forecasting. This comprehensive review paper highlights the evolving landscape of weather and climate research through the lens of machine learning (ML) and deep learning (DL) methodologies. As AI continues to redefine scientific inquiry, the latest advancements, applications, and challenges in leveraging ML and DL for meteorological and climatological insights has been documented. Surveying a broad spectrum of research, the review encapsulates the transformative impact of these intelligent systems on short-term weather forecasting, prediction of extreme events, climate forecasting, and refinement of weather and climate models. As a compendium of current knowledge, it serves as a guiding resource for researchers, practitioners, and policymakers navigating the dynamic intersection of climate science and machine learning, laying the groundwork for future advancements in the applications of AI frameworks in weather and climate prediction.

Keywords: *AI; ML; DL; Weather; Climate; LULC; Urban meteorology; Air pollution; Tropical Cyclones*

1. Introduction

The prevailing weather conditions exert a significant impact on human lives, influencing a substantial portion of our daily activities and livelihood. Unforeseen weather conditions have led to considerable loss of life and property. The atmosphere is primarily a physical system pertaining to most of its behaviors being governed by the laws of Physics that can be expressed in the form of mathematical equations. These equations account for the conservation of momentum, mass, energy, and water (or chemical species) and the equation of state which can be used to predict the fate of the thermodynamic state. The state of the atmosphere (or weather) at a certain time (initial state) can be specified using the observations, and then the equations can be computed to calculate the change of state over time or the future state of the atmosphere, called weather forecasting (prediction). Forecasting is important because the weather has an immediate influence on an individual's every day routine. It holds the potential to reduce or prevent the severity of losses and enhance operational efficiency. The impact of accurate forecasting extends to a diverse range of applications, with notable significance in defence, aviation, agriculture, etc. In the agricultural sector, timely forecasting plays a pivotal role in determining the optimal period for sowing, transplanting, irrigation, and harvesting, leading to increased crop productivity, yield and steady food supply chains. Similarly, the energy sector is facilitated by efficient management of demand supply and distribution, optimizing power generation, etc. The transportation industry also relies heavily on weather predictions for planning and scheduling flights, trains, and maritime activities. Also, accurate prediction of extreme weather events, such as cyclones, thunderstorms, etc., is vital for disaster management, providing the opportunity for early warnings and essential mitigation.

The complex equations involved in weather forecasting are non-linear and require powerful computational resources to bring out the solutions. With the increasing complexities, the accuracy decreases because of the number of inherent assumptions made. The first event in formulating the current weather forecasting was initiated by Leverrier (1855) in the Paris Astronomical Observatory. However, the importance of initial conditions was demonstrated much later by Bjerknes (1904). Using this knowledge, the first attempt of weather prediction was made by Richardson (1922) by solving the hydrodynamic equations numerically. Thus, during the early 1950s, the most important achievement in understating the physical properties of the atmosphere was the solution of hydrodynamic equations using the Numerical Weather Prediction (NWP). Earth's atmospheric conditions are characterized by sporadic and unpredictable shifts, which are typical and widespread phenomena occurring across the globe. In most cases, operational weather forecasting relies on NWP, which involves solving a set of nonlinear (primitive) equations. However, in recent times, artificial neural network (ANN) has evolved as a potent tool for data modeling, which is capable of capturing and representing intricate relationships between the inputs and outputs. It was conceived with the aim of implementing artificial systems capable of executing intelligent tasks akin to those performed by the human brain. In essence, ANNs have the capability to approximate any nonlinear function (Nielsen, 2015).

The deep neural network (DNN) is a type of ANN characterized by a multi-layered architecture. Essentially, they possess the capacity to autonomously learn features through a neural network (NN) rather than relying on manual feature selection (Wang and He, 2004). This contributes to achieving enhanced accuracy and improved generalization utilizing the acquired features. Therefore, in recent times, machine learning (ML) and deep learning (DL) applications have found their importance in the time series problems particularly those characterized by intricate correlations (Liu and Hu, 2013) such as weather and climate prediction. However, when the behavior of a system is predominantly influenced by spatial or temporal context, traditional ML approaches may not be optimal. Under such circumstances, DL architectures are more proficient in automatically extracting spatio-temporal features, and prove to be more effective in gaining comprehensive insights into such systems (Reichstein et al., 2019). It is anticipated that leveraging data-driven methods, such as ML/DL, will help overcome certain conventional challenges associated with weather forecasting. However, not many studies have incorporated such approaches for complex weather and predictions including the city-specific applications.

The objective of the current review extends beyond the examination of NN architectures tailored for diverse meteorological data types, besides conducting a comprehensive comparative analysis considering factors such as spatio-temporal scales, datasets, and benchmarks. The review highlights possible applications of AI/ML/DL frameworks in atmosphere and ocean studies. Notably, Singh et al. (2022c) reviewed many aspects of earth system sciences, including statistical downscaling, seismological events, short and medium range data driven weather forecasting, extended range forecasting, seasonal and climate scale forecasting, improving the physical processes in dynamical models, nowcasting weather and tracking storm cells, NWP, hydrogeological modeling, climate and human health, etc. Unlike Singh et al. (2022c), the current review encompasses both national and international level applications of ML/DL-based approaches specifically for weather and climate studies in an extensive manner.

2. Weather and Climate Prediction

Weather (short-lived scenarios) forecasting primarily focuses on predicting the atmospheric conditions within a timeframe ranging from a few hours up to seven days. The objective is to provide highly precise and timely information that allows the governing authority to make prompt decisions. It mostly includes maximum and minimum temperatures, precipitation (probability and intensity), wind, relative humidity, cloud cover, etc. (Reichstein et al., 2019). Additional considerations may involve visibility conditions, as well as warnings about extreme weather events like thunderstorms, cyclones, etc. Moderate to long term climate forecasting focuses on predicting the changing climatic conditions over extended durations, ranging from months to several years

(Howe and Wain, 1993). Unlike weather forecasts, climate forecasts focus on the average states or long-term trends of climate (e.g., temperature (minimum, maximum and average), precipitation (trend and pattern), ocean-atmosphere phenomenon like El Niño or La Niña conditions, etc.,), and the probability of extreme climatic catastrophes such as droughts (floods), along with anticipated cyclone activities (Hantson et al., 2016). The projections also cover decadal climatic trends like global warming. However, the accuracy of the long term prediction is often arguable when compared to short term weather predictions. It is primarily due to the complex, multi-scale, and multi-faceted interactions embedded with the global climate scenario, and absence of comprehensive long term datasets (Chen et al., 2023).

