



Leveraging satellite products and machine learning/deep learning models for the upgrading of agro-advisory systems in India: A bibliometric and systematic narrative review

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Abstract

A comprehensive bibliometric review was conducted to evaluate the most relevant literature retrieved from the Scopus database, resulting in the identification of 125 relevant publications from an initial pool of 1948 records through a screening process based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The bibliometric analysis revealed a significant increasing trend in year-wise publications and citations, wherein India and the US emerged as the leading contributors with total publications of 34 and 25 respectively. Notably, the systematic narrative review highlights that agro-advisory systems (AAS) have increased farmer income by 83 %, improved crop yields by 6–25 % and enhanced farm profitability by 15–26 % in India. Despite these achievements, conventional AAS frameworks that rely predominantly on automatic weather stations (AWS) continue to face critical limitations, including sparse spatial coverage, restricted agro-meteorological observations, data discontinuities and inadequate representation of local microclimatic variability. To address these limitations, the study highlights the importance of integrating AWS observations with high-resolution satellite products through downscaling and subsequent assimilation within the Weather Research and Forecasting Data Assimilation (WRFDA) framework to improve the spatial accuracy of weather forecasts and facilitate the delivery of reliable block-level and village-level agro-advisories. However, the operational implementation of satellite-assisted weather forecasting using the Weather Research and Forecasting (WRF) model is often constrained by latency in data availability, as many high-resolution satellite products require several hours to multiple days for processing and dissemination. In order to overcome this limitation, the review further demonstrates the considerable potential of machine learning (ML) and deep learning (DL) models trained using historical satellite observations along with meteorological predictors derived from numerical weather prediction (NWP) systems for enhancing downscaling capabilities and improving forecast accuracy. The results inferred that the satellite-based weather forecasting using ML and DL architectures achieved strong predictive performance, with reported R^2 values of up to 0.982, 0.976 and 0.95 for rainfall, temperature and aerosol concentration respectively. These findings demonstrate the increasing potential of satellite-driven ML and DL approaches for high-resolution weather forecasting and their applicability to next-generation, location-specific agro-advisory services. However, their operational utilisation depends on the availability of adequate computational infrastructure, skilled human resources, economic feasibility, institutional coordination and farmer acceptance. Therefore, the future of satellite-based AAS lies in developing computationally efficient, economically viable and farmer centric decision support platforms capable of translating complex forecast information into timely, understandable and actionable recommendations for climate-resilient agriculture.

Keywords: agriculture; automatic weather station; India; machine learning models; satellite; Weather Research and Forecasting

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1. Introduction

The occurrence of extreme weather events including heavy rainfall, droughts, hailstorms and heat waves, have increased under global warming and climate

change, affecting agricultural systems at global, regional and local scales (1). It is observed that the majority of developing nations experience severe economic damage due to extreme weather events, which lead to significant financial losses. Among these, India faces

increased drought and flood risks, with projections indicating that these events are likely to occur more frequently under future climate scenarios (2). Since agriculture is heavily weather-dependent in India, as it is a tropical country, the weather-induced variability of crop production generally exceeds 10 % and may reach as high as 50 % under adverse conditions (3). Currently, India experiences a negative productivity impact of 4.5–9 % from climate change, which results in annual economic losses that reach 1.5 % of Gross Domestic Product (4). This implies that the faster rate of change in climate variables, combined with the occurrences of extreme weather events results in deceleration of agricultural productivity (5). Therefore, a foremost concern at this stage is to mitigate the impacts of climate change and variability, which can be addressed through Climate smart agriculture (CSA). Climate smart agriculture focuses on developing resilient food production systems that enhance food and economic security amid increasing climatic changes and unpredictable weather patterns (6). Prominently, the major goals of CSA involve the introduction of climate-resilient crop varieties, incorporation of climate-smart agricultural management practices and developing efficient agro-advisory systems (AAS) for accurate and reliable data transfer (7). Among these methods, development of efficient and smart AAS is highly crucial because it converts weather, crop, soil and climate information into actionable recommendations that farmers can use during critical stages of crop production. The utilisation of AAS extends across several agricultural activities, including selection of suitable sowing windows, crop and variety selection, irrigation scheduling, fertiliser application, pest and disease management, harvesting and protection of crops from weather-related hazards (8). Timely agro-advisories have been reported to improve crop yield gain of 10–15 % and reduce cultivation costs by 2–5 % through improved input management and crop protection at critical growth stages (9). Thus, AAS serves as an operational bridge between meteorological information and farm-level decision-making.

In India, the Agricultural Meteorology Division of the India Meteorological Department (IMD) has established 130 Agro-Meteorological Field Units (AMFUs) across the country to support the farmers through Gramin Krishi Mausam Sewa (GKMS) project (10). Under this programme, block-level agrometeorological advisories are disseminated to farmers, along with need-based crop advisory content tailored to local weather conditions. Additionally, Numerical Weather Prediction (NWP) based medium-range forecasts introduced through the National Centre for Medium Range Weather Forecast (NCMRWF) in collaboration with Indian Council of Agricultural Research (ICAR) and State Agricultural Universities (SAUs) became an important foundation of India's agrometeorological advisory services, which had evolved into district level integrated advisories (11). Furthermore, Mission Mausam provides an important national framework for strengthening next-generation

agro-advisory services by integrating high-resolution observations from satellites and ground-based systems with advanced NWP, high-performance computing, artificial intelligence and machine learning (AI/ML)-based forecasting, impact-based decision support, thereby facilitating the transition from generalised weather information towards more precise and location-specific agricultural advisories. Alongside these institutional approaches, Indigenous technical knowledge (ITK) contributed traditional weather forecasting, primarily based on astronomical and calendar-based indicators, including nakshatra based observations and traditional Panchang interpretations (12). Recently, Tamil Nadu Agricultural University (TNAU) has developed a web cum mobile application named TNAU-AAS, which represents one of the automated agro-advisory initiatives in India and it is reported to be utilised by more than 45000 farmers (13). Such indigenous systems demonstrate the feasibility of integrating locally available observations, numerical weather prediction, crop knowledge and automated advisory generation for agricultural decision support.

Despite these advances, a major operational challenge exists in translating meteorological information into reliable, location-specific data for providing village-level advisories. The spatial resolution of conventional observations and forecast products is inadequate for capturing localised variations in rainfall, temperature, soil moisture and other agro-climatic variables (14). Consequently, advisories generated at a relatively coarse spatial scale may not adequately represent the actual conditions experienced by an individual village, which means that the need for high-resolution weather forecast is necessary for village level agro-advisory generation (15). Moreover, establishing and maintaining Automatic Weather Stations (AWS) across all villages in the country for precise agro-advisory support is not economically feasible (14). So, in order to meet this constraint, the agro-advisory services should be integrated with Information and communication tools (ICT) namely, Remote Sensing and Geographic Information System (RS and GIS), Internet of Things (IoT) based sensors and artificial intelligence (AI), ML and DL models (16). Among these tools, remote sensing can provide spatially continuous information on vegetation, soil moisture, land surface temperature, crop condition and other environmental variables, while IoT and on-farm sensors provide near real-time observations at field scale (17). Moreover, GIS facilitates spatial integration and visualisation of heterogeneous datasets (18), whereas AI, ML and DL can support data fusion, weather prediction, pattern recognition, hazard detection and generation of location-specific recommendations (19). For instance, India's Bharat Forecasting System offers high-resolution predictions, utilising AI to improve weather forecasting down to village levels (20). Similarly, GenCast is a new ML-based probabilistic weather model that significantly outperforms the European Centre for Medium Range Weather Forecasts (ECMRWF) in medium range weather forecasting (21).



Together, these technologies can transform AAS from a predominantly weather-information dissemination system into a high-resolution, data-driven decision support platform.

Ultimately, the value of these technological developments lies in their utilisation by farmers. These technologies enable farmers to manage their resources efficiently through real-time information, which assists them in making crop management, irrigation and pest control decisions (22). Concurrently, the technology provides early weather hazard alerts while it streamlines supply chain processes to help farmers share knowledge and create new ideas (23). Above all, real time deep mining of data with higher resolution serves as the major requirement for improving fine tuning efficiency of the AAS (24). Several studies show that farmers can enhance their crop management during the growing season, technology selection and marketing strategies through ICT-based climatic information platforms and AAS (25). The transition from generalised advisories to village and farm-specific recommendations is therefore essential for maximising the practical value of AAS under increasing climate variability. Considering all these points, the study aims to detail the importance of integrating high resolution spatially gridded weather data in the AAS system, with particular emphasis on its operational mechanism, associated constraints and methods to overcome the constraints for more precise village-level advisory distribution using various ML and DL forecasting techniques. This study also emphasises the key roles, significance and components of AAS, with detailed consideration of how these advisories are utilised by farmers for efficient crop management. In addition, the study provides the bibliometric insights which details the information of the countries which are involved in this kind of studies along with the spatio-temporal trend in the publications which are represented in the form of spatial maps, line graphs and network visualisation map.

Bibliometric analysis

The initial step in bibliometric analysis is to collect the relevant literature about the study. Scopus database was used to document the research activities that took place worldwide. Among these, Scopus is preferred for the bibliometric analysis because users can easily export data to other software applications and Scopus offer structured methods to screen all published research documents.

