Journal of Multi Disciplinary Engineering Technologies
ISSN(P) 0974-1771 ISSN(O) 2581-9372
Volume 19, Issue 02 DOI: https://doi.org/10.64992/jmdet.vol.19.issue.2.2

A Review of Ancient and Modern Rainfall Prediction Methods over Indian Region

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Abstract

Weather has been studied for a long time. The major milestone for modern meteorology started with the invention of weather instruments. However, the various aspects of meteorology prior to that, here referred to as ancient meteorology, were written down in many ancient scriptures and have remained unfamiliar till recent times. These texts have references to hydrologic processes, including rainfall and its prediction. One such text is *Brihat Samhita*, written around 500 A.D. by Varaha Mihira, with great details of the atmosphere for rainfall prediction. A rigorous discussion on the features of processes of ancient meteorology, especially rainfall, from the *Brihat Samhita* is missing. There are many variables that determine rainfall. Clouds are a key component among them and their types have been given emphasis for rainfall prediction by ancient as well as modern meteorology. Cloud types can be visually identified, physically or in meteorological data such as satellites, but that is more of a qualitative approach. Various cloud products are available for determining the presence of clouds in satellite images. But defining cloud types quantitatively from the same is still difficult and thereafter affecting rainfall prediction. However, Artificial Intelligence/Machine Learning (AI/ML) techniques have emerged as a new option for development of quantitative approach from large data such as satellite data. Thus, this review paper discusses the aspects of rainfall prediction, in the ancient and the modern eras, and further use of AI/ML techniques for cloud classification from satellite data.

Keywords: Brihat Samhita, Ancient Meteorology, Machine Learning, Rainfall prediction

1 Introduction

The present state of the atmosphere is known as the weather and the elements that describe weather are pressure, temperature, humidity, clouds, precipitation, visibility and wind [1, 2]. The average weather over a long period of time is the climate [1]. As stated in IPCC reports,

Paper Presented in RAICE Conference 2025; Accepted 13 July 2026; Available online 20 July 2026

climate change is accountable for the increasing frequency and intensity of extreme events [3]. Because of climate change, it is expected that the frequency as well as the severity of the extreme events will be rising [3–5]. One such extreme event is related to rainfall. Heavy rainfall causes flooding and poor rainfall causes famine.

Rainfall is one of the weather elements that has a significant impact on every kind of life on the Earth, especially humans. Extreme rainfall leads to floods that result in unprepared damage to infrastructure, human lives, etc [1, 4, 6]. On the other hand, insufficient rainfall leads to drought, which also leads to damage to human lives. Hence, rainfall prediction is important for human preparedness. Rainfall affects all service sectors, including airports, hospitals, power supply, communications, transportation, etc. Rainfall has direct or indirect implications on a nation's economy. Many developing countries, like India, rely on rainfall for agriculture. Indian summer monsoon rainfall (ISMR) accounts for 78% of the annual precipitation of India [6]. Hence, prediction of rainfall in advance is essential to control and mitigate its direct and indirect impact on humans.

Rainfall prediction is not a new concept. It has been studied for centuries. There are many ancient texts, such as *Meteorologica*, *Book of Signs*, *Brihat Samhita*, etc. There is a weather folklore - "A halo around the moon portends rain" [1]. Today, it is realized that as the light passes through ice clouds it is bent, causing the halo and these clouds are often the forerunners of an approaching cyclonic storm [1]. In 1884, Blanford established an inverse relationship between ISMR and preceding winter snow cover over the Himalayas [6, 7]. According to National Institute of Hydrology (2018) snow or frost has also been mentioned to predict rainfall in the rainy season in *Brihat Samhita*, an ancient text written by Varahmihir. Even though rainfall and its predictors are mentioned in ancient texts, their understanding is not as comprehensive as the modern-day knowledge which is used to predict rainfall. Moreover, implementation of the ancient knowledge of weather is limited in the present-day methods. This suggests a need to investigate ancient texts and blend them with our present knowledge.

The major evolution in meteorology came with the invention of weather instruments around the 1400s [1, 8, 9]. At present, there are very advanced observation tools such as satellites and radars. Satellites give a lot of information about clouds [10, 11]. Current data assimilation and climate applications rely on precise identification of cloud types. Although cloud types can be directly identified visually by experts, there are efforts to develop cloud products that can reliably provide this information [12–15]. Cloud type is an important input parameter in heavy rainfall forecasting as per India Meteorological Department (2021). Cloud regimes are related to meteorological conditions due to the strong association between cloud types and atmospheric dynamics [13, 14]. With the increasing frequency ofextreme events, identifying cloud type accurately can help in analysing them better [12, 13].

Various algorithms are used for cloud detection. These algorithms can be broadly classified into two categories, threshold-based algorithms and classification-based algorithms [15]. The threshold-based algorithms utilise spectral and textural parameters available in the sensors of satellite images [11, 12]. On the other hand, classification-based algorithms utilise cloud features to optimise the model parameters using training data [12, 15, 16]. Previous works have used satellites including MODIS, SPOT, GOES, Kalpana-1 for cloud detection [12]. Most of these studies have used classification-based approaches for cloud-related studies. INSAT-3D is a geostationary satellite of India which is used for cloud detection by the Indian Meteorological Department (IMD). It majorly uses thresholding

techniques [11]. Thresholding techniques are efficient in detecting clouds but are effective at only a regional scale and lack universality [15]. At present, the INSAT cloud products give information on either the presence or absence of clouds, including the cloud cover percentage. However, cloud type data products are not available
citeimd2021. This has been understood as a limitation of the cloud detection techniques; there is a possibility of improving these techniques to include cloud type detection in INSAT cloud products. Hence, there is a need to understand the existing cloud detection techniques used by INSAT 3D, their limitations and suggest future work to include alternate techniques for cloud type detection as well.

The primary objective of the paper is to review ancient and modern rainfall prediction methods with a view to identifying common conceptual points and to explore if these can be used synergistically. The paper has been structured to give a review of ancient and modern rainfall prediction methods. Further, modern methods have been subdivided into current and evolving techniques. The outline of the paper is as follows: Section 2 will describe the ancient rainfall prediction methods in terms of elements of weather prediction, rainfall forecasting techniques. Section 3 will share the present meteorology and rainfall forecasting techniques. Section 4 will discuss the new methods which are at present being evolved. Section 5 will present a discussion on limitations.