Historically, weather and climate prediction has been approached as a physical problem, with meteorologists dedicating efforts to enhance forecast accuracy through an understanding of associated processes. However, the scenario has shifted with the explosion of multi-scale and multi-dimensional meteorological data, transforming the entire landscape into spatio-temporal challenges. Conventionally, future weather conditions are ascertained by integrating the governing partial differential equations derived from current atmospheric states (Bauer et al., 2015). These equations encapsulate the dynamical, thermodynamical, and chemical processes within the atmosphere. The NWP models relying on the physical equations usually operate on a discretized grid system and simulate atmosphere and ocean conditions. While these models have achieved considerable success, they face limitations in certain applications (Vogel et al., 2018). One significant constraint is in terms of horizontal resolution of global NWP models, which can be taken at the most 10 kilometers while simulating the states of atmosphere and ocean that hinders the accurate representation of critical processes like cloud microphysics. Therefore, these models employ parameterizations to approximate the effects of these phenomena. Also, data assimilation (DA) techniques are adopted for accurate representation of the current state of the atmosphere and are necessary for initializing the model. Moreover, NWP models demand substantial computational resources, especially for ensemble forecasting, adding to their complexity and operational costs (Ben-Bouallegue et al., 2023; Garg et al., 2022; Rasp et al., 2020).

In recent years, data-driven models have emerged as promising alternatives (de Burgh-Day and Leeuwenburg, 2023; McGovern et al., 2023). These models have shown comparable or even superior performance in certain cases. These approaches based on ML/DL frameworks consider the initial datasets as inputs, which strive to discern the inherent laws or relationships within the input data. (Keisler, 2022) developed a model based on a graph neural network (GNN) with a spatial resolution of 1° and 13 vertical levels, demonstrating accuracy comparable to some operational NWP models. Subsequently, Lam et al. (2023) scaled a GNN to a higher resolution of 0.25°, enriching the legacy. Pathak et al. (2022) introduced FourCastNet, utilizing a modified vision transformer at the same spatial resolution, showcasing improved accuracy in weather forecasting. Bi et al. (2023) developed Pangu-weather, incorporating a variation of the vision transformer architecture, and achieved superior performance compared to the high-resolution Integrated Forecast System (IFS) developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). While data-driven models have demonstrated impressive performance, a significant challenge lies in their interpretability (Bommer et al., 2023; Mayer and Barnes, 2021). Unlike traditional physical models where the equations and processes are well-defined and understood, data-driven models often operate as black boxes, making it difficult to interpret how they arrive at their predictions (McGovern et al., 2019). This lack of transparency opens up a new realm of research focused on enhancing the interpretability of data-driven models.

2.1 How NWP Works

NWP models are tools that help to simulate atmospheric and ocean conditions and predict the weather based on current conditions. They take into consideration the current state and utilize relevant equations to forecast the future state of the atmosphere. The observed data sets may be utilized to feed the models. To address the unevenly spaced observations, DA techniques and objective analysis approaches are utilized, providing quality control and getting values at areas that the model's mathematical algorithms can use (often an equally spaced grid). The data is then utilized as an initiation point for the model's prediction. Primitive equations are a set of nonlinear equations used to anticipate atmospheric physics and behavior. After these equations have been initialized using the gridded data, the rates of change are determined. The rates of change are used to anticipate the future state of the atmosphere. The equations are then applied to this newly formulated atmospheric condition to calculate new rates of change, which are subsequently used to forecast the atmosphere at a later date and/or time. This time stepping procedure is performed until the response achieves the desired predicted time. The distance between the points on the computational grid determines the duration of the time step in the model, which is selected to offer numerical stability.

Currently, the NWPs are widely used in the global (hydrostatic) and mesoscale (non-hydrostatic) models (e.g., MM5 (Dudhia, 1993), LM (Doms et al., 1997), COAMPS (Hodur, 1997), ARPS (Xue et al., 2000), WRF (Skamarock and Klemp, 2008)). The numerical simulations are used to forecast mesoscale phenomena (e.g., the convective clouds over tropics) with a horizontal resolution of a few kilometers or less. However, the NWP is an intricate non-linear system, where physical forcing dominates the dynamics within the sub-grid scale, hence need the physical parametrization schemes. The physical parameterizations deals with the processes (e.g., radiation, convection, cloud, precipitation, diffusion, orographic drag, etc.) that could not be represented by the basic thermodynamic variables in the primitive equations. However, a high-resolution numerical model is required to accurately represent these physical processes.

The applications of NWP are not only limited to the weather prediction of the Earth but also expanded across the planets of the solar system. There are several models available for planets, which use a range of physical parameterization schemes that are widely developed from the Earth version of the Models. Notably, the simulations from different models may vary significantly, especially at the near-surface, because of the rapidly changing grid spacing, which primarily impacts the prediction of prognostic variables. Also, the key processes responsible for influencing the prediction varies for different planets. For example, in the case of Mars, the airborne dust and water ice are the key modulators of its weather and climate (Guha et al., 2021a, 2021b, Guha and Panda, 2022). Since the NWP model is a computer program that produces weather forecasts at a given location for a given future time duration by using the primitive (nonlinear) equations, this could lead to problems and uncertainties such as the approximation of initial conditions incorporated while compiling the model, the process of data assimilation. Also, an incomplete understanding of the complex atmospheric processes could unavoidably introduce errors. Besides, NWP models produce terabytes of simulation results, which is computationally expensive, and compels researchers to deduce computationally simpler methodologies (Ren et al., 2021).