Search strategy

The Scopus database enables users to conduct searches through multiple fields, including abstract, affiliation, article title, author name, document types, journal name, keywords, publication year, subject area and other fields. The search mechanism follows a four-tier procedure, namely identifying, initial screening, review screening and data analysis (Fig. 1).

Data collection

The methodology proceeded by a preliminary search in Scopus using the title, abstract and keyword (TITLE-ABS-KEY) search as Satellite based Precision Agriculture. This yielded 1948 publications (n). Since satellite-based precision agriculture research is a relatively new field that is becoming more popular worldwide, the literature collection should focus on recent years in order to avoid using outdated techniques. As a result, the publication period was limited to 2006–2025 (20 years) and 1712 publications were identified out of the total number of publications (n = 1948) after the removal of 236 records.

Initial screening

The first screening level involved the identification of studies containing keywords relevant to this work. Since the research integrates multiple domains, namely agro-advisory decision support, remote sensing, weather forecasting, machine learning and artificial intelligence, the search strategy was designed to capture publications that involve combinations of these fields. During the initial screening, all keywords were enclosed within quotation marks because, in the Scopus database, quotation marks retrieve exact matches of the specified search terms, thereby improving the precision of the search results. The keyword search query was represented as "precision agriculture" AND "agro-advisory" AND "forecasting" AND "weather" AND "satellites" AND ("machine learning" OR "deep learning" OR "artificial intelligence"). This search strategy yielded a total of 158 publications. Furthermore, the second screening was executed by filtering the document types. Through this process book chapters, conferences, research articles and review articles were selected (n = 157) and rest other document types were discarded (records removed = 1) to enhance the quality of review process. Finally, the third screening was computed by selecting the publications confined within the subject areas mainly agricultural and biological sciences, computer science, earth and planetary sciences, engineering, environmental science and physics and astronomy for the proper refinement, which resulted in 151 number of records after the removal of 6 records.

Review screening

The review screening involves the final screening to remove all the false-positive results. The first and foremost process in the review screening stage is the removal of duplications from the records identified, followed by the removal of records other than English language. There were no duplications and 9 records other than English were discarded to obtain the final result. As a result, the total number of records limited to English language after the removal of duplications were 142. However, within the 142 records identified, 17 records were final unpublished copies/preprints, which were discarded during the final stage of review screening stage. Finally, 125 records were identified using PRISMA flowchart technique to undergo a detailed study on developing an innovative system that

combines geospatial datasets and ML models for enhanced weather forecasting and the upgradation of AAS. Thus, the study found that 125 publications met the required standards after all false-positive results had been removed.

Data analysis

The final shortlisted records ($n = 125$) were imported into Datawrapper for the country-wise spatial mapping of publications or citations and VOSviewer for generating the network visualisation map of keywords. The temporal trend in publications and citations was computed with the help of Microsoft Excel and the R program.

Bibliometric indicators

The study gathered bibliometric data from literature sources, which were later used to create Microsoft Excel spreadsheets. The exported data contains information on author details, citations count, keywords, number of

publications from each country and year-wise publications and citations.

Network visualisation map

The Excel spreadsheet containing the bibliometric data was imported into VOSviewer software (26) to create a network visualisation map of keywords. VOSviewer displays the Total link strength (TLS) values for all the parameters through its graphical interface. Generally, a higher TLS value indicates a greater keyword frequency. However, for identifying the most recurrent keywords from the final shortlisted 102 records, a threshold was established in such a way that, those keywords occurring at least 10 times (10 % of the final shortlisted records) were considered for network visualisation mapping using VOSviewer. Overall, the map revealed 27 main bibliometric markers for this study (Fig. 2). Among these, remote sensing was the most frequently occurring keyword, followed by Precision Agriculture as observed from TLS.

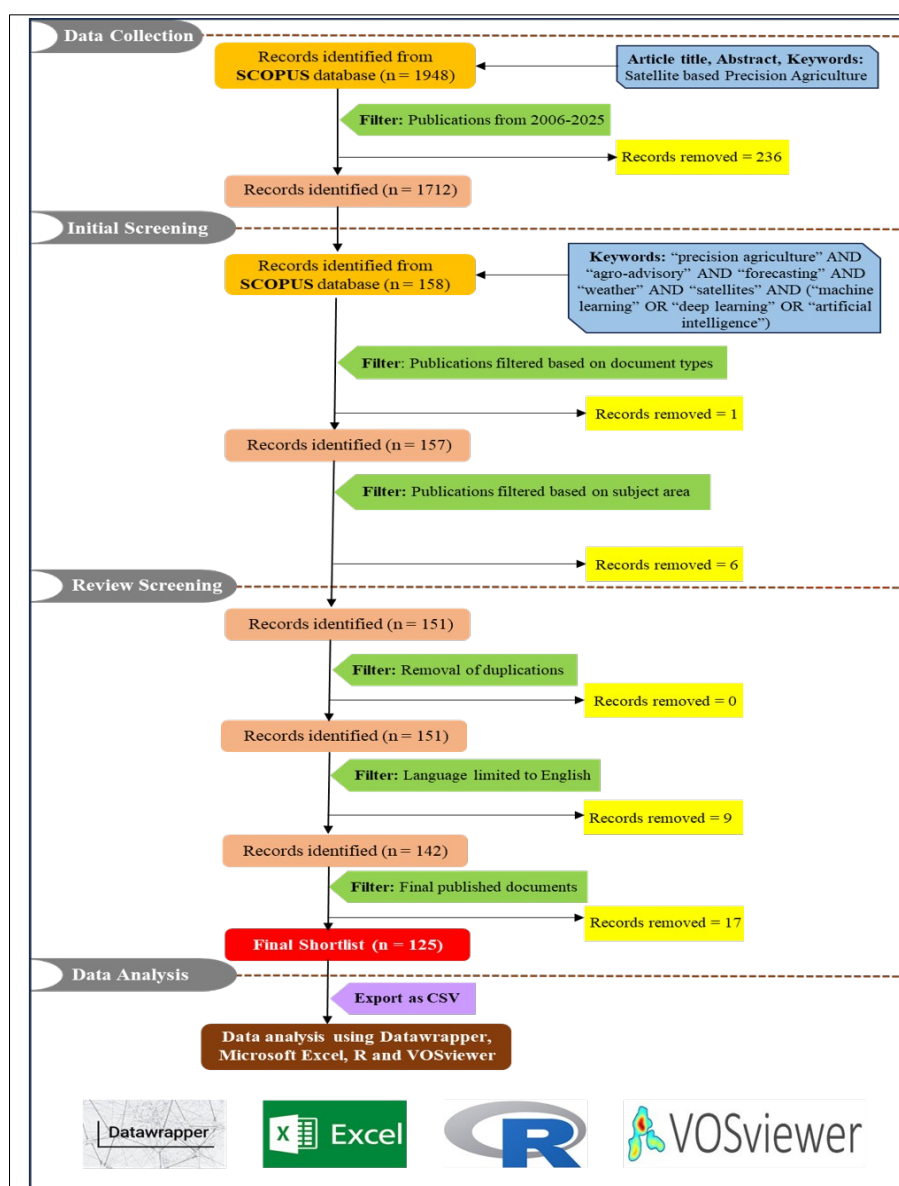


Fig. 1. PRISMA flowchart containing the step-wise collection and screening of articles (n = number of articles). PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

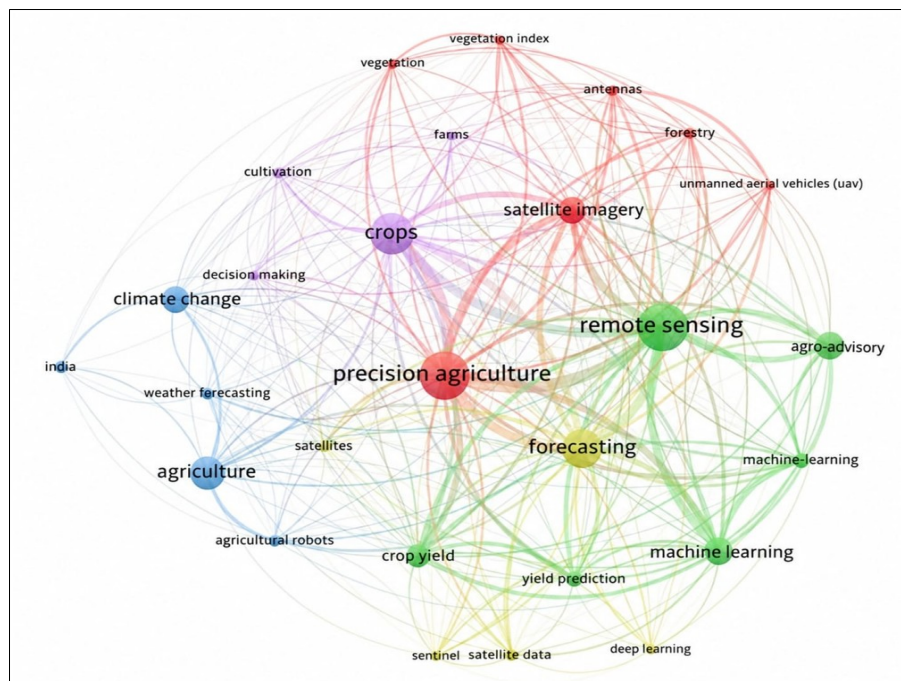


Fig. 2. Network visualisation map of keywords.