2 Methodology of Review

Relevant literature related to rainfall prediction, ancient meteorology, numerical weather prediction, and AI/ML-based cloud classification was collected from books, research articles available through databases including Google Scholar, Scopus, SpringerLink, and Elsevier, as well as technical reports and publications of meteorological organizations such as IMD, WMO, ECMWF, and NOAA. The reviewed studies were broadly classified into: Ancient rainfall prediction approaches, Modern statistical and numerical forecasting methods, and Emerging AI/ML-based cloud classification techniques.The methods were compared based on their forecasting approach, atmospheric parameters used, operational applicability, and limitations. Special attention was given to the role of clouds and cloud types in rainfall prediction in both ancient and modern meteorology.

3 Ancient Rainfall Prediction

Ancient methods of rainfall prediction are worth mentioning. There are various ancient civilizations that have been a part of the building block of the present knowledge of meteorology.

3.1 Early works

The Babylonians are one of the early civilizations which developed calendars based on lunar cycles and later adjusted them to the seasons [9]. One of the common indicators used by them is the observation of the halo around the sun and the moon to predict weather events such as rain, floods etc.

The Chinese started keeping records of weather elements like temperature and precipitation [9]. The calendars used by them were based on the moon, the sun and weather events.

Aristotle was a Greek philosopher who wrote treatise *Meteorologica* which includes chapters on astronomy, water, physics and more, with very important sections on weather

[1, 9]. Theophrastus, Aristotle's successor, wrote the treatise *Book of Signs*. Most of his work is based on lore type of ideas and his work gives ways to predict the weather based on natural signs such as the color and shape of clouds, the intensity at which flies bite etc [1, 9].

In India, the beginnings of meteorology can be traced back to ancient times [8]. Early philosophical writings of 3000 B.C. era, such as the Upanishadas, contain serious discussion about the processes of cloud formation and rain and the seasonal cycles caused by the movement of the earth around the sun [8]. The knowledge of hydrology was pervasive in ancient India starting from the pre- Indus Valley Civilization and has been discussed in-depth in Vedas, Puranas, Arthasastra, Astadhyayi, Vrhat Samhita, Ramayana, Mahabharat, Meghmala, Mayurchitraka, Jain and Buddhist and many other ancient literatures [17, 18]. Varahamihira's classical work, the *Brihat Samhita*, written around 500 A.D., provides clear evidence that a deep knowledge of atmospheric processes existed even in those times [8, 17].

3.2 Brihat Samhita

Brihat Samhita has been reported to have described the atmospheric phenomenon in detail [8, 17, 19–21].

It is a compilation of various fields such as astronomy, meteorology, architecture, etc. The three chapters of *Brihat Samhita*: pregnancy of clouds (Chapter 21), pregnancy of air (Chapter 22), and quantity of rainfall (Chapter 23); have explained rainfall prediction in detail [17]. Varahmihira discusses the conditions determining rainfall, he says that if there is no frost in Magha (January–February), no vigorous wind in Phalguna (February – March), no clouds in Chaitra (March–April), no hailstorm in Vaisakha (April–May) and no scorching heat in Jyestha (May–June), there is insufficient rain in the rainy season [17, 19]. Verses 23 and 24 of chapter 21 of *Brihat Samhita* state that extremely white or dark clouds resembling aquatic animal like huge fish, shark or tortoise and seen before the rainy season, are a source of abundant rainfall [17]. The forecasting of rainfall on the basis of natural phenomena like the colour of sky, clouds, lightening, rainbow, planets etc. was noteworthy.

Varshneya, et al. [19] attempted to do rainfall prediction based on the Antariksha method, which is one of the astro-meteorological methods based on sky observations. The prediction of the monsoon season for Barshi, Maharashtra in 2004, 2005, 2006, 2007 and 2008 were made from rainfall conception observations. The overall average skill score for rainfall prediction is 78.8 %. It was concluded that this method can be used successfully for rainfall prediction for that locality. However, the data used for prediction was collected at the specific station for the period and the predictions were made based on regional data.

Dheebakaran, et al. [20] published a study conducted at Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore, during 2015–16 to improve the accuracy of numerical model rainfall forecast using astrometeorological principles. Daily rainfall forecasts were developed for each location of seven agro climatic zones of Tamil Nadu viz., Cauvery Delta zone (CDZ, Thiruverumbur, 10.7516° N x 78.8291 °E), Hilly Zone (HZ, Udhagamandalam, 11.4064°N x 76.6932°E), High Rainfall Zone (HRZ, Thiruveattaru, 08.4430° N x 77.3060° E), North Eastern Zone (NEZ, Sriperumbudur, 12.9670° N x 79.9420°E), North Western Zone (NWZ, Pappireddipatti, 11.9120° N x78.3700°E), Southern Zone (SZ, Aruppukottai, 09.5030oN x 78.0500oE), Western Zone (WZ, Coimbatore, 11.0200oN x 76.9710°E)., through different source and methods viz., WRF (numerical model), astrometeorology (planet), probability, a private agency forecast and hybrid forecast (superimposing astro and probability forecast on WRF) and were compared using forecast accuracy ratio and critical success index. In general, irrespective of locations and seasons, the hybrid forecast had higher forecast accuracy (0.75 to 0.88) and a critical success index (0.56 to 0.76). Among the different individual forecasts, the astrometeorological forecast had the highest forecast accuracy (0.74 to 0.87) and the critical success index (0.52 to 0.71). The study concludes that, astrometeorology could be a good option for alternate forecasting methods to numerical weather forecast and hybrid forecasts developed by integrating astrometeorology, numerical and probability methods will improve the rainfall forecast accuracy and critical success index, in turn, will increase the usability of forecast in agriculture.

According to *Brihat Samhita*, the cause of rainfall in the monsoon season is the occurrence of pregnancy of clouds in the prior seasons. This cause has been described in detail in Chapter 21. Hence, in this section the understanding of ancient meteorology as given in the Chapter 21 of translated texts of the *Brihat Samhita* [21, 22] which is about clouds, will be discussed.

3.3 Rainfall Prediction in Brihat Samhita

The predictors stated in *Brihat Samhita* for rainfall prediction can be broadly categorised into astronomical, atmospheric, bioindicators and animals. The astronomical predictors included meteors, sunspots, constellation of stars called nakshatras, and the movement of planets. Atmospheric predictors include wind speed, wind direction, temperature, clouds and their types, thunderstorms, humidity, earthquakes, halos, rainbows, and rainfall. Bioindicators include trees and plants like trees growing well. The behaviour of animals, like happiness, singing of birds, were also used for rainfall prediction.