2.2 How ML Works

Soft computing is a collection of approaches that are based on biological processes like thinking, genetic evolution, organism survival, and the human nervous system. It's a broad word that encompasses research on reasoning simulation, the human nervous system, and evolution in various domains. For example, the Fuzzy Logic approach can recognize the ambiguity of a solution and present it with a degree of vagueness appropriate for human decision-making. It is commonly used in a variety of AI-based ANN applications. The NNs are inspired by the biological networks of neurons and are based on artificial neurons. They use mathematical models as information processing units to uncover patterns in data that are too complicated for people to notice. Human brains are capable of describing real-world conditions that machines are unable to do. NNs were developed in the 1950s to address this problem. An ANN attempts to mimic the network of neurons that make up a human brain so that computers may learn and

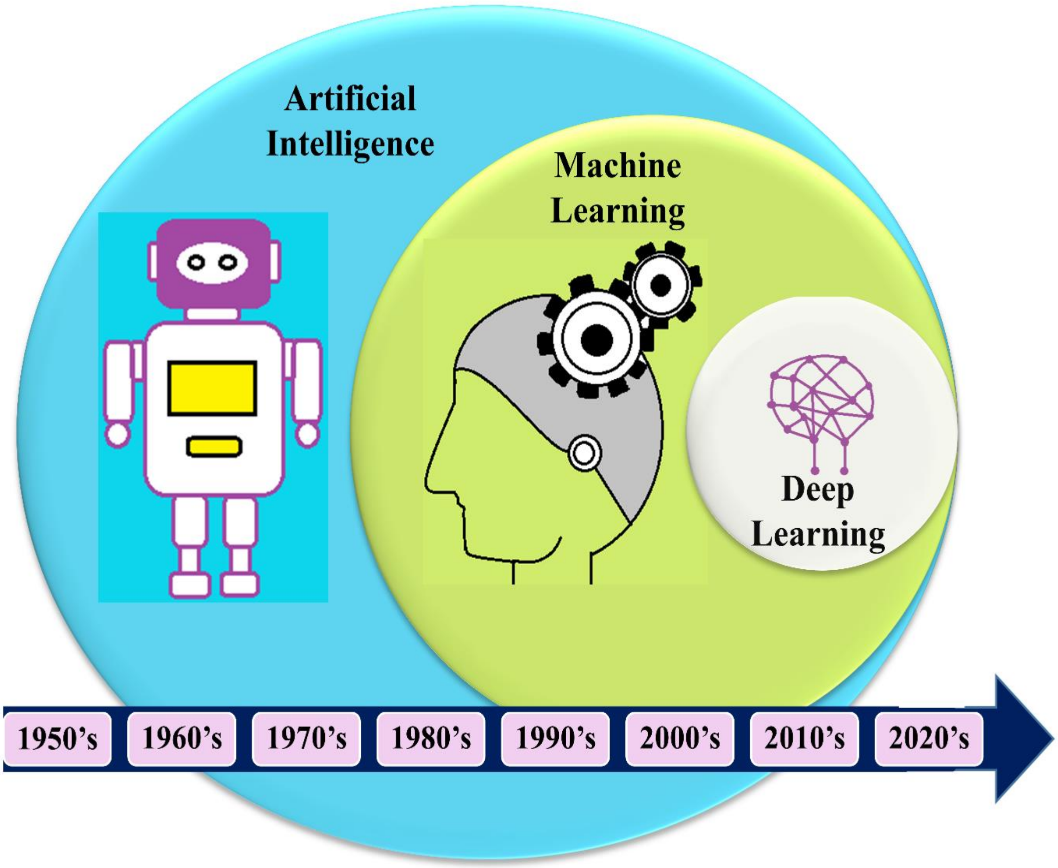

Figure 1: Venn diagram depicting the relationship between artificial intelligence, machine learning and deep learning, and its evolution over the years.

make decisions in the same way humans do. ANN is made up of normal computer programs that are linked together like brain cells that work by training imprecise numerical data representing a system's behavior. A method of learning from samples supplied to the model is used to complete this objective. Because of this learning capability, ANN is an excellent tool for environmental modelling. These networks, which are made up of input layers, intermediate layers, and an output layer, are employed to detect nonlinear interactions. ANN is beneficial over other methods since it makes no assumptions about the distribution of the data.

AI applications and techniques provide increased capabilities for data analysis, model creation, and decision-making, and are becoming an intrinsic part of climate and weather prediction. Forecasts at different scales have significantly improved over the last several decades due to the use of numerical techniques and rising processing capacity. Large amounts of meteorological and environmental data can be effortlessly processed by AI algorithms from a variety of sources, such as weather stations, contemporary equipment, satellites (sensors), aircraft, etc. Such algorithms are quite proficient at detecting patterns, trends, and correlations in complex datasets, hence leading to more precise forecasts. The basic processing elements of an ANN are neurons, which are stacked in layers and coupled to neurons in subsequent layers. Because the ANN is a feedforward architecture, only connections between neurons in one layer and neurons in the next layer are allowed. Interconnections between neurons within the same layer or with neurons in the preceding layers is restricted.