Year-wise elucidation

The total number of publications and citations recorded between 2006 and 2025 were 125 and 2051, respectively. Among the years, 2025 recorded the highest number of publications, with 49 publications, whereas 2019 recorded the highest number of citations, with 822 citations. Conversely, 2008 and 2009 did not record even a single publication or citation (Fig. 3). In order to find the trend in the year-wise publications and citations, the final shortlisted records from the Scopus database were subjected to Mann-Kendall (MK) test and Sen's slope estimator using the modifiedmk (27) package in R program. The results exhibited a significant increase in both publication count and citation frequency throughout the study period (p -value < 0.05, Sen's slope > 0.5).

Spatial elucidation

The geospatial representation of publications was generated with the help of Datawrapper (Fig. 4). The country-wise visualisation revealed that India contributed the highest number of publications, with 34 publications, followed by the USA with 25 and China with 15.

Role of agro-advisory systems in addressing global agricultural and climatological challenges

Agro-advisory systems function as structured systems that provide scientifically validated agricultural guidance to farmers based on their specific regional requirements. It consists of 8 major components as represented in Fig. 5. Through the meteorological and soil advisory components, AAS help farmers decide when to sow, irrigate, fertilise, spray, harvest and modify farm operations according to the prevailing and forecasted

weather conditions (28). The risk management component enables farmers to prepare for droughts, floods, heat waves, heavy rainfall and other climate-related hazards, thereby reducing potential crop and livelihood losses (29). Notably, the ICT tools component can improve the spatial precision and accessibility of advisories, while socio-economic advisory helps farmers consider input costs, market conditions and profitability (30). Building upon this foundation, AAS offer feedback mechanism which allows farmers to validate and refine advisories, whereas the institutional and policy support component facilitates capacity building programmes to familiarise farmers with climate-resilient technologies and practices through extension agencies, mobile platforms, radio and other locally accessible communication channels (31). For instance, customised climate services increased land productivity by 200 % and doubled labour productivity in Dano, Burkina Faso, despite the consecutive rainfall extremes (32). Similarly, trained farmers achieved approximately 17 % higher yields than untrained farmers in Niger. More recently, climate-informed Information Services for Agricultural Transformation (iSAT) advisories delivered through local language voice services in Senegal increased millet yields by 41 % and groundnut yields by 21 %, demonstrating the importance of localised and accessible advisory delivery for smallholder farmers (33). Therefore, AAS can play a critical role in addressing global agricultural and climatological challenges by enabling farmers to anticipate climatic risks, optimise inputs and natural resources, protect crop productivity and strengthen livelihood resilience under increasing climate variability and change. Apart from these, AAS align with the mission to strengthen the Sustainable development goals (SDGs). The key roles

of AAS in supporting the SDGs extend beyond weather-based crop recommendations to climate-smart agriculture, food security and nutrition, sustainability and

natural resource management, economic empowerment of farmers and global networking and knowledge sharing (Fig. 6).

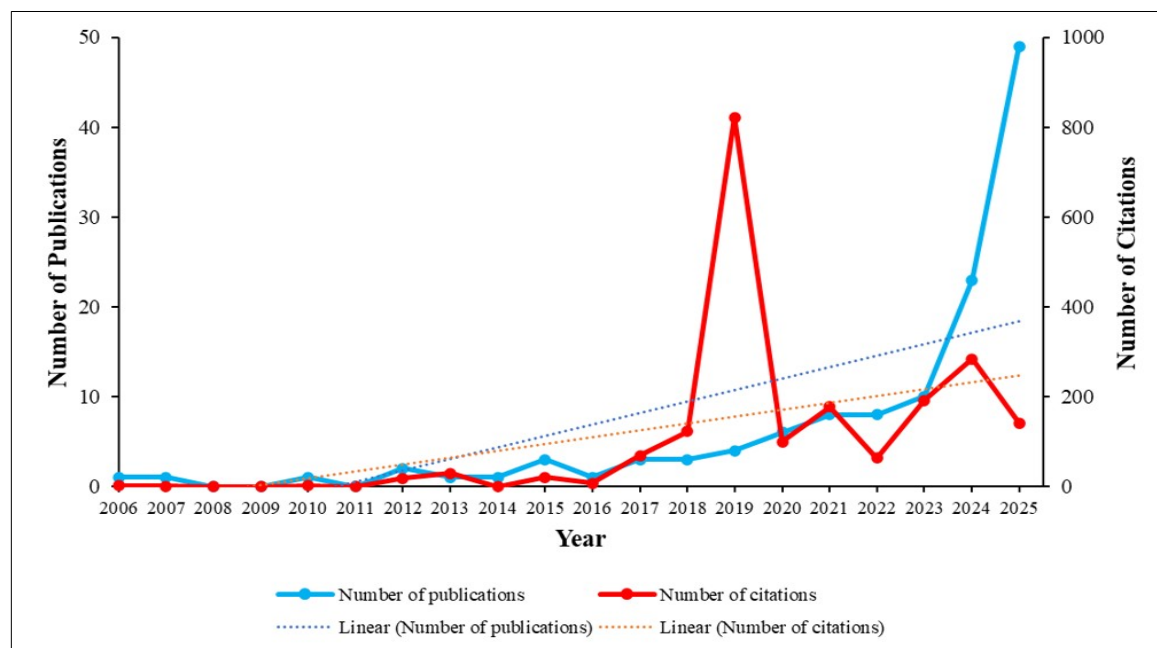


Fig. 3. Year-wise trend in publications and citations.

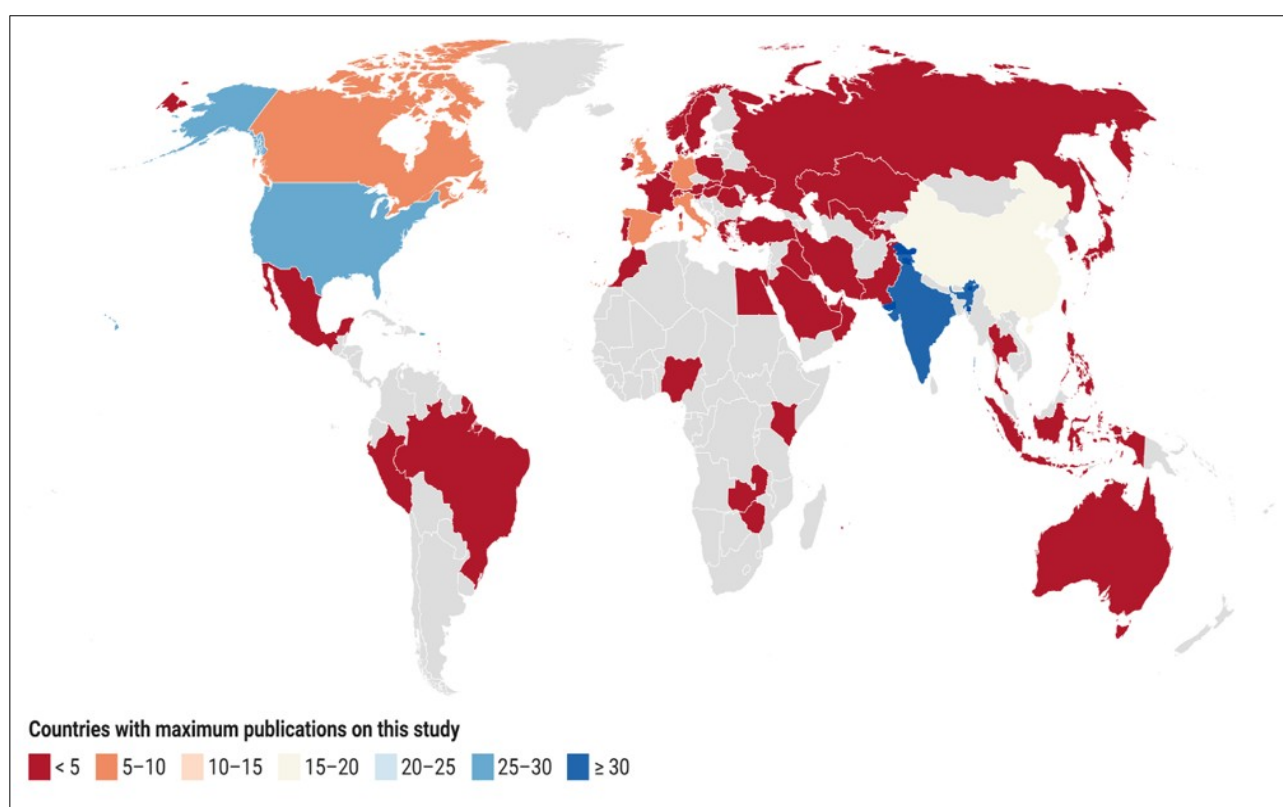


Fig. 4. Country-wise representation of maximum publications.