The nine planets known then are the Sun, Moon, Saturn, Venus, Mars, Mercury, Jupiter, Rahu and Ketu. The direction of movement of these planets in space with respect to the Earth was used for rainfall prediction. The close alignment of the planets, called conjunction, had a significant impact on rainfall. The appearance of meteors and sunspots were also important for rainfall prediction. The predictors have been summarised in figure 1.

The predictors mentioned above were used to observe a phenomenon called Megha Garbhadharan. It is considered the main cause of rainfall in the rainy season. Hence, its observation was critical. With the occurrence of Megha Garbhadharan, other details, such as month, sky conditions and nakshatra of the moon are noted down.

The space was divided into regions, which were identified using nakshatras. The nakshatra in which the moon was present at the time of observation was called the nakshatra of the moon. Along with the nakshatra of the moon, it is important to note down the month of Megha Garbhadharan. The Gregorian calendar has 12 months. Similarly, the calendar used in the *Brihat Samhita* had months. The list of nakshatras and months are listed in Table 1 with reference to [17, 21, 22].

A month is divided into two parts based on the phases of the moon. The first half where the phases of the moon increase from new moon to full moon is called the Shukla Paksh. The second half where the phases of the moon decrease from full moon to new moon is called the Krishna Paksh. The observation of Megha Garbhadharan starts from the day when the moon is in the nakshatra Purva Aashadha in Margshirsha Shukla Paksh to Chaitra Krishna Paksh.

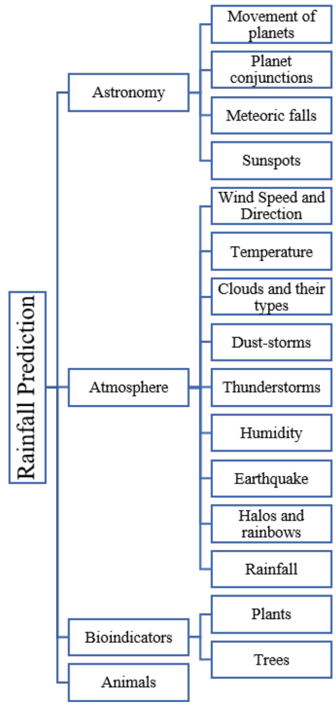

Fig. 1: Predictors of rainfall prediction from the Brihat Samhita

Table 1: List of Nakshatras and Months from Brihat Samhita

Nakshatra	Ashwini	Bharani	Krittika	Rohini
	Mragshira	Ardra	Punarvasu	Pushya
	Ashlesha	Magha	Purva Phalguni	Uttara Phalguni
	Hasta	Chitra	Swati	Vishakha
	Anuradha	Jyeshtha	Moola	Purva Ashadha
	Uttara Ashadha	Shravana	Dhanishtha	Shatabhisha
	Purva Bhadrapada	Uttara Bhadrapada	Revati	
Months	Chaitra (Mar–Apr)	Vaishakha (Apr–May)	Jyeshtha (May–Jun)	Ashadha (Jun–Jul)
	Shravana (Jul–Aug)	Bhadrapada (Aug–Sep)	Ashwin (Sep–Oct)	Kartik (Oct–Nov)
	Margashirsha (Nov–Dec)	Pausha (Dec–Jan)	Magha (Jan–Feb)	Phalguna (Feb–Mar)

The concept of *Megha Garbhadharan* may qualitatively correspond to atmospheric moisture accumulation, moisture convergence, and the gradual development of large-scale instability prior to monsoon rainfall. In the study, the cloud initiation period extends from *Margashirsha Shukla Paksha* to *Chaitra Krishna Paksha*, during which various atmospheric indicators such as cloud formation, winds, halos, thunder, and lightning are observed. Scientifically, such prolonged cloud development may reflect evolving synoptic-scale atmospheric conditions favorable for future rainfall. This interpretation is further supported in the present study through the incorporation of cloud mass and cirrus cloud mass derived from DARDAR satellite observations as predictive variables in the machine learning framework [23].

Similarly, the halos described around the Sun and Moon in *Brihat Samhita* may correspond to cirrostratus cloud formations containing suspended ice crystals. The manuscript specifically mentions that the Sun and Moon are surrounded by “clear, thick, white halos” during favorable rainfall initiation conditions. In modern meteorology, halos are commonly associated with high-altitude cirrostratus clouds [1].

Furthermore, the winter cloud observations discussed in *Brihat Samhita* may also be linked with seasonal-scale atmospheric teleconnections influencing the Indian monsoon. The observation period described in the text spans approximately December to April, which coincides with the evolution phase of several large-scale climatic drivers such as ENSO, Indian Ocean Dipole, and western disturbances. Therefore, the ancient observational framework may reflect long-term empirical understanding of precursor atmospheric conditions related to seasonal monsoon variability. However, these interpretations remain exploratory and qualitative, and further long-term observational and climatological studies are required for rigorous scientific validation. The methodology for rainfall prediction based on observation of Megha Garbhadharan has been summarised in Table 2 and could be represented as shown in figure 2. The traditional indicators described in *Brihat Samhita* and their possible modern meteorological interpretations are presented in Table 3.

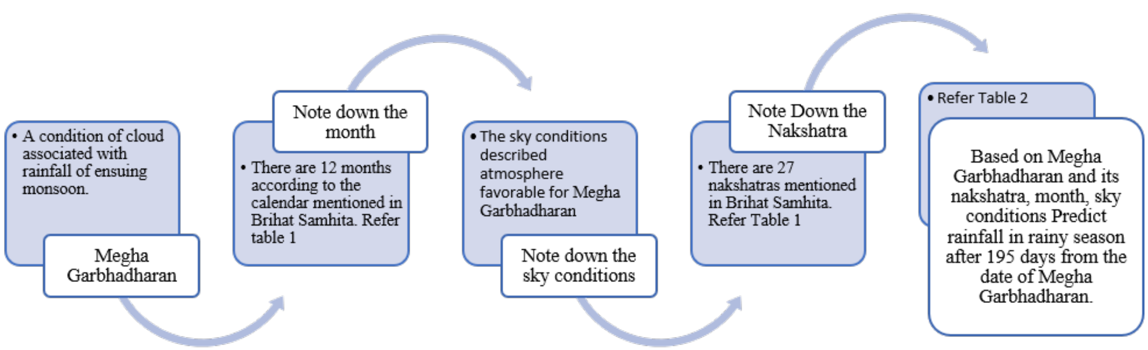

Fig. 2: Methodology of rainfall prediction using Megha Garbhadharan

4 Modern Rainfall Prediction

Conditions of Megha Garbhadharan

1. Winds are gentle and agreeably blowing from north or north-east or east, feel good to humans, clear sky, and the sun & moon are surrounded by halos.
2. Clouds are huge, bright, dense, needle-like or sword shaped, red; sky is dark, or moon & stars appear white.
3. Twilight is marked by rainbow, low rumbling of thunder, lightning, mock-sun or parhelion, and vocal signals from groups of birds & animals coming from north, north-east or east directions.
4. The quantity of rainfall is not above one-eighth of a Drona (a measuring unit).
5. Planets appear with large bright disc, their course lies to the north of constellations, free from abnormal affections.
6. Trees grow well without diseases.
7. Men and cattle are happy.