The basic evolution of AI is depicted in figure 1. ML is an application of AI that builds a mathematical model based on sample historical data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. DL is part of a broader family of ML methods based on ANNs with representation learning. DL models have seen a

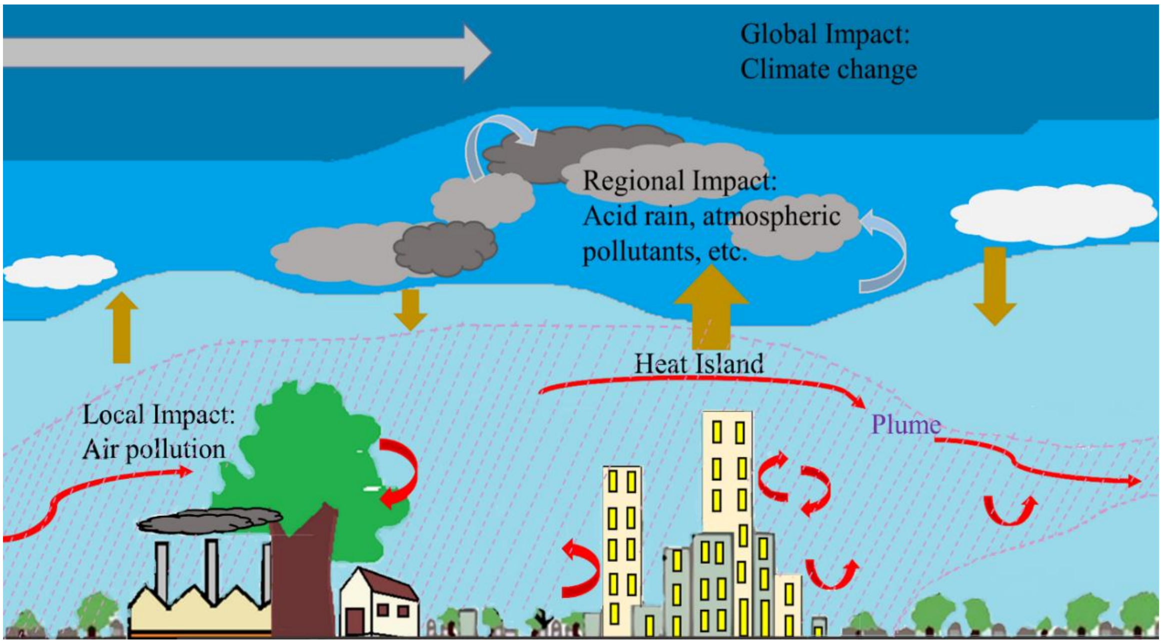

Figure 2: Schematic diagram showing the urban-atmosphere interaction.

massive rise in popularity for land and atmospheric studies over the past few years. That mainly has been because of the reliability and accuracy of results produced using these models. DL has taken over almost all of the widely researched subjects in the field of science and definitely in weather forecasting, climate studies, air quality research and prediction, land use and land cover (LULC) related studies, remote sensing application-based studies, and many more areas. Such models can automatically extract relevant features from large and complex weather and climate datasets. This helps in identifying important patterns and relationships between atmospheric variables, like temperature, humidity, pressure, and wind speed. For instance, Liu et al. (2016) developed a deep convolutional neural network (DCNN) framework coupled with Bayesian-based hyper-parameter optimization scheme to detect patterns and increase accuracy of forecasts. Also, these techniques are capable to handle spatial and temporal data concerning weather and climate (LeCun et al., 2015; Goodfellow et al., 2016). DL models in particular, excel in capturing spatial dependencies and temporal patterns (e.g., Convolutional Long Short Term Memory or ConvLSTM), making them suitable for such tasks. These algorithms can effectively model non-linear relationships between different meteorological variables and can process large volumes of data quickly, making them suitable for real-time weather forecasting applications, leading to more accurate and timely predictions. Besides, multiple ML/DL models are often combined to create an ensemble framework that can facilitate more robust and reliable forecasts by considering multiple sources of uncertainty in weather and climate studies (Weyn et al., 2021). The following section encompasses further details regarding the ML/DL applications in weather and climate studies.

3.1 Applications pertaining to urban studies

Meteorological challenges associated with cities have become a growing concern on the international stage. Initially, this area of study was primarily undertaken by atmospheric and environmental scientists. However, since 2010, interest in urban climate has expanded significantly to the energy, and engineering sector (Masson et al., 2020). The urban-atmosphere interaction has its effect across various scales, i.e., from smaller scale (such as urban environment and individual buildings) to regional-scale (such as regional climate change) phenomena. Urban features influence the atmospheric flow, and microclimates, thereby altering the transfer, distribution, and deposition of atmospheric pollutants within the urban areas (Figure 2). Therefore, mapping the transformation of the urban LULC forms the basis of most of the urban-related studies. Also, the impact of cities on temperature, precipitation, wind patterns, etc., has been extensively studied as it can alter the mesoscale weather systems like thunderstorms and, consequently, the precipitation patterns.

The precise spatial characteristics of the urban LULC have encouraged the use of ML algorithms in the classification of high-resolution images in general (Ma et al., 2019). Although many medium-resolution (10-30 m) satellite imageries, such as Landsat and Sentinel-2 data, are freely available for LULC mapping, it is difficult to use typical DL methods directly to these images due to the lack of clarity in distinguishing intricate structures. Convolutional neural network (CNN) is probably the most popularly used algorithm in LULC classification due to its inherent capability in handling spatiotemporal imageries. It can also be used to retrieve land surface temperature (LST) from AMSR-2 datasets and yield satisfactory results (Tan et al., 2019). LST can be estimated using Deep Belief Network (DBN) from the AMSR-E and AMSR2 data (Wang et al., 2020). It helps in better understanding of NNs, especially for estimating LST from satellite observations. Temporal CNN (Temp-CNN) algorithm can be used to classify time series satellite imageries (Pelletier et al., 2019). Usually, Temp-CNNs are more precise than random forest (RF) or other Recurrent Neural Networks (RNNs) for satellite image time series classification. Similar studies have been carried out using various ML algorithms, viz., RF (Tassi and Vizzari, 2020; Talukdar et al., 2020), support vector machine or SVM (Tassi and Vizzari, 2020; Talukdar et al., 2020), classification and regression tree or CART (Delalay et al., 2019; Shetty, 2019; Arpitha et al., 2023), etc. Use of DL algorithms (e.g., LSTM and U-Net) for earth observation satellite image classification concerning LULC has successfully been implemented and in some instances proven better than conventional ML approaches (Uba, 2016; Parente et al., 2019; Carranza-García et al., 2019; Naushad et al., 2021; Yassine et al., 2021). Besides, DL-based algorithms have been implemented in studies relating to image segmentation, object based image analysis, object detection, etc. (Abdi et al., 2017; Branson et al., 2018; Ma et al., 2019).