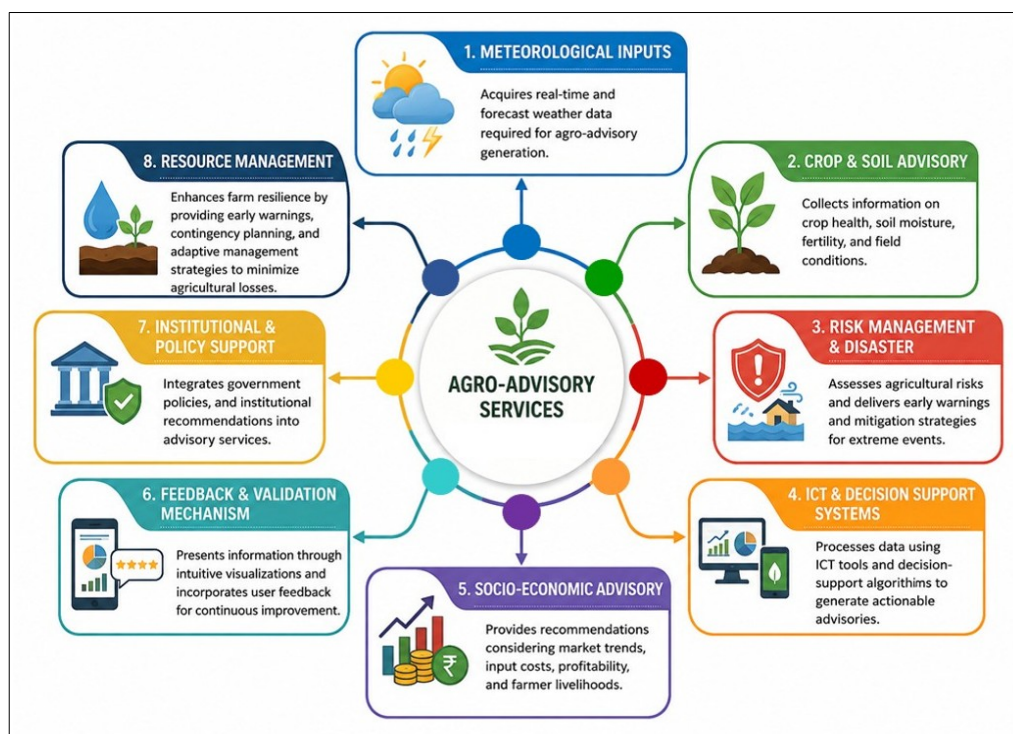


Fig. 5. Components of agro-advisory systems.

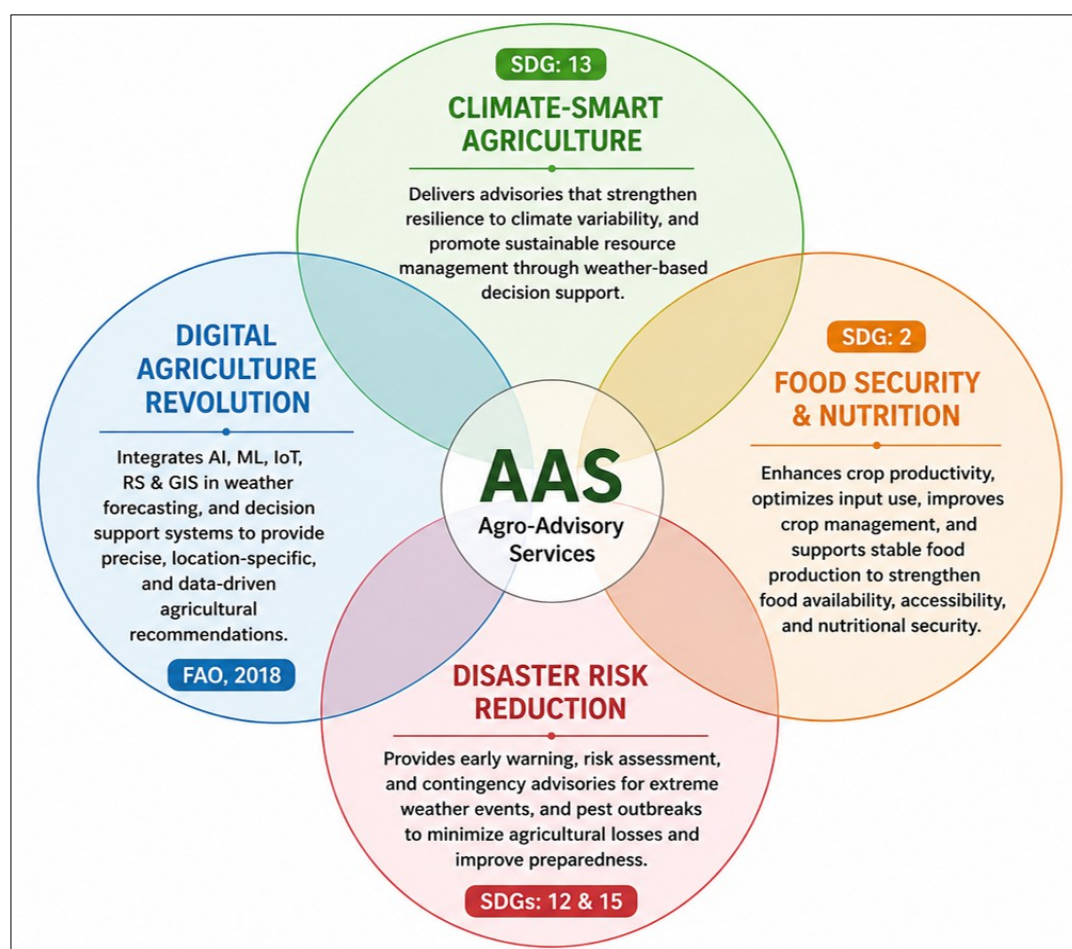


Fig. 6. Key roles of agro-advisory systems.

Climate-smart agriculture

Agro-advisory systems strengthen climate resilience by delivering region-specific recommendations for crop selection, sowing schedules, irrigation management and integrated pest and disease control management. These advisories help farmers adapt to climate variability while contributing to the goals of the Paris Agreement and SDG 13: Climate Action (34). Recent evidence from Ethiopia indicates that access to weather and climate services increased maize and wheat productivity by 27 % and 17 % respectively (35).

Food security and nutrition

The AAS forecasts and recommendations enable farms to maintain food production during climate stress conditions, which helps to meet the projected food demand of a global population nearing 10 billion by 2050, thereby supporting SDG 2: Zero Hunger (36). At present, food insecurity remains a major global challenge, with approximately 8.2 % of the global population experiencing hunger in 2024 and nearly 2.3 billion people experiencing moderate or severe food insecurity (37).

Sustainability and natural resource management

Agro-advisory systems guide farmers, which helps them manage soil fertility and water-use efficiency, resulting in reduced need for chemical inputs, improved resource efficiency and better environmental protection. These practices align with SDG 12: Responsible Consumption and Production and SDG 15: Life on Land (38).

Economic empowerment of farmers

Agro advisories reduce production risks and improve farm profitability by offering market-linked advisories on pricing, timing and diversification into high-value crops and allied sectors (39). For instance, the Asia-Pacific region with a market share of around USD 760 million registered a compound annual growth rate of nearly 15.7 %, largely driven by the increasing adoption of mobile platforms, satellite data and government backed

agro-advisory programs in countries like India and China (40).

Global networking and knowledge sharing

Agro-advisory platforms act as international collaboration tools which enable organisations like The Food and Agriculture Organisation (FAO), Consultative Group on International Agricultural Research (CGIAR), World Meteorological Organisation (WMO) and Indian Council of Agricultural Research (ICAR) to function as worldwide knowledge sharing networks. The networks perform critical functions that deal with agricultural challenges that cross national boundaries, such as desert locust infestations and wheat rust outbreaks (35).

Significance of agro-advisory systems in India: A statistical outlook

Agro-advisory systems have demonstrated significant benefits for Indian farmers across all agro climatic zones and multiple states in India with significant advantages, which include boosting crop yields and reducing operational expenses while increasing profitability (Fig. 7). The National mKisan Portal and Gramin Krishi Mausam Sewa (GKMS) under India Meteorological Department (IMD) system provided continuous local weather forecasts along with the necessary agro-advisory measures that have raised farmer income by 83 % and produced USD 7.575 billion (41). The Gramin Krishi Mausam Sewa (GKMS) report states that, AAS users in Karnataka's rainfed regions achieved yield improvements of 24 kg/acre for pigeon pea, 41 kg/acre for pearl millet, 52 kg/acre for jowar and 102 kg/acre for maize. Similarly, the AAS program in Punjab led to net profit increase of 17–21 % for cotton and 18–26 % for wheat, while 60 % of farmers reported better decision-making capabilities for irrigation, fertiliser application and pest and disease control. Whereas, in Himachal Pradesh the tomato growers experienced tomato yield enhancements between 10 to 12.4 % and they achieved 4.8 to 10.5 % lower cultivation expenses with less pesticide usage of up to 2.1 to 14.7 % (42).

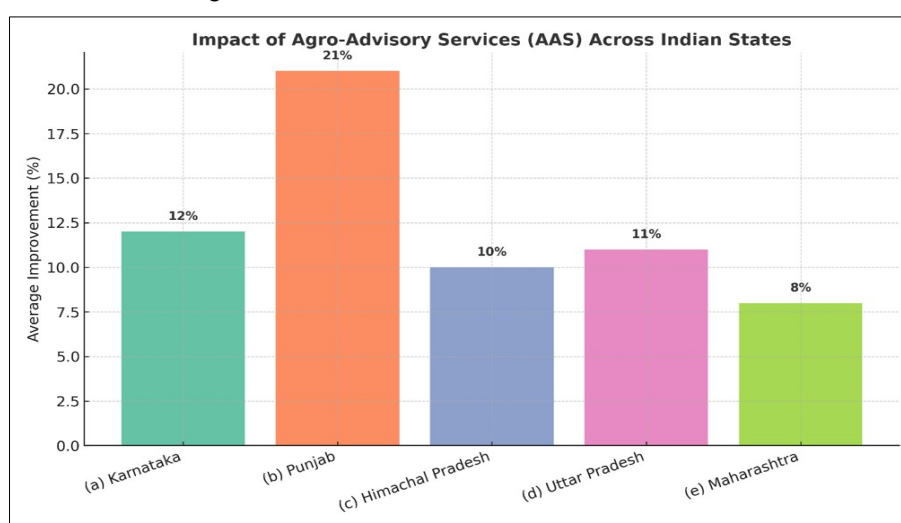


Fig. 7. Average improvement (%) associated with agro-advisory systems. a: yield from multiple crops; b: net profit from cotton and wheat production; c: yield and net profit from tomato production; d: yield from rice, banana and coconut; e: savings/benefits as % equivalent.