8. The color of the clouds are pearls or silver color of the bark of the Tamala tree or blue lotus.
9. Clouds of Megha Garbhadharan are exposed to the hot rays of the sun, covered by drops of rain and blowing gentle winds.

Table 2: Rainfall prediction methodology based on *Megha Garbhadharan*.

Month	**Sky conditions for the month**	**Nakshatra in which the moon is at the time of Megha Garbhadharan**	**Rainfall Prediction***
Margshirsha Shukla Paksh	1. The sky appears red before sunrise and after sunset 2. Clouds are surrounded by halos 3. Not too cold	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Jyeshtha Krishna Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 8 days in Jyeshtha Krishna Paksh
		Other Nakshatras	Rainfall in Jyeshtha Krishna Paksh
Margshirsha Krishna Paksh	–	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Aashadha Shukla Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 8 days in Aashadha Shukla Paksh
		Other Nakshatras	Rainfall in Aashadha Shukla Paksh
Pausha Shukla Paksh	1. The sky appears red before sunrise and after sunset 2. Clouds are surrounded by halos 3. Not thick frost	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Aashadha Krishna Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 6 days in Aashadha Krishna Paksh
		Other Nakshatras	Rainfall in Aashadha Krishna Paksh
Pausha Krishna Paksh	–	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Sravana Shukla Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 6 days in Sravana Shukla Paksh
		Other Nakshatras	Rainfall in Sravana Shukla Paksh
Magha Shukla Paksh	1. Strong winds 2. Discs of the sun and moon should be dimmed by the fall of snow 3. Extreme cold 4. The rising and setting sun is hidden by clouds	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Sravana Krishna Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 16 days in Sravana Krishna Paksh
		Other Nakshatras	Rainfall in Sravana Krishna Paksh
Magha Krishna Paksh	–	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Bhadrapada Shukla Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 16 days in Bhadrapada Shukla Paksh
		Other Nakshatras	Rainfall in Bhadrapada Shukla Paksh

Month	Sky conditions for the month	Nakshatra in which the moon is at the time of Megha Garbhadharan	Rainfall Prediction*
Phalguna Shukla Paksh	1. Strong winds 2. Fine clouds march from place to place 3. Broken halos in sky 4. The sun is gold or red	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Bhadrapada Krishna Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 24 days in Bhadrapada Krishna Paksh
		Other Nakshatras	Rainfall in Bhadrapada Krishna Paksh
Phalguna Krishna Paksh	–	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Ashwin Shukla Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 24 days in Ashwin Shukla Paksh
		Other Nakshatras	Rainfall in Ashwin Shukla Paksh
Chaitra Shukla Paksh	1. Winds, clouds, rain and halos in the sky	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Ashwin Krishna Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 20 days in Ashwin Krishna Paksh
		Other Nakshatras	Rainfall in Ashwin Krishna Paksh
Chaitra Krishna Paksh	–	Purva Bhadrapada, Uttara Bhadrapada, Purva Aashadha, Uttara Aashadha and Rohini	Abundant rainfall in Kartik Shukla Paksh
		Shatabhisha, Ashlesha, Ardra, Swati and Magha	Rainfall for 20 days in Kartik Shukla Paksh
		Other Nakshatras	Rainfall in Kartik Shukla Paksh

* Rainfall is predicted to occur at approximately the 195th day when the moon comes in the same nakshatra as was observed at the time of *Megha Garbhadharan*.

Table 3: Rainfall indicators described in *Brihat Samhita* and their possible modern meteorological interpretations.

Ancient Indicator	Modern Equivalent	Scientific Interpretation
Halo around Sun/Moon	Cirrus cloud formation	Presence of suspended ice crystals in high-altitude clouds, often associated with approaching weather systems and increasing atmospheric moisture.
Cloud formation during *Megha Garbhadharan*	Moisture convergence and atmospheric instability	Gradual atmospheric moisture build-up and development of favorable conditions for monsoon rainfall.
Thunder and lightning	Convective instability and cumulonimbus activity	Strong vertical uplift, latent heat release, and unstable atmospheric conditions associated with intense rainfall events.
Wind direction observations	Monsoon circulation and pressure gradients	Atmospheric moisture transport associated with monsoon circulation patterns.

Meteorology, as we perceive it now, may have had its firm scientific foundation in the 17th century with the invention of the thermometer and the barometer along with the formulation of the laws that govern the behaviour of atmospheric gases [8]. With time, instruments were improved, more observations were made and better understanding of climate processes became possible. The climate system is activated due to energy imbalance [24]. Considering the Earth-atmosphere as one system, the climate processes can be categorised as external and internal. The external climate processes include astronomical influences which can change the incoming radiation. The main source of incoming radiation is the Sun. The two main causes of change in insolation are changes in solar output and changes in the Earth-Sun distance. The sunspot cycle and solar activity are the reasons that change the solar output. Changes in eccentricity, obliquity or precession change the distance between the sun and the earth which in turn, changes the insolation. Changes in albedo due to snow cover, cloud cover or vegetation cover would alter the outgoing radiation from the system.

The internal climate processes are more about the atmospheric structure which changes the distribution of energy within the Earth-atmosphere system. Chemicals such as water vapor, CO2 etc. absorb the insolation and are responsible for the greenhouse effect in the atmosphere. Volcanic eruptions also emit sulphates into the atmosphere. Changes in the concentration of these chemicals due to anthropogenic and natural changes alter the climate. Tectonic plate movements change the ocean and land locations with respect to the equator, which in turn alters the continental scale circulations such as monsoon. Earth's overall average equilibrium temperature changes only slightly from one year to the next. The Earth–atmosphere system has a number of processes called feedback mechanisms that can either intensify or weaken tendencies toward climate change. Interactions between the ocean and the atmosphere bring about changes in the temperature of the ocean and their variations from normal (decadal or yearly average) are considered as oscillations. These oscillations are not deterministic and are not easy to predict. The various processes of climate have been summarised in figure 3[1, 2, 25–31].