Considering that the majority of human activities occur in cities, understanding the consequence in the global warming scenario is crucial. Anthropogenic influences, primarily from emission of greenhouse gases (GHGs) and aerosols, are the leading contributors to the ongoing global warming trend (IPCC, 2007, 2023). Energy production and consumption (CO2 and CH4 emissions) are major sources of GHG emissions, with industrial activities and transportation also playing significant roles (Carmichael et al., 1999; Crutzen, 2004). Also, the tropospheric Ozone (O3), a byproduct of urban pollutants, is on the rise, contributing further to the urban climate change issue (Hidalgo et al., 2008). Some distinctive characteristics of urban weather and climate include: (i) warmer city temperature compared to surrounding rural areas is one of the most distinguishable features of urban climate commonly known as the urban heat island (UHI) effect (Garstang et al., 1975; Oke, 1982, 1995), (ii) alterations in wind pattern (Oliveira et al., 2003; Brazel et al., 2005), (iii) urbanization-induced clouds and precipitation (Shepherd 2013; Theeuwes et al., 2019), (iv) urban boundary layer (Song and Wang, 2016), (v) urban air quality and pollution (Seinfeld, 1989; Mage, 1996; Cohen et al., 2004), etc.

AI-based algorithms have been employed to downscale global climate models, and develop high-resolution datasets to facilitate climate researchers focusing on urban areas (Dibike and Coulibaly, 2006; Serifi et al., 2021; Park et al., 2022). NNs contribute to modeling and simulations by incorporating different climate variables and predicting long-term climate trends in urban settings (Knutti et al., 2003; Krasnopolsky et al., 2013). Besides, it improves the accuracy of short-term weather forecasts by analyzing historical data, atmospheric conditions, and real-time information, therefore providing early warning systems for extreme weather events. Climate resilience planning by conducting different scenario specific analysis considering different climate projections, is also supported by AI-driven models. This assists urban planners and policymakers for making informed decisions to enhance the resilience of cities to climate change impacts. Also, ML and DL frameworks have been extended to the study of

UHI impacts (Mathew et al., 2019; Han et al., 2022; Mohammad et al., 2022; Lin et al., 2023), evapotranspiration (Saggi and Jain, 2019), solar radiation (Patel, 2021), urban air quality (Iskandaryan et al., 2020; Kalaivani and Kamalakkannan, 2022; Gokul et al., 2023; Gupta et al., 2023; Wang et al., 2023b), O3 (Aljanabi et al., 2020; Cheng et al., 2021; Han et al., 2022), energy consumption (Zhang et al., 2021), water management (Fu et al., 2022), extreme events (Gope et al., 2016; Sankaranarayanan, 2020; Khan and Maity, 2022), etc. with successful implementations over various cities.

3.2 Air pollution studies

Environmental contamination is currently being regarded as a big problem for all countries of the world. Air pollution is a big and concerning environmental matter caused by increased mechanization, transportation, and population. South and East Asian locales are regarded as the most polluted ones in the world, according to the 2020 World Air Quality Report study through IQAir's air quality information platform. Notably, India is home to more than 20 most polluted cities (out of 50) of the world. According to WHO, Indian cities surpass the minimum standards for particulate matter (PM2.5) levels in the atmosphere by 500% on average. In India, mostly automotive traffic and diesel generators contribute to air pollution. The scenario across rural India gets worsened by the use of fossil fuels for cooking purposes. Besides, industrial activities, burning of waste and crop residue after harvesting are some of the major causes of air pollution in India. The influence of air pollution is determined by the variables present. The principal pollutants include O3, carbon monoxide (CO), Sulphur dioxide (SO2), Nitrogen monoxide (NO), and Nitrogen dioxide (NO2), etc. Once in the atmosphere, these elements can participate in subsequent chemical processes, resulting in smog and acid rain. The most important cause of concern about rising air pollution is its harmful effects on human health. Long-term air pollution exposure has been linked to an increase in respiratory and cardiovascular disorders such as asthma, bronchitis, lung cancer, and heart attacks.

More than half of the health problems related to air pollution are usually asthmatic.

A Legendre NN for prediction of air pollution parameter was devised by Nanda et al. (2011). It was concluded that the performance was better than regression models. One dimensional convnets and bidirectional GRU were used by Tao et al. (2019) for time series forecasting of PM2.5 concentration. DL-based strategies outperformed shallow ML models in terms of prediction accuracy. Bidirectional GRUs process time series both chronologically and anti-chronologically, capturing patterns that one-direction GRUs may miss, and thereby increasing the time series feature learning capabilities. A notable research in air pollution modeling with DL was done by Ayturan et al. (2018). They discovered that generative adversarial networks (GANs) are particularly effective at creating content using two competing networks: one for generating synthetic forecasts and the other for identifying actual values from synthetic data. Although learning how real data behaves is vital for predictive models, they tend to produce better results when the model is trained properly in the presence of sophisticated data synthesizers.

Comparison of the performance of various DL models with ARIMA was done by Arsov et al. (2021). The results suggested that DL models can be utilized to predict air pollution well. They used air quality measurements and meteorological data to forecast air pollution in the Skopje city region for 6, 12, and 24 hour time periods. The suggested architecture (based on LSTM networks and CNNs) performed admirably and accurately forecasted PM10 concentrations in the short run. The short-term predictions are much better than the ARIMA baseline model. Because it is more difficult to forecast occurrences further in the future, the model's performance falls as the time horizon grows. Fan et al. (2017) created a spatio-temporal prediction framework for air pollution using deep RNN. It has a high degree of precision in predicting both severe pollution occurrences and average patterns. A detailed review of data mining and machine learning for air pollution epidemiology was conducted by Bellinger et al. (2017) to infer that data mining has a lot of potential to support more useful applications in the field of air pollution using different ML algorithms like decision tree (DT), SVM, k-means clustering and the APRIORI.