In Uttar Pradesh, paddy (6.3–9 % in kharif and 7.3–19.2 % in rabi), banana (10.3–12.2 % under rainfed and 6.4–12.1 % under irrigated conditions) and coconut (7.3–8 %) showed yield improvements (43). Whereas, 35.3 % farmers of Palghar district in Maharashtra saved the production expenses between ₹6000 and ₹10000, while 32 % managed to save up to ₹5000 in production cost (44). Thus, AAS adoption enables farmers across India to achieve 2 to 5 % cost savings and 10 to 25 % better crop yields according to broader analyses conducted by the IMD (45).

Limitations of agro-advisory systems based solely on Automatic Weather Stations (AWS)

Agro-advisory systems that depend exclusively on Automatic Weather Stations (AWS) networks create fundamental obstacles that diminish the capacity to provide precise and dependable results in their operational scope. The primary concern lies in the sparse and uneven distribution of AWS networks because it creates advisories that do not match actual microclimatic conditions in those areas (14). During the process of calibration and maintenance of AWS units, data quality reduces due to inaccurate maintenance procedures (15). Additionally, the operational and maintenance expenses of AWS networks become a financial burden (14). However, most AWS devices only measure basic weather elements which include temperature, humidity, rainfall and wind speed while they do not measure essential agro-meteorological indices needed to create precise crop-specific recommendations (46). Apart from these issues, countries like India are prone to extreme weather events, so there is a high chance of weather induced damages in the AWS infrastructure which results in data interruptions, power outages and network problems for extended periods (2). Moreover, India's topography is highly diverse, meaning AWS placement is not uniform across the country due to logistical difficulties in establishing stations in mountainous terrains, undulating surfaces, dense forests and swampy areas (47). Furthermore, the technical nature of AWS data requires expert interpretation and institutional capacity to transform raw observation data into user-friendly advisory information (28). Therefore, the research demonstrates that AAS systems which depend exclusively on AWS face the risk of generating broad and less dependable alerts hence they require an integrated multi-source data system to enhance agricultural decision support. So, in order to overcome these constraints, satellite products can be utilised to provide the crop advisories (18).

Advantages of satellite-based agro-advisory systems

Integrating satellite and remote sensing data with AWS systems offers several significant advantages for agro-meteorological applications. One of the primary benefits is enhanced spatial coverage. This leads to better representation of regional variability, enabling advisories that reflect diverse agricultural landscapes rather than isolated local conditions (48). Similarly, satellite datasets improve data reliability and continuity by filling gaps, correcting inconsistencies and supporting cross-validation of AWS observations (49). Another key

advantage is the expansion of agro-meteorological parameters, with satellites derived vegetation indices viz., Enhanced vegetation index (EVI), Leaf area index (LAI), Normalised difference vegetation index (NDVI) and Normalised difference moisture index (NDMI) (18). The availability of near real-time data through cloud-based platforms further ensures uninterrupted access, even in cases of connectivity or power issues affecting AWS systems. Moreover, satellite-derived indices (Standardised Precipitation Index and Palmer Drought Severity Index) and thermal data (Land Surface Temperature) enable advanced crop and pest monitoring (50). Satellites also enhance system resilience by acting as a backup source of data when AWS infrastructure fails during extreme weather events (49). Furthermore, the integration of satellite data with GIS, soil maps and land use information allows for the generation of highly customised and location-specific advisories (20). Overall, this integration strengthens the agrometeorological decision support and enhances the reliability of agro-advisories (Table 1).

Mechanism of integrating high-resolution satellite data in Medium Range Weather Forecasting (MRWF) for satellite-based agro-advisory generation

Medium Range Weather Forecasting (MRWF), typically covering a period of 3–10 days, plays a crucial role in agricultural decision-making because it strikes a practical balance between accuracy and usability during agricultural practices (51). It supports a wide range of critical farm decisions such as sowing, fertiliser application, irrigation scheduling, pest and disease management and harvesting. Moreover, MRWF forms the backbone of AAS, where weather-based advisories are issued to farmers at district or village levels twice a week (11). Compared to Short Range Weather Forecasting (SRWF), MRWF enhances preparedness and compared to Long Range Weather Forecasting (LRWF), it improves reliability and operational relevance (51). The foundation of MRWF in India lies in global Numerical Weather Prediction (NWP) models. Among these, the most important is the Unified Model (UM), which runs operationally at high resolution to simulate atmospheric processes (52). In addition, outputs from international models like the Global Forecast System (GFS) are also used as supporting inputs. These models ingest vast amounts of observational data to produce forecasts of temperature, rainfall, wind speed, humidity and pressure up to 10 days ahead (53). A key feature of MRWF in India is the use of Ensemble Forecasting, where multiple simulations are run with slightly varying initial conditions. This approach helps in capturing uncertainty in the atmosphere and provides probabilistic forecasts using a Multi-Model Ensemble (MME) technique, which improves forecast accuracy and reliability compared to any single model (54). However, to make forecasts more relevant at local scales, especially for agriculture, global model outputs are further refined through downscaling techniques. Generally, the Weather Research and Forecasting (WRF) model is used to generate higher-resolution forecasts (55).



Table 1. Comparison between agro-advisory systems based solely on automatic weather stations and agro-advisory systems integrated with geospatial data and automatic weather stations component

AAS based solely on AWS	AAS integrated with geospatial data and AWS component
Sparse network coverage AWS provides data only at specific points, often sparsely distributed	Spatial completeness - Satellites provide continuous spatial coverage - Remote sensing derived gridded datasets capture regional to global variations - Example: Landsat, MODIS, Sentinel etc.
Point specific data AWS data represent only local conditions, not wider variability	Wider area representation - RS and GIS offer large-scale datasets supporting multiple farmers across heterogeneous landscapes - Example: CHIRPS, ERA5, MERRA etc.
Data quality and gaps AWS suffer from calibration errors, outages and data gaps	Cross validation with satellites - Satellite-based climate datasets can be used to cross-validate and fill the gaps in AWS data, ensuring continuity and reliability - Example: IMERG, TerraClimate etc..
Limited parameters AWS usually measure basic weather	Expanded agro-met variables - Satellites provide additional parameters: a. Soil Moisture-Source: SMAP, Sentinel-1 SAR etc. b. Vegetation Health (EVI, LAI, NDVI)-Source: Landsat, MODIS, Sentinel etc. c. Evapotranspiration and Drought Indices-Source: MODIS, SSEBop, SPEIbase etc. d. Solar Radiation and Energy Balance-Source: CERES, ERA5, MODIS etc.
Connectivity and power issues AWS data transfer may fail due to power interruptions	Near real time cloud platforms - It provides near real-time access to global satellite products, bypassing local infrastructure limits - Example: Google Earth Engine (GEE), NASA POWER, etc.
No crop and pest forecasting AWS cannot predict crop condition or pest and disease outbreaks	RS-driven models - Satellite-derived vegetation indices and thermal anomalies help monitor crop stress and predict pest and disease spread - Example: FAO's Desert Locust Monitoring System integrates RS data for transboundary pest early warnings
Vulnerability to weather damage AWS hardware can fail during extreme weather events	Redundancy via satellites Satellites ensure redundant and independent monitoring, keeping advisory services running even if AWS are damaged
Generic advisories AWS-based advisories may be too generic for farmers in diverse landscapes	Customised geo-spatial advisories - GIS integrates AWS along with satellite, soil maps and LULC data to deliver hyper-local customised advisories - Example: Irrigation scheduling, sowing suitability, drought risk maps etc.

AWS: Automatic weather station; RS: Remote sensing; GIS: Geographic information system; MODIS: Moderate resolution imaging spectroradiometer; EVI: enhanced vegetation index; LAI: leaf area index; NDVI: normalised difference vegetation index; SSEBop: operational simplified surface energy balance; SPEIbase: Standardised Precipitation Evapotranspiration Index base; CERES: Clouds and the Earth's Radiant Energy System; ERA5: fifth-generation ECMWF reanalysis; GEE: Google Earth Engine; NASA: National Aeronautics and Space Administration; LULC: land use/land cover; CHIRPS: Climate hazards group infraRed precipitation with station data; MERRA: Modern-Era Retrospective analysis for Research and Applications; IMERG: Integrated Multi-satellitE Retrievals for GPM; SMAP: Soil Moisture Active Passive; SAR: synthetic aperture radar; FAO: Food and Agriculture Organisation of the United Nations.



Mechanism of Weather Research and Forecasting model

The Weather Research and Forecasting (WRF) model functions as a complete modelling system which encompasses multiple components that perform data preprocessing, numerical simulation and post-processing tasks for meteorological data (56).