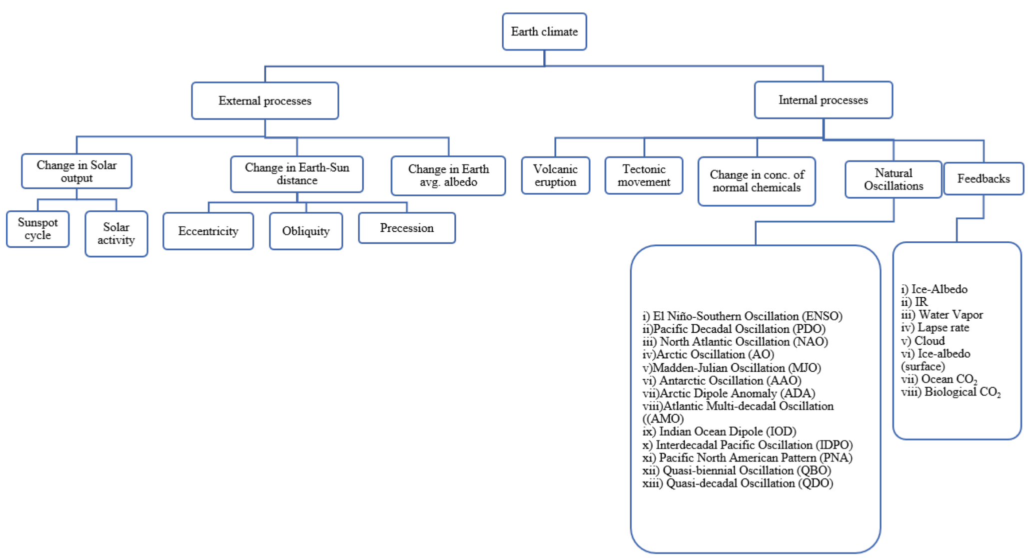

Fig. 3: Summary of Climate Processes in Modern Meteorology

The understanding of climate processes has led to the development of techniques for rainfall prediction. Based on the techniques used for forecasting the future state of the atmosphere, the forecasting methods can be broadly categorised as: numerical and statistical.

4.1 Statistical models

The traditional statistical models such as linear regression, power regression, dynamic stochastic transfer, parametric, etc., are based on the long-term measurement of rainfall and its dependence on various meteorological parameters [4, 32, 33]. These methods use time series data for rainfall prediction. Statistical models like auto-regressive moving average (ARMA), auto-regressive integrated moving average (ARIMA), Statistic Decomposition Models (SDM), Exponential Smoothing Models (ESM), GNSS-derived precipitable water vapor etc., have been employed for rainfall prediction but they have a huge dependence on user experience and knowledge [4, 34]. Moreover, statistical models are based on the assumptions of stationarity of the model's parameters and do not consider non-linearity of rainfall [4, 32, 34, 35].

4.2 Numerical Weather Prediction (NWP)

Models for numerical weather prediction are based on approximations of solutions to motion equations. Using inputs from the observational network, the initial state of the Earth system (including the atmosphere and Earth) is determined. The radiosondes, weather stations, aircraft measurements, and remote sensing products make up the observational network. However, because the observations are incomplete, heterogeneous, and dispersed, they cannot accurately represent the initial state. Assimilation of data is used to close this gap. Data assimilation interpolates in time and makes adjustments to the observations to make them consistent with state variables (such as temperature, pressure, wind, etc.). A model's grid spacing is determined by area coverage and available processing power. The NWP model uses this information as input to approximate the motion equations and determine the future state of the atmosphere for each grid cell. The current operational NWP models have greatly improved as a result of new capabilities in the Earth observation system, particularly satellites and radars. The NWP model can simulate atmospheric processes based on the initial conditions. The Navier-Stokes equations, which describe the atmosphere in terms of momentum, mass, and enthalpy, are numerically solved to produce the future atmospheric state in each grid cell of the model. Empirical parameterizations are used to capture processes that take place at scales smaller than the grid size of the model. The first forecast product of the NWP workflow is the direct model output. The grid boxes in modern global NWP models have an area of several square kilometers. An additional step is added to the NWP workflow to produce end-user forecast products at a finer scale.

For rainfall forecasting on various time scales, NWP models have been adopted by numerous meteorological organizations worldwide. The operational models for various countries are summarized in Table 4 along with their time scale, spatial domain, horizontal resolution, and vertical resolution [36–41]. While global models have a resolution of 12 km, regional models have a fine resolution of about 4 km.

5 New Methods Currently Under Evolution

Modern weather prediction systems strongly rely on massive mathematical modelling and simulations which require high-performance computing [42]. Although we are witnessing a rapid increase in computing power and physics, there are still various challenges in the weather prediction systems. Due to the unpredictable events in the atmosphere, even a small change in the initial stage can lead to a huge impact on the weather forecast [42–44].

The limitations of the physics-based models led to research on artificial intelligence techniques for meteorological applications. Recent applications of Artificial Intelligence/ Machine Learning techniques (AI/ML) in atmospheric remote sensing have demonstrated improvements in current methodologies in atmospheric science such as, neural networks have been employed to infer vertical structures of clouds from MODIS imagery, etc. [13]. For the purpose of monsoon monitoring and forecasting, various meteorological centers are exploring the use of AI/ML for weather services [32]. To address random variations in rainfall, several machine learning (ML) tools, including artificial neural networks (ANN), k-nearest neighbours (KNNs), decision trees (DT), etc. are used to learn patterns in the data to forecast rainfall [45]. But the success of machine learning depends hugely on feature extraction and finding the useful features is itself a difficult task [46]. Deep learning approaches, subset of machine learning, extract significant features from the raw data [12]. Convolutional neural network (CNN) is an architecture for deep learning consisting of an input layer, feature extraction layer, classification layer and an output layer. The feature extraction layer mainly consists of convolution layers and pooling layers. The classification layer consists of a fully connected layer. The architecture of CNN is shown in figure 4. CNN has been utilised to classify clouds, one of the variables that determine rainfall. Both the approaches, be they ancient or modern, had special emphasis on observation of clouds and their types for rainfall prediction. Clouds affect the energy budget between the earth and the atmosphere and hence affect the water exchange that describes the climate [12].