A comparison of various ML regression models was performed by Harishkumar et al. (2020) to analyze air pollution (mainly PM2.5) over Newport, Taiwan using Taiwan Air Quality Monitoring Network (TAQMN) data sets. PM2.5 concentration was forecasted to infer that gradient boosting regressor model performed better in terms of multiple error metrices such as mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE) and coefficient of determination (R2). Several other studies utilized ML/DL frameworks to predict air quality by using time series occurrences including the pollutants such as O3 (Freeman et al., 2018; Hong et al., 2023), PM2.5 (Tong et al., 2019; Zhang et al., 2021), NO2 (Ghahremanloo et al., 2021; Sonawani et al., 2021), SO2 (Kurnaz et al., 2022; Shaziayani et al., 2023), PM10 (Bouakline et al., 2020; Aceves-Fernández et al., 2020; Kurnaz et al., 2022), etc.

3.3 Extreme weather events

Among the extreme weather events, ML finds its application in case of tropical cyclones (TCs), thunderstorms, heavy rainfall events, etc. TCs are a major weather hazard that feature low atmospheric pressure, high winds and heavy rain. It can also be accompanied by gales, gusts, rainstorms and storm surges that can generate winds greater than 119 km (~74 miles) per hour. In the early stages, TCs could only be identified by observing changes in weather conditions and warm sea surfaces. But with the help of satellites, detection and tracking of TCs became easier. Numerous satellites orbit around the Earth and capture continuous images of Earth's surface in visible and infrared wavelengths. This helps in detecting cold, high cloud tops using infrared images, which also show deep convective features of a TC, and its location and intensity as well. Meteorologists use these observed satellite images along with numerical models for the simulation of TCs and predict their location, future path, and intensity of the cyclone.

TC forecasts are mainly focused on predicting the track, intensity, and landfall characteristics. ML algorithms make use of the meteorological and ocean datasets from historic data archives, along with satellite observations to predict TC events. For predicting genesis of TCs, ML uses meteorological observations to envisage whether a depression will evolve into a TC and its frequency, which makes it a classification and regression task. Mainly used algorithms are DTs, logistic regression, SVM, RF, multi-layer perceptron (MLP) and CNNs (Kim et al., 2019). For TC track forecasts, both ML and DL based models can be used to forecast the position of TCs using DTs, MLP, RNNs, and CNNs (Giffard-Roisin et al., 2020). Spatiotemporal changes/formation of TCs can also be predicted using CNN-LSTM frameworks (Chen et al., 2019). CNNs are mainly used to estimate intensity using satellite images (Pradhan et al., 2017; Wimmers et al., 2019; Chen et al., 2019). Hybrid networks of CNN and LSTM further improve results (Chen et al., 2019; Wang et al., 2021) too. The problem of rapid intensification (RI) which hinders intensity prediction is treated as a classification or regression problem and can be predicted using DTs, SVM and RNN (Mercer and Grimes, 2017; Chandra, 2017; Chen et al., 2022). Features of TCs, precipitation and tidal data can be used to predict storm surges which occur during the time of TC. It helps in prediction of disastrous impact forecasts using MLP, Support Vector Regression (SVR) (Lee, 2009; Chen et al., 2012; Hashemi et al., 2016; Huang et al., 2018). For wind field forecast, CNN and SVR are commonly used (Park et al., 2016; Loridan et al., 2017). ML can also be used for advancing the parameterization schemes in NWP models (e.g., Mercer and Grimes, 2017).

In recent studies, genesis forecasting is denoted as a classification task of ML for envisaging whether TC symptoms will evolve into TCs. There is a study by Wijnands et al. (2016) that worked on choosing the TC symptoms for short-term forecasting (upto 72 hours) of TC genesis using the Peter–Clark algorithm. Other studies (Richman et al., 2017; Nath et al., 2016) also highlighted the use of SVR and MLP for TC activity forecast, along with identifying potential predictors. Path prediction was attempted using a matrix neural network (MNN)-based (Zhang et al., 2018) and RNN-based (Moradi et al., 2016) models to generate effective results in comparison to other methods. Giffard-Roisin et al. (2020) proposed a fusion neural network model that combined past trajectory data and re-analyzed images (3D wind and pressure) while adopting a moving frame of reference to track the storm for 24 hours. This fused network was so efficient that it forecasted the storms in seconds, and thus, acts as an important asset for real time TC forecasting. Wang et al. (2023a) developed a DL-based framework combining GRU and CNN called “GRU_CNN” to forecast TC tracks. Three additional environmental factors, steering flow, sea surface temperatures (SST), and geopotential height, along with historical trajectory data, were used as input, and it was found that historical steering flow is crucial for short-term predictions (within 24 hours), while SST and geopotential height contribute to improved forecasts for 24–72 hours. The proposed model even outperformed the Central Meteorological Observatory (China) forecast results, making it suitable for short-term TC track forecasting. Besides, Kumar et al., (2023b) used ML models like RF, eXtreme Gradient Boost (XGB), etc., for bias correction of TC intensity forecasts obtained from the National Centre for Medium Range Weather Forecasting (NCMRWF) Ensemble Prediction System (NEPS) over the North Indian Ocean (NIO). Varalakshmi et al., (2021) incorporated ML models like DT, KNN, LR, RF, XGB as classifiers in place of a fully connected layer in CNN to enhance prediction accuracy of TCs which was comparable to conventional ML/DL approaches.