Weather Research and Forecasting model simulation process consists of four essential stages viz., Collection of input data, WRF Preprocessing System (WPS) mechanism, WRF model core mechanism and post-processing including visualisation (Fig. 8). Among the stages, WPS (WRF Preprocessing System) initiates the workflow by processing input data required for model initialisation and boundary conditions (57). It processes two types of data, which include static geographic information about terrain height, land use, soil type and vegetation, while it also handles dynamic meteorological data, which is acquired from Global Forecast System (GFS) and European Centre for Medium Range Forecasts (ECMWF) sources (58). However, the three main programs of WPS include `geogrid.exe`, `ungrib.exe` and `metgrid.exe`. The final outputs from WPS serve as the essential input for the main WRF modelling system (59).

Following preprocessing, the WRF model core uses either the (Advanced Research WRF) Advanced Research WRF (ARW) dynamic solver or the Nonhydrostatic Mesoscale Model (NMM) core to conduct simulations on the pre-processed data (58). The ARW solver which researchers frequently use depends on two main executables mainly `real.exe` and

`wrf.exe` files which produce the main forecast or simulation outputs at user specified intervals (57). These Network Common Data Format (NetCDF) output files encompass three-dimensional atmospheric and surface variables, which include temperature, wind components, pressure, humidity and precipitation (59). Finally, post-processing and visualisation of WRF outputs are performed using tools like ARWpost, National Centre for Atmospheric Research (NCAR) Command Language (NCL), Python libraries (`wrf-python`, `xarray`, `cartopy`, `metpy`), or software such as Panoply and QGIS (60). These tools allow users to transform model output into different formats that they can analyse and visualise while creating spatial plots and performing temporal studies.

Incorporation of high-resolution satellite products into the WRF model through WRF Data Assimilation (WRFDA) system

Although, GFS and ECMWF data are issued in every six hours (00, 06, 12 and 18 UTC) and forecast files become available within 2–3 hr of issuance, they lack finer resolution and deeper information which can result in less accuracy of the simulation or forecast while computing it for village level advisories. So, in order to improve the accuracy of WRF model simulations, geospatial observations and remote sensing products can be incorporated using the WRF Data Assimilation (WRFDA) system, which blends model generated background fields with external observations to correct and enhance the model's initial state (57).

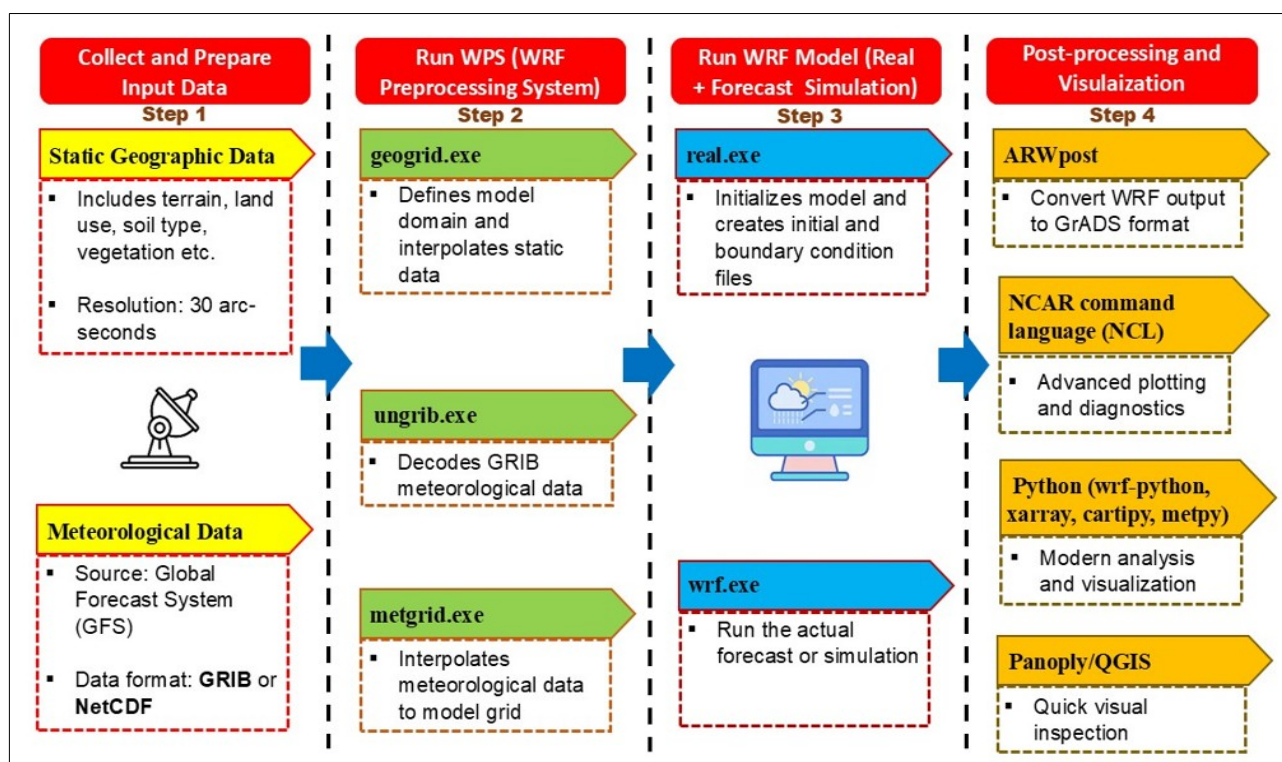


Fig. 8. Mechanism of medium-scale weather forecasting using the Weather Research and Forecasting model.

The process involves four main steps which include identifying and gathering appropriate geospatial data, changing the input data into WRFDA format, selecting the WRFDA assimilation method and conducting WRFDA modelling operations which conclude with visualisation as shown in Fig. 9. The WRFDA uses geospatial data to combine satellite derived radiances, precipitation estimates, soil moisture, vegetation indices, wind vectors, aerosol optical depth and radar reflectivity (61). However, the observations require processing through obsproc.exe or custom scripts, which convert them into Little_R or BUFR formats that the WRF system can use. The WRFDA system also provides multiple assimilation approaches, which include Three-Dimensional Variational Data Assimilation (3DVAR), Four-Dimensional Variational Data Assimilation (4DVAR), Ensemble Kalman Filter (EnKF) and hybrid methods that combine variational and ensemble methodologies (62). Additionally, the model uses observational datasets to improve the initial condition file by generating a new file (wrfvar_output) which replaces the standard wrfinput used in traditional WRF operations (61). As a result, the system improves simulation accuracy for temperature, rainfall, humidity and other meteorological variables through better initial atmospheric and land surface states (63). The forecast accuracy enhancement process begins after the validation of simulated results against actual station data using various statistical metrics (64), mainly Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

During the process, the first and foremost step in the WRFDA system, which includes the identification and gathering of appropriate geospatial (satellite) data, is the most crucial step because the forecast varies based upon the resolution of the satellite products (65). The satellite products which have the potential of using it for block level and village level forecasting are listed in the decreasing order of resolution as represented in Table 2. Among the satellite products (Table 2), Fifth-generation ECMWF Reanalysis (ERA5), Global Precipitation Measurement (GPM) Integrated Multi-satellite Retrievals for GPM (IMERG), Global Satellite Mapping of Precipitation (GSMaP), Indian National Satellite System (INSAT)-3D/3DR, Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS), European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT), Japan Meteorological Agency (JMA) Himawari-8/9, KAI GEO, OpenWeatherMap and Open-Meteo provide information on weather variables at high resolution. In contrast, National Oceanic and Atmospheric Administration (NOAA) Visible Infrared Imaging Radiometer Suite (VIIRS), Moderate Resolution Imaging Spectroradiometer (MODIS) (Terra/Aqua) and TROPospheric Monitoring Instrument (TROPOMI) on Sentinel-5P lack sufficient information on weather variables. These products mainly contain geophysical and topographical datasets, including variables such as

Land Surface Temperature (LST), Sea Surface Temperature (SST), aerosol concentration and greenhouse gas (GHG) emission flux. Among these techniques, each satellite data is subjected into the WRFDA system and validated to identify the most suitable satellite data which contain the information of majority of the variables with best forecast accuracy. Sometimes, the most suitable satellite product lacks certain meteorological variables, so in that case the satellite data that gives the best forecast accuracy for that particular variable is selected and the agro advisory is generated using a multi-satellite approach (66). Those satellite products with poor forecast accuracy (values reaching below the threshold range given by the various statistical metrics) are discarded. Overall, the assimilation of geospatial datasets improves the weather forecasts and enhances the agro-advisory with accurate, reliable and wider forecast information for the successful dissemination of village-level and block-level agrotechnology transfer (16, 49).