Table 4: NWP models used by meteorological centers in different countries

Model name	**Forecast range**	**Domain**	**Horizontal Resolution (in km)**	**Vertical Layers**
Country: Japan; Center: JMA				
GSM (Global Spectral Model)	Medium range	Global	20	128
GEPS (Global Ensemble Prediction System)	Medium range, Extended range	Global	40 and 55	128
MEPS (Meso-Scale Ensemble Prediction System)	Short Range	Regional	5	
MSM (Meso-Scale Model)	Short range	Regional	5	76
LFM (Local Forecast Model)	Very short range	Regional	2	76
Seasonal Ensemble Prediction System	Seasonal	Global		
Country: India; Center: IMD				
Global forecasting system (GFS)	Medium range	Global	12	64
Unified model-NCMRWF	Medium range	Global	12	
Global Ensemble Forecasting System (GEFS)	Medium range	Global	12	64
Global Unified model ensemble prediction system-NCMRWF	Medium range	Global		
Weather research forecast (WRF) Meso scale model	Short range	Regional	3 and 9	
Unified Meso scale regional model	Short range	Regional	4	
High-Resolution Rapid Refresh (HRRR) WRF model	Short range	Regional	2	
Country: Europe Center: ECMWF				
SEAS5	Long range	Global	36	91
High-resolution system	Medium range	Global	9	137
ECMWF Ensemble Prediction System	Medium range	Global	18	137
ECMWF Ensemble Extended Prediction System	Extended range	Global	36	137
Country:Germany Center: Deutscher Wetterdienst				
ICON (Icosahedral Nonhydrostatic)	Medium range	Global	13	90

Model name	Forecast range	Domain	Horizontal Resolution (in km)	Vertical Layers
ICON-EU	Medium range	Regional	6.5	60
COSMO-DE (Consortium for Small-scale Modeling)	Short range	Regional	2.8	50
ICON-EPS (ICON Ensemble Prediction System)	Extended range	Global and Regional	40	60
COSMO-DE-EPS	Short range	Regional	2.2	65
Country: UK Center: MetOffice				
Unified Model (UM)	Medium range	Global	10	70
Unified Model (UM)	Short range	Regional	1.5	70
MOGREPS-G	Medium range	Global	20	70
MOGREPS-UK	Short range	Regional	2.2	70
Country: USA Center: NCEP/NOAA				
GEFS (Global Ensemble Forecast System)	Medium range, Extended range	Global	0.25°/0.5°	64
GFS (Global Forecast System)	Medium range, Extended range	Global	0.25°	
North American Mesoscale (NAM)	Short range	Regional	12	60
NAM-HIRES	Short range	Regional	3	60
Short Range Ensemble Forecast (SREF)	Short range	Regional	40–16	
Rapid Refresh Analysis & Forecast System (RAP)	Short range	Regional	13	50
High Resolution Rapid Refresh Analysis & Forecast System (HRRR)	Short range	Regional	3	
Weather Research and Forecasting (WRF)	Short range	Regional	8	
Advanced Research WRF (ARW)	Short range	Regional	3.5–4.2	50
Nonhydrostatic Multiscale Model on B-grid (NMMB)	Short range	Regional	3–3.6	50
North American Ensemble Forecast System (NAEFS)	Medium Range, Extended range	Global	70	
High Resolution Ensemble Forecast (HREF)	Short range	Regional	3	
Climate Forecast System (CFS)	Long range	Global		
Country: China; Center: CMA				
Global-Regional Assimilation and Prediction System (GRAPES_GFS)	Medium range	Global	0.25°	60–87
GRAPES_TYM	Short Range	Regional	0.12° to 0.09°	50–68
GRAPES_Meso	Short Range	Regional	10	51
GRAPES_GEPS	Medium range	Global	0.5°	61
GRAPES_REPS (Regional EPS)	Short range	Regional	0.1°	51
FODAS (Forecast System on Dynamical and Analogy Skills)	Long range	Regional	2.5° × 2.5°	

Climatological research can benefit a lot from cloud identification and classification [12, 13, 47–49]. Current data assimilation and climate applications have a huge dependency on satellite imagery. Hence, better study of clouds from satellite imagery would be very beneficial [12, 13]. Continuous cloud classification through satellite images is an approach which is very important in rainfall forecasting [50–52].

Zhang, et al. [53] proposed a new convolutional neural network model, called CloudNet, for accurate ground-based meteorological cloud classification. They used the Singapore Whole-sky Imaging Categories (SWIMCAT) dataset which consists of 5 categories of cloud, and built a ground-based cloud data set called Cirrus Cumulus Stratus Nimbus (CCSN) which consists of 11 categories under meteorological standards. It was the first time that contrails were taken into consideration as one new type of cloud in ground-based cloud classification. Their extensive experimental results indicate that CloudNet achieves high efficiency with the SWIMCAT data set and performs well with the complicated CCSN data set in the ground-based cloud classification challenge.

[32] states that cloud type is one of the important input parameters in the 48-hour rainfall forecast. At present, this input is taken from synoptic charts. Also, manual interpretation of cloud type from satellite images is done.

Gupta & Nanda [12] have reviewed articles between 1970 and 2020 about various cloud detection methods and their related applications such as cloud classification from multi-spectral satellite images. The article embodies cloud detection based on: i) spatial and textural parameters ii) classifiers based on neural network methods iii) deep neural networks. The article is reviewed on images from satellites such as Landsat, GOES, AVHRR, Meteosat, MODIS, SPOT, Kalpana-1, Gao Fen-2.

Mahajan & Fataniya [15] reviewed literature from 2004 to 2018 on cloud detection from satellite images. The various forms of cloud detection such as cloud/no cloud, thin cloud/thick cloud, snow/ice detection, and cloud/cloud shadow are reviewed. They classified the approaches into two categories: i) Classical algorithm-based approach in which specific steps are followed for an input image and ii) Machine learning approach. Classical approaches are mainly based on threshold methods. Machine learning approaches include support vector machine, fusing multi-scale convolution features, deep learning, decision tree, Bayesian classification, random forest-based methods, object-based convolution neural network, etc. Satellite images are available from different sources such as Spot series of satellites from Europe, Sentinel-1/2 satellites from France, FY2G—India Ocean InfraRed Satellite, GaoFen-1 (Gaofen-1 is a high-resolution Chinese Earth observation satellite), MODIS data, GOSAT—The Greenhouse Gases Observing Satellite, Landsat-8 which is an American Earth observation satellite, GOES—Geostationary Satellites, Meteosat-Series of satellites are geostationary meteorological satellites, NOAA—Advanced Very High-Resolution Radiometer, QuickBird Satellites, Ikonos satellites, INSAT 3D/3DR, Kalpana-1 satellites from Indian Space Research Organization.