Alike TCs, thunderstorms pose a significant threat to human safety and property due to lightning (Holle, 2014, 2016), heavy rain (Davis, 2001; Smith et al., 1996), hail (Battaglia et al., 2019; Hohl et al., 2002), and strong winds (Allen and Allen, 2016; Dotzek, 2003). These risks, which develop rapidly within a short timeframe, are challenging to precisely predict using numerical weather models. The NWP models can provide a general outlook for thunderstorms in a region, but they struggle to pinpoint the exact location and timing of severe impacts (Sun et al., 2014). Therefore, it is more effective to issue localized short-term warnings based on nowcasting, a statistical method that predicts near-term developments using the latest available observational data. Traditionally, weather prediction systems relied on a mix of empirical and dynamical approaches. The recent progress in employing ML to model complex and dynamic phenomena, coupled with their notable successes in various applications, has prompted a closer examination of their potential for predicting thunderstorms (Geng et al., 2021; Pan et al., 2021; Zhou et al., 2020). ML approaches in thunderstorm prediction leverage diverse data sources for model training, including radar networks, multispectral imagery, lightning data, NWP model outputs, Digital Elevation Models (DEM), and precipitation data (Leinonen et al., 2023; Leinonen et al., 2022b). Notably, ground-based radar observations emerge as a crucial predictor, with satellite observations follow closely behind. Leinonen et al (2023) introduced a recurrent-convolutional DL model designed to predict the occurrence of thunderstorms. The model generates probabilistic forecasts, enabling users to set thresholds for issuing warnings and taking precautionary measures for lightning, hail, and intense precipitation events. The model, based on the architecture utilized by Leinonen (2021) and Herruzo et al. (2021), demonstrated superior performance compared to competing structures like U-Nets and transformers. The success of this DL model is indicative of the transformative potential of ML in advancing thunderstorm prediction capabilities. The use of ML in thunderstorm prediction aligns with the inherent challenges faced by traditional NWP models. ML models demonstrate enhanced accuracy in capturing complex patterns and relationships within atmospheric data. They offer a real-time processing advantage crucial for dynamic weather events, enabling timely and accurate predictions (Leinonen, 2021; Leinonen et al., 2022b). This adaptability is particularly important given the localized and rapidly evolving nature of thunderstorm hazards. As ML continues to make strides in thunderstorm prediction, ongoing research efforts are essential to address challenges such as the need for extensive and high-quality training datasets and the interpretability of complex models. As research in this area progresses, the synergy between meteorological expertise and ML innovation will pave the way for even more sophisticated and reliable thunderstorm prediction models.

Extreme rainfall can happen due to TCs, or thunderstorms or any other convective systems. In the world of weather forecasting, extreme rainfall prediction has never been easy due to its chaotic nature. With the changing climate, more extreme rainfall occurrences (and intensity) are anticipated (Goswami et al., 2006). Therefore, accurate forecasts demand a thorough scientific knowledge of the dynamics and patterns of rainfall. At present, there are several early warning systems operational (e.g., Heffer, 2013). Currently, the forecasting of extreme rainfall events is executed with the help of NWP models and there has been limited exploration through ML approaches, especially over India. A DL framework has been developed and trained to predict such events over Mumbai and Kolkata (Gope et al., 2016) using an anomaly frequency method (AFM)-SVM framework. Vitanza et al. (2023) adopted the Affinity Propagation algorithm along with K-means clustering to detect extreme rainfall events in Sicily. Some researchers like Hu and Ayyub (2019) focused on projecting the intensity of the rainfall during heavy rainfall events using ML approaches. An interesting study was presented by Sangiorgio et al. (2019), who analyzed the atmospheric water vapor content along with variables like temperature, pressure, humidity, etc., and used them to forecast the genesis of extreme rainfall events using DNN. Nayak and Ghosh (2013) considered past weather patterns in predicting extreme rainfall through SVM. Folino et al. (2023) introduced a Rainfall Estimation Model (REM) named “DeepEns-REM”, and used the model on real-time data from a region in southern Italy to highlight its effectiveness compared to traditional methods like Kriging interpolation and other ML techniques, particularly for predicting extreme rainfall events accurately. The model automatically integrates diverse data from multiple sources, employing residual blocks in base models along with a snapshot procedure for ensemble creation. Other researchers have also adopted ML/DL approaches for the forecasting of extreme events leading to floods (Yeditha et al., 2020; Keum et al., 2020; Motta et al., 2021; Kunverji et al., 2021), appreciable runoff (Dastorani et al., 2018; Frame et al., 2022; Singh et al., 2022a), etc.

3.4 Regional-scale weather and climate

A precise prediction of weather and climate can help people make everyday decisions as well as more serious long term decisions. This can help in saving lives and property in times when bad weather events are approaching and also assessing the risks involved in a long run. For instance, it can be helpful for a country to make better decisions for its economy and growth. Forecasts for rainfall and temperature will be extremely useful for agriculture and, in turn, for world markets and the economy. The process of weather forecasting has improved and changed tremendously over time, from predicting the weather by examining cloud patterns to utilizing barometers and thermometers to analyzing satellite imaging and radar data. ML and DL models were introduced off late, to predict weather and simulate long-term changes or to perform climatological analysis and forecasting in the digital era by evaluating large amounts of data. These models have the benefits of making predictions based solely on historical data and employing a physics-free approach. For instance, DTs have been employed to classify a weather event with parameters like average temperature, humidity, sea level pressure etc. (Rajesh Kumar 2013; Bhatkande and Hubballi, 2016). Arbitrary DTs give better accuracy because they use the Maximus classifier (Dudde and Apte, 2013). Similarly, DTs have given satisfactory accuracy for modelling rainfall prediction (Geetha and Nasira, 2016). RF algorithm has proven to give better results with higher number of parameters (Karthick et al. 2021). Also, it can be adopted for error-balancing in unbalanced data sets. An application of SVM is implemented for atmospheric temperature prediction and proven worthy to replace some of the NN-based models for weather forecasting applications (Radhika and Sashi, 2009). A similar comparative research has been done using SVM, MLP and Naive Bayes classification for weather and rainfall prediction (Prabha and Radha, 2019; Rao et al., 2012; Rani and Rao, 2013). Another comparative research using SVR, Lasso Regression and multiple linear regression (MLR) has predicted rainfall and appraised SVR to be a valuable and adaptable algorithm (Mohammed et al., 2020).