Constraints in leveraging high-resolution satellite products in the WRF model

The WRF model experiences primary operational delays and latency in receiving the high-resolution satellite data because the majority of the high-resolution satellite products require several hours to multiple days for their processing and pre-processing (80). Therefore, waiting for delayed high-quality data is not practical because the prediction of weather patterns remains essential, as it enables people to prepare for sudden extreme weather (81). To address this problem, forecasters implemented multiple data collection methods by beginning their model setup with fast access to global NWP datasets (GFS and ECMWF data that become available within 1 to 3 hr), later the high-resolution satellite data from near real time sources (e.g. Moderate Resolution Imaging Spectroradiometer (MODIS) near-real-time (NRT), Visible Infrared Imaging Radiometer Suite (VIIRS) near-real-time (NRT) and Integrated Multi-satellite Retrievals for GPM (IMERG)) are added whenever the data becomes available within six hours of its collection. This methodology is known as the Forecast Now and Correct Later strategy (61). Thus, real-time forecast accuracy is achieved using operational and near real-time data sources initially, while delayed high-quality satellite observations are assimilated later to refine the simulation or reinitialise the model (82). This integrated method allows regional weather forecasting systems to deliver results that meet both timing and accuracy requirements (61). For instance, researchers use blended datasets to maintain forecasting continuity, such as combining GFS forecasts with Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG) rainfall estimates or using past satellite records (83). Another promising method is the integration of ML and DL techniques in weather forecasting and downscaling. This combinational framework offers enhanced capabilities for data reconstruction and high-resolution downscaling (84).

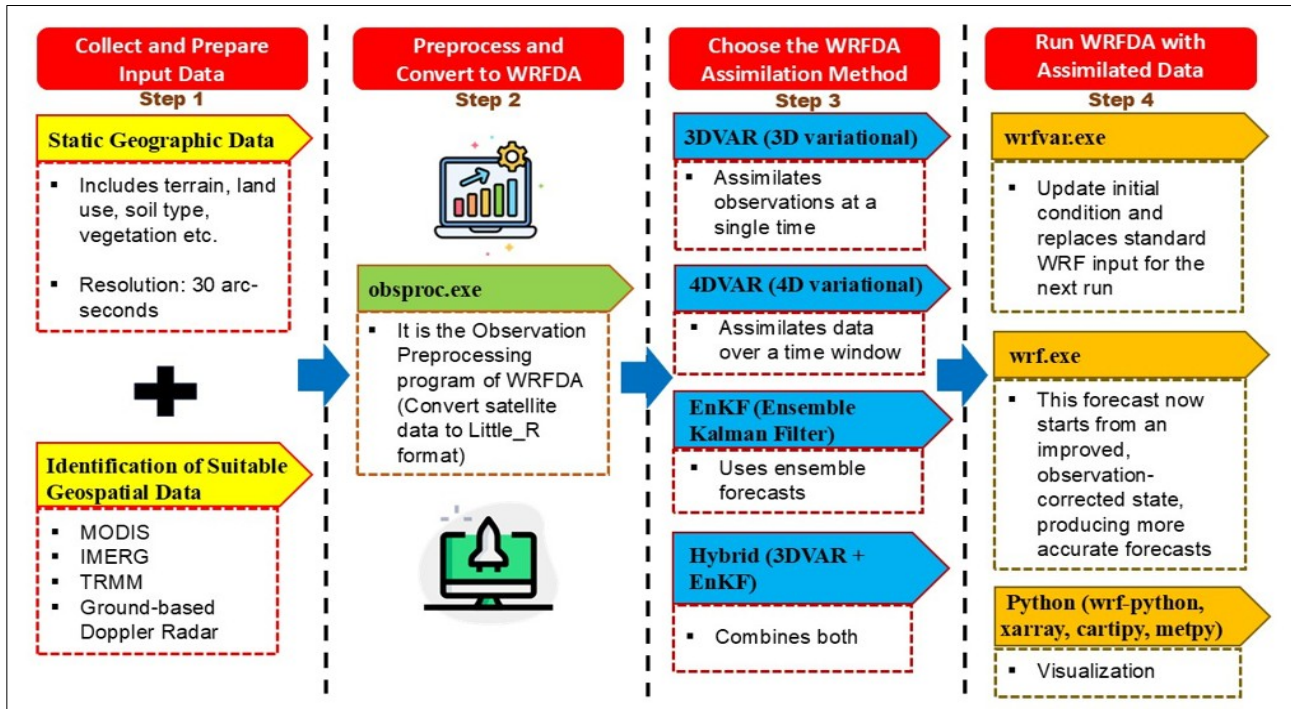


Fig. 9. Mechanism of incorporating satellite data in the weather research and forecasting model using the WRF data assimilation system.

Table 2. High resolution satellite datasets applicable for village and block level agro-advisory generation in India

Satellite products	Weather variables	Resolution	Latency period	Coverage	Study (Year)
ERA5-Land Hourly - ECMWF (Fifth generation) Climate Reanalysis	Evaporation, MaxT, MinT, Pressure, RF, RH, SR, WS	11.1 km	1 week	Global	(67)
GPM IMERG: Global Precipitation Measurement- Integrated Multi-satellite Retrievals	RF	11.1 km	1 day	Global	(68)
GSMaP Operational: Global Satellite Mapping of Precipitation	RF	11.1 km	1 day	Global	(69)
Open-Meteo (Aggregated Satellite + NWP Models)	CC, Humidity, RF, SR, Temperature, WD, WS	1–11 km	1 hr	Global	(70)
CHIRPS Daily: Climate Hazards Center Infrared Precipitation with Station Data	RF	5.6 km	2 days	Global	(71)
Indian National Satellite System (INSAT) composite - MOSDAC	CC, Fog, LST, OLR, RF, WS	4 km	30 min	India and South Asia	(72)
European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT)- Meteosat-9,10,11	CC, LST, RF, SR, SST, WS,	3 km	15 min	Europe, Africa, and Indian	(73)

JMA Himawari-8/9	Aerosols, CC, RF, SST, WS	0.5–2 km	10 min	Asia-Pacific	(74)
KAI GEO – Korean Multi-purpose Satellite KOMPSAT-2A (AMI)	Aerosols, CC, Rainfall, SST	0.5–2 km	10 min	Asia-Pacific	(75)
OpenWeatherMap (Satellite + Radar)	CC, Humidity, Pressure, RF, Temperature, UV index, WS	1 km	10 min	Global	(76)
Sentinel-5P Tropospheric Monitoring Instrument (TROPOMI)	Aerosols, Cloud physical properties and GHGs	1 km	2 days	Global	(77)
Moderate Resolution Imaging Spectroradiometer (MODIS) - Terra and Aqua	Aerosols, Albedo, CC, LST, SC, SST	0.25–1 km	1–2 days	Global	(78)
NOAA Visible Infrared Imaging Radiometer Suite (VIIRS)	Aerosols, CC, LST, SC, SST, Vegetation	375–750 m	1–2 days	Global	(79)

(Weather variables: CC: Cloud cover, GHGs: Greenhouse gases, LST: Land surface temperature, MaxT: Maximum temperature, MinT: Minimum temperature, OLR: Outgoing longwave radiation, RF: Rainfall, RH: Relative humidity, SC: Snow cover, SR: Solar radiation, WD: Wind direction, WS: Windspeed, SST: Sea surface temperature and UV: Ultra violet).

Potential of ML and DL models in satellite-based weather forecasting

Several studies found that ML methods function as time-based solutions for satellite data delays, which affect real-time WRF-based forecasting (85). The ML models are trained using historical satellite observations alongside meteorological predictors from NWP models such as GFS and prior WRF runs, which enable them to learn the spatio-temporal relationships between model outputs and high-resolution satellite observations (86). This approach is particularly valuable where conventional dynamical downscaling is computationally expensive, or the satellite-derived inputs are too delayed for operational use (87). At present, a wide range of ML and DL models have been used in weather forecasting (Table 3). These models include ensemble-based techniques like Random Forest (RF) and XGBoost, kernel-based strategies like Support Vector Regression (SVR) and geostatistical models like Gaussian Process Regression (GPR). On the deep learning side, encoder-decoder systems, feedforward and recurrent architectures and foundation and generative models are represented. Furthermore, spatiotemporal hybrid models including Convolutional Long Short-Term Memory (ConvLSTM) and Convolutional Gated Recurrent Unit (ConvGRU) are also included.

The rapid advancement of these models has enabled data-driven approaches that can learn complex, nonlinear spatiotemporal relationships directly from satellite-derived datasets, often at a fraction of the computational cost of conventional NWP simulations (19). Architectures such as Convolutional Neural

Networks (CNNs) capture spatial patterns in satellite imagery and Long Short-Term Memory (LSTM) networks model temporal evolution, while hybrid frameworks like ConvLSTM and U-Net integrate both dimensions for short-term nowcasting tasks (91, 92, 96, 97). Furthermore, Table 4 summarises representative studies employing satellite-based ML and DL models for forecasting key atmospheric variables, including rainfall, temperature, solar radiation, cloud cover and aerosols. These studies demonstrate the diversity of model architectures, satellite data sources, forecast horizons and performance metrics, highlighting the growing potential of satellite-driven ML and DL approaches to enhance the accuracy, spatial resolution and operational capability of modern weather forecasting.

From research to operational deployment: Framework for scaling satellite-based AAS for utilisation by farmers and future implications

Satellite-based AAS integrated with ML and DL models detailed the considerable potential of improving the spatial and temporal accuracy of weather forecasting. However, high predictive performance demonstrated under research conditions does not necessarily translate into operational readiness. The transition from experimental models to operational AAS requires an integrated framework encompassing computational infrastructure, data management, human capacity, economic viability, institutional coordination and farmer adoption (110). Recent developments in operational AI-based weather prediction by ECMWF require dedicated high-performance computing, data pipelines, software frameworks, validation procedures and technical expertise

rather than the model alone (111). So, computational infrastructure represents one of the primary constraints for developing countries like India. Conventional machine learning (ML) models such as Random Forest (RF), Support Vector Machine (SVM) and gradient boosting approaches generally require comparatively lower computational resources. In contrast, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Convolutional Long Short-Term Memory (ConvLSTM), U-Net, generative models and large foundation models require substantial computational resources for training, particularly when high-resolution satellite imagery and long historical datasets are involved (112). Moreover, operational implementation requires reliable data storage systems, automated workflows, institutional computing environments, backup systems, reproducible datasets and resources for model training. Therefore, computationally efficient models and shared pre-trained models could make advanced forecasting more feasible (113).