The machine learning methods have a precondition that the training as well as testing data should be in the same feature place and have the same distribution [46]. Knowledge transfer is beneficial in cases where it is hard to gather sufficient data [13, 46]. To overcome such difficulties, transfer learning is used in which knowledge is transferred from a source domain with large-scale labelled data to a limited annotated dataset [54]. Such pre-trained CNN can be fine-tuned for new application implementation [46].

Marais et al.[13] used pretrained CNN and fine-tuned CNN to classify cloud regimes and aerosols in MODIS or VIIRS into 7 classes. It is time-consuming to hand label satellite images and there are certain categories such as aerosols in which the events in the observations are less. Hence, they used transfer learning for cloud classification from satellite images. The different methods used are: FCNN (fine-tuned CNN), PCNN (Pre trained CNN), MeanStd (mean standard deviation). They demonstrated in the paper that with additional fine-tuning of a pretrained CNN, by further estimating the convolutional filters where the initial values are of a pretrained CNN, the classification performance of radiometer images can be further improved [13].

Dey Roy et al.[55] used CNN for cloud pattern classification on the SWIMCAT dataset and classified it into 4 classes i.e., Cirroform, Stratoform, Cumuloform, and Nimboform. Six pretrained CNN, namely VGG16, VGG19, GoogleNet, AlexNet, Inception, and Resnet, were used in two ways: first, the features were extracted using the feature extraction layer of CNN models followed by classification using SVM classifier and second, by fine-tuning the pretrained models. It was observed that CNN architectures with feature extraction method had higher accuracy [55].

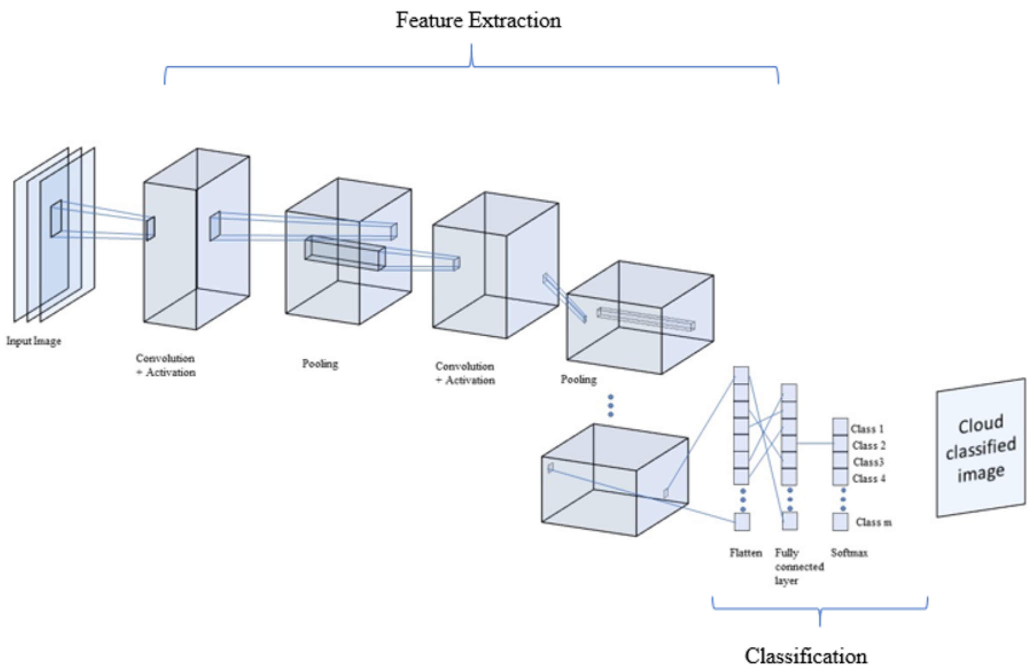

Fig. 4: Architecture of Convolutional Neural Network for Cloud Detection

Pretrained models such as VGG16, VGG19, GoogleNet, AlexNet, Inception, Resnet, which were originally trained on the ImageNet dataset, have been widely used for different datasets using transfer learning.

Kuril et al.[50] proposed cloud classification method using Haar Discrete Wavelet Transform as a feature extractor and Radial Basis Function as the neural network for classification. IMD directory's satellite cloud database was classified into 3 categories, namely low-level, middle-level, and high-level. This method requires improvement in computational time and classification rate.

S H et al. [56] planned for detection of fog/low clouds over the Delhi region using a ceilometer to detect cloud base height and compare it with the INSAT 3D/3DR fog product which is obtained under clear sky conditions. The ceilometer was better at detecting fog/low clouds in single- and multi-layer cloud scenarios but it gives only point data.

Mitra et al.[10] used RGB composites of INSAT-3D satellite in the RAPID (Real-time Analysis of Products and Information Dissemination) for identification of fog, snow and low clouds. Threshold based methods were used for the classification.

Mitra et al.[11] used RGB composites of INSAT-3D satellite in RAPID for identification of pre-monsoon severe weather events such as thunderstorms with rain or hail using threshold technique.

Table 5: Comparison of AI/ML-based cloud classification and rainfall prediction studies

Study	**Dataset**	**ML/DL Model**	**Accuracy/ Performance**	**Limitation**
Zhang et al. [53]	SWIMCAT and CCSN datasets	CloudNet (CNN)	High cloud classification efficiency	Limited generalization to different geographical regions and weather conditions
Dey Roy et al. [55]	SWIMCAT dataset	VGG16, VGG19, AlexNet, GoogleNet, Inception-V3, ResNet101 with SVM	High classification accuracy using feature extraction approach	Requires large labelled datasets and computational resources for training
Marais et al. [13]	MODIS and VIIRS satellite images	Pretrained CNN and Fine-tuned CNN	Improved cloud and aerosol classification performance	Transfer learning models are computationally expensive and require GPU support
Kuril et al. [50]	IMD satellite cloud database	Haar Wavelet Transform with Radial Basis Function Network	Moderate classification performance	Lower computational efficiency and limited classification categories
Wang et al. [48]	FY-4A satellite images and Himawari-8 labels	UATNet (Transformer-based network)	Improved cloud recognition capability	Complex architecture with high computational requirements
Li et al. [51]	Landsat-7/8, Gaofen-1 and Google Earth images	Multi-scale convolutional feature fusion	Improved cloud detection for multi-resolution images	Performance depends strongly on training data quality
Wu & Shi [47]	GF-1 WFV satellite images	Feature Concatenation Network and Multi-window Guided Filtering	Effective cloud detection in satellite imagery	Limited applicability under highly heterogeneous cloud conditions
Pugazhenthi & Kumar [49]	INSAT-3D satellite images	Improved K-means and Fuzzy C-means clustering	Efficient cloud segmentation	Threshold and clustering methods are less adaptive to complex cloud patterns
Mitra et al. [10]	INSAT-3D RGB images	Threshold-based classification	Operationally simple and fast	Limited ability to classify diverse cloud structures
Mitra et al. [11]	INSAT-3D RGB images	Threshold technique	Effective for severe weather identification	Manual threshold selection reduces automation capability
Barrera-Animas et al. [35]	Meteorological time-series data	LSTM, Stacked-LSTM, Bidirectional-LSTM, XGBoost, AutoML	Improved rainfall forecasting performance	Deep learning models require large training datasets and high computation
Espeholt et al. [42]	MRMS, GOES and HRRR datasets	MetNet-2	High short-term precipitation forecasting capability	Requires large-scale computational infrastructure