Abdulla et al. (2022) conducted a comparative analysis for evaluating the performance of adaptive DL models for weather prediction. It was found that employing a bidirectional LSTM (BiLSTM) model alongside adaptive learning significantly enhances temperature forecasting accuracy, reducing prediction error rates by 45%. When applied to various meteorological datasets, the proposed model consistently achieves a Mean Absolute Percentage Error (MAPE) between 8% and 10%, indicating its robustness and effectiveness. Weyn et al. (2021) introduced an ensemble Deep Learning Weather Prediction (DLWP) system, which forecasts six essential atmospheric variables at six-hour temporal resolution. This computationally efficient model uses CNNs on a cubed sphere grid to produce global forecasts. Singh et al. (2022b) developed a DL-augmented NWP framework to improve short-range global precipitation at 1-, 2-, and 3-day forecasts. This hybrid model converted the spherical global data into a cubed sphere grid by using a modified DLWP-CS architecture.

Besides, ARIMA model can be used to forecast future climate i.e. rainfall, and maximum and minimum temperature (Kocharekar et al., 2019). Hernandez et al. (2016) used an auto encoder and MLP for predicting the accumulated rainfall for the next day, by using data of previous days. Yen et al. (2019) developed a forecasting model using Reservoir Computing (RC). It is a supervised learning strategy for RNNs that employs echo state networks (ESNs) and deep echo state networks (DeepESNs). DeepESN's correlation coefficient was found to be higher than that of ESN and commercial NN techniques. Sawale and Gupta (2013) employed ANN to find a non-linear relationship between historical data for temperature, wind speed, and humidity analysis and forecasting. The prediction error was found to be extremely low, and learning converges quickly. DL algorithms were employed by several researchers for the forecasting of atmospheric parameters including temperature (Haque et al., 2021; Gong et al., 2022), rainfall (Narejo et al., 2021; Wei and You, 2022; Fahad et al., 2023; Panda et al., 2024; Singh et al., 2024), wind speed (Chen et al., 2018; Afrasiabi et al., 2020; Jiang et al., 2021), humidity (Setiawan et al., 2022; Khudhur and Kareem, 2022), cloud cover (Berthomier et al., 2020; Baran et al., 2021), solar irradiance (Rajagukguk et al., 2021), lightning (Zhou et al., 2020; Geng et al., 2021; Leinonen et al., 2022a; Singh et al., 2023), etc.

Downscaling of low-resolution data into high-resolution observation data has recently become a popular approach in earth sciences. For instance, downscaled datasets have been prepared for summer monsoon rainfall and local precipitation over the Indian region using DL approaches like super-resolution convolutional neural network (SRCNN), stacked-SRCNN, DeepSD, Super-Resolution Generative Adversarial Networks (SR-GAN), ConvLSTM, and U-Net (Kumar et al., 2021, 2023a). Such approaches produced more accurate and reliable estimates of meteorological variables, facilitating validation of the climate model forecasts at the local to regional level.

Climatological analysis of long term atmospheric datasets has been utilized for the analysis and forecasting of extreme events like floods (Fang et al., 2021; Moishin et al., 2021; Liu et al., 2024), droughts (Abbes et al., 2023; Danandeh Mehr et al., 2023; Nourani et al., 2023), El Niño (Ham et al., 2019; Mu et al., 2021)., etc. Danandeh Mehr et al. (2023) developed a conjugated CNN-LSTM to predict multi-temporal drought indices, specifically three-month and six-month standardized precipitation evapotranspiration (SPEI-3 and SPEI-6), within Ankara province, Turkey. A similar study was performed over the drought-prone areas of the southern part of Alberta, the difference being the DL model adopted, i.e., LSTM (Nourani et al., 2023). In the case of flood forecasting as well, LSTM combined with CNN is a commonly adopted framework.

Climatological events like the variations in El Niño Southern Oscillation (ENSO) are associated with numerous regional climatic extremes and ecological consequences and impact global weather and climate. Ham et al. (2019) trained a CNN framework for the prediction of ENSO events based on historical simulations and reanalysis datasets, which was found to be comparable to dynamical forecast systems. In fact, the proposed model predicted detailed zonal distribution of SST with higher accuracy as compared to dynamical models, hence proving to be a powerful tool for forecasting ENSO events and the associated characteristics. The climatological events like forecasting of the Indian summer monsoon rainfall (ISMR) using earth observation and ground station datasets has also been attempted by several researchers using DL frameworks such as the ConvLSTM (Kumar et al., 2022), stacked auto-encoder and ensemble regression model (Saha et al., 2021), etc.

4. Concluding Remarks

The integration of ML and DL techniques into weather and climate prediction has emerged as a transformative paradigm, promising advancements in accuracy, efficiency, and the understanding some of the complexities associated with atmosphere and ocean. This study has explored the multifaceted use of these intelligent systems in a range of fields, highlighting how they may be used to improve climate modeling, anticipate extreme weather, and advance short-term weather prediction capability. These data-driven methods have proven their capability to manage non-linear interactions, adapt to changing conditions, and contribute to a more nuanced knowledge of localized weather occurrences by overcoming traditional limits associated with NWP models. In particular, their importance in fine-tuning global climate models to provide more precise projections suitable for cities has been brought to light by the investigation of downscaling concept using ML algorithms. This has practical implications for city planning and management, where accurate and localized climate information is indispensable for addressing the unique challenges posed by urbanization. This study, therefore adds to the expanding corpus of information that lays the path for a more robust and sustainable future at the nexus of meteorology, climatology, and AI. We can improve disaster preparation, promote sustainable urban growth, and better prepare society to deal with the challenges posed by a changing climate by continuously improving and broadening the applications of ML and DL in weather and climate prediction. The continued collaboration between AI and atmospheric research is extremely promising as it provides a mechanism to comprehend and forecast the Earth's climate system in a way that is more precise, flexible, and responsive.

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