The dataset of satellite INSAT 3D/3DR has been majorly used for cloud classification into low, middle and high clouds using threshold techniques. Limited work has been done on using AI/ML techniques for cloud classification into categories such as cirrus, aerosols, fog, stratiform, etc., using INSAT 3D-3DR.

6 Brief Analysis of Reviewed Rainfall Prediction Methods

This paper examines ancient and contemporary methods for predicting rainfall. The development of instruments around the year 1400 served as the foundation for contemporary rainfall prediction methods. All the subsequent improvements led to the present knowledge. However, there has not been enough research on modelling of ancient systems, particularly with a view integrating them with the current models.

Section 2 covered ancient methods for forecasting rain. According to a number of sources, *Brihat Samhita* provided an in-depth description of the atmospheric phenomena and rainfall is discussed in chapters 21–28. Chapter 21 of the *Brihat Samhita* discusses clouds and cites Megha Garbhadharan as the cause of rainfall during the monsoon season. To predict rainfall, the methods combined data from astronomy, atmosphere, living things, and plants. Snow was one of the predictors used by IMD for long-range forecasting up until 2006. Megha Garbhadharan has also given consideration to this predictor. As a result, the ancient techniques' potential has not yet been fully realized. Megha Garbhadharan was observed during the winter and spring then. This could be related to natural cloud seeding since it is more likely to happen in the winter. More research must be done regarding Megha Garbhadharan, though. Two groups of contemporary rainfall prediction methods—current techniques and emerging strategies—have been examined. The two models of weather prediction that are now in use are statistical and numerical. While using continuous measurements of rainfall and other variables, statistical models fail to account for the unpredictable character of rainfall. The equation of motion that describes the atmosphere is the foundation of NWP models, which involve several computations. The majority of NWPs are grid models, where the horizontal resolution is the distance between grid cells. Some global models such as spectral models take into account the number of waves that the model can resolve. In order to produce accurate forecasts, NWP models simulate the dynamics of the atmosphere. One of NWP's most significant drawbacks is the high-level of processing resources required for operation, which limits the outputs' geographic and temporal precision. Moreover, methods to improve resolution are only dependent on data from a small number of key variables. Table 4 summarises the various NWP models adopted by various meteorological agencies worldwide. These models are either global or regional in scope. These models are divided into four categories according to their lead time i.e. long, medium, short, and very short. Compared to global models, regional models have better resolution. Global models are also restricted to long-range and medium-range scenarios. It is necessary to represent the atmosphere at finer resolution to improve the physics of the models. However, it is likely to be computationally expensive. In the previous section, it was mentioned that a coarser horizontal resolution might not accurately depict topography and land surface characteristics, which would ultimately affect the accuracy of rainfall forecasts. Better orographic and mesoscale features were provided by the finer resolution, which can be seen as a crucial step toward precise short-term rainfall forecasts. The computational cost rises as the resolution increases. A vast amount of data is available due to the expanding observational network, which includes satellites and radars. Extraction of patters from such huge data has led to the emergence of AI/ML, where transformations of data are learned. The importance of deep learning, a part of AI/ML, increases as a result of the model's inclusion of feature extraction, which was previously done manually. Numerous atmospheric events result in small datasets being generated. Such datasets can be used to train pre-trained CNNs with a little fine tuning. It seems difficult to merge the ancient and modern approaches in their current form due to the conceptual distinctions between them. However, both seem capable of providing inputs that can be effectively used for rainfall prediction on their own.

7 Conclusion

The ancient rainfall prediction used a very integrated approach including astronomy, atmospheric changes, bioindicators and animal behaviour. There is a possibility that the use of astronomy was not merely for time-keeping but there may be more to it. In atmospheric changes there were month-wise sky conditions favourable for Megha Garbhadharan from chapter 21 of Brihat Samhita. It has shown similarities with the predictors used in long range forecasting adopted by IMD. But there are more details along with the sky conditions that are also to be observed for better rainfall prediction. There should be more research on understanding the ancient approach to rainfall prediction, particularly in view of the rising frequency and intensity of extreme events. It may be beneficial to investigate the ancient methods such that they can be integrated with modern approaches so that the potential of both are combined to develop common systems. Clouds and their types had a special importance in rainfall prediction in both ancient as well as modern rainfall prediction. Visual identification of clouds is a qualitative approach used by humans. The increasing observational network, including satellites, provides huge amounts of data. To process this data, there is a need to develop a quantitative approach to seeing patterns, which is not possible visually. AI/ML techniques can be used to extract patterns in weather systems from satellite data requiring less human intervention. Such techniques reveal the potential to extract spatial-temporal relations automatically and gain further knowledge, helpful for improving forecasting and modelling of observed physical phenomena at multiple timescales. One area of focus for AI/ML is cloud type classification from satellite data. Previous works have used satellites including MODIS, SPOT, GOES, Kalpana-1 for cloud detection. Currently, two operational meteorological satellites used by IMD are mainly INSAT-3D and INSAT-3DR in which Visible and SWIR band interpretations, channel differencing of different bands, and threshold techniques are primarily used for cloud detection, which is mainly confined to the presence or absence of clouds and cloud cover percentage. However, cloud detection with cloud type from satellite data could play a vital role for rainfall prediction. Thus, AI/ML techniques are highly appealing for its analysis of cloud type classification. This would be helpful to couple the versatility of data-driven machine learning with physical process models, resulting in improvements in rainfall prediction.

Declarations

- The authors received no specific funding for this study.

- The authors declare that they have no conflicts of interest to report regarding the present study.
- No Human subject or animals are involved in the research.
- All authors have mutually consented to participate.
- All the authors have consented the Journal to publish this paper.
- Authors declare that all the data being used in the design and production cum layout of the manuscript is declared in the manuscript.

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