Secondly, capacity building is equally important for converting technological advances into usable AAS. Operational systems require trained personnel capable of interpreting forecast uncertainty, validating ML/DL based predictions and translating satellite-derived meteorological outputs into crop-specific recommendations. At the farmer interface, extension personnel must be able to communicate probabilistic and technical information in locally understandable forms.

Thus, capacity building should extend from model developers and meteorological institutions to extension workers and ultimately to farmers (114). Thirdly, data governance and standardisation constitute another major requirement for operational AAS. Advanced AAS combine satellite observations, IoT measurements, reanalysis products, crop information and socioeconomic datasets (16). Differences in spatial resolution, temporal frequency, coordinate systems, units, metadata and quality-control procedures can hinder seamless integration. Therefore, operational AAS should adopt standardised data formats, quality-control protocols, metadata requirements, uncertainty documentation, interoperability standards and defined data-sharing and ownership policies (115). Fourthly, cost-benefit assessment is essential before scaling technologically enriched AAS. The economic evaluation should move beyond model performance metrics and determine whether computational and infrastructure costs generate measurable benefits for farmers. For instance, AAS adoption enabled farmers achieve 2–5 % hike in cost savings and a 10–25 % increase in crop yields across India (45). Whereas, the Brazilian Agricultural Research Corporation (EMBRAPA) initiated Agricultural Zoning of Climate Risk (ZARC) and AgroAPI which integrated satellite imagery, vegetation indices and weather data under a common platform for enhanced agro advisory, which ultimately resulted in generation of USD 410 million in Latin American (116).

Table 3. Overview of machine learning and deep learning models used in weather forecasting

Model name	Model type	Model mechanism	Study (Year)
Random Forest (RF)	Ensemble based ML model	a. RF construct a large number of decorrelated decision trees by bagging and random feature selection at each split, then averaging their predictions to reduce variance and improve generalisation over single decision trees	(88)
Gradient Boosting Machine (GBM) and XGBoost	Ensemble based ML model	a. GBM iteratively fit shallow decision trees to the residuals (errors) of the current ensemble using gradient descent in function space b. XGBoost is an optimised and scalable implementation of gradient boosting with column subsampling and parallel tree construction	(89)
Support Vector Machine (SVM) and Support Vector Regression (SVR)	Kernal based ML model	a. SVM finds the maximum-margin hyperplane that separates classes with the largest possible gap and reduce overfitting whereas SVR is SVM extended to regression	(90)
Convolutional Neural Network (CNN)	Convolutional DL model	a. CNN has learnable convolutional filters, pooling layers and shared weights which can automatically extract hierarchical spatial features	(91)
U-Net	Encoder-Decoder DL model	a. U-Net is a symmetric encoder-decoder CNN with skip connections that bridge corresponding encoder and decoder layers at each resolution scale b. This allows the decoder to recover fine-grained spatial detail lost during down-sampling, enabling precise pixel-level segmentation from very limited labelled training data	(92)
Artificial Neural Network (ANN) and Deep Neural Network (DNN)	Feedforward DL model	a. ANN, DNN and MLP compute gradients of a loss function through a network of layers using the chain rule, enabling efficient training of multi-layer perceptrons and establishing the modern supervised deep learning paradigm	(93)
Pangu-Weather	Foundation DL model	a. Pangu-Weather is a 3D Earth specific Swin Transformer trained on 39 years of ERA5 reanalysis, using four	(94)

Generative Adversarial Network (GAN)	Generative DL model	hierarchical sub-models (1hr, 3 hr, 6 hr, 24 hr)	(95)
		b. It is the first AI based model to outperform ECMWF Integrated Forecasting System (IFS) on all tested variables and all lead times from 1 hr to 7 days	
Long Short-Term Memory (LSTM)	Recurrent DL model	a. GAN is a game theoretic framework where a generator network learns to produce realistic synthetic data by competing against a discriminator network that learns to distinguish real samples from generated samples	(96)
		a. LSTM is a gated recurrent architecture with an input gate, forget gate, output gate and a separate cell state that allows the network to selectively store, update and retrieve information across arbitrarily long sequences	
ConvLSTM	Convolutional + Recurrent DL model	a. ConvLSTM model is described as a solution for spatiotemporal modelling by replacing the matrix multiplication operations inside LSTM gates with 2D convolutions	(97)
ConvGRU	Convolutional + Recurrent DL model	a. ConvGRU applies the GRU gating mechanism with convolutions instead of matrix multiplications, which create a lighter alternative to ConvLSTM with two convolutional gates (reset and update) instead of three	(97)

RF: Random forest; GBM: Gradient boosting machine; XGBoost: Extreme gradient boosting; SVM: Support vector machine; SVR: Support vector regression; CNN: Convolutional neural network; U-Net: U-shaped network; ANN: Artificial neural network; DNN: Deep neural network; MLP: Multilayer perceptron; Pangu-weather: Pangu weather; GAN: Generative adversarial network; LSTM: Long short-term memory; ConvLSTM: Convolutional long short-term memory; ConvGRU: Convolutional gated recurrent unit; ML: Machine learning; DL: Deep learning; ERA5: Fifth-generation European Centre for medium-range weather forecasts (ECMWF) Reanalysis; ECMWF: European Centre for medium-range weather forecasts; IFS: Integrated forecasting system.

Table 4. Satellite based weather forecasting using machine learning and deep learning architecture

Satellite data	Model name	Model type	Sample size	Forecast horizon	Key findings	Study (Year)
Rainfall						
CHIRPS v2.0	Categorical Boosting (CatBoost), XGBoost and LSTM	Ensemble based ML model, Recurrent and Convolutional DL model	Decadal rainfall: Training samples (1981–2018); Testing samples (2019–2025)	90 days	i. This study developed a ML and DL based precipitation forecasting framework for four semi-arid Moroccan oasis regions (Errachidia, Figuig, Tata, Zagora) using CHIRPS v2.0 ii. The results inferred that CatBoost emerged as the best model ($R^2 = 0.9818$)	(98)
GPM IMERG	ConvLSTM (Convcast)	Convolutional + Recurrent DL model	Point data: Training samples (1276 points); Testing samples (242 points)	150 min	i. The study used an embedded ConvLSTM architecture for short-term precipitation nowcasting using GPM IMERG satellite data at 30 min interval ii. The results showed an overall accuracy of 0.93 with RMSE = 0.805 mm/hr at 30 min lead time and 0.87 with RMSE = 1.389 mm/hr at 150 min lead time	(99)
GPM IMERG + GFS	ConvLSTM + U-Net	Convolutional-Recurrent + Encoder-Decoder DL model	Point data: Training samples (100000 points); Testing samples (15000 points)	4 hr	i. The study presented a hybrid ConvLSTM + U-Net DL architecture for 30 min global precipitation nowcasting using GPM IMERG and GFS data ii. The regression network excelled at light precipitation	(100)

Spinning Enhanced Visible and Infrared Imager (SEVIRI) – Meteosat	PAUNet	Encoder-Decoder DL model	Point data: Training samples (159235 points); Testing samples (840 points)	4–8 hr	(<1.6 mm/hr)	
					i. This study introduced PAUNet for precipitation prediction from multi-band satellite radiance	(101)
					ii. The results demonstrated Critical Success Index (CSI) scores above the Weather4cast 2023 baseline across multiple forecast time slots	
Temperature						
ERA-5	ConvLSTM and SAVP (Stochastic Adversarial Video NW Prediction)	Convolutional-Recurrent and Generative DL model	Hourly temperature: Training samples (11 years); Testing samples (1 year)	12 hr	i. The study forecasted hourly air temperature over Europe using the SAVP model and the ConvLSTM model	
					ii. The results showed lower MSE (2.3 K ²) in the air temperature values forecasted using the SAVP model, whereas the ConvLSTM model yielded higher MSE	
MODIS + Sentinel	ANN	Feedforward DL model	Overall samples (14600 records)	24 hr	i. The study implemented an ANN-based weather prediction using Earth observation data from meteorological stations and large satellite datasets for hourly air temperature forecasting in the Ararat Valley, Armenia	
					ii. The model achieved 87.31 % accuracy for 3 hr ahead predictions and 75.57 % accuracy for 24 hr ahead predictions	
SEVIRI	RF	Ensemble-based ML model	Overall samples (126 weather stations)	24 hr	i. The study developed and validated a methodology for Near Surface Air Temperature (NSAT) estimation using RF regression with 20 selected Land Surface Analysis Satellite Application Facility LSASAF satellite predictors and topographic parameters over Greece	
					ii. The results achieved MAE of 0.96 °C, MBE of −0.01 °C and R ² of 0.976	
					iii. Model performance was consistent under both cloud-free and cloudy conditions with limited seasonality effects	
Solar radiation						
FY-4A (FengYun-4A) Geostationary Satellite	RF and SVM	Ensemble-based ML model (70 % of samples used for training and 30 % for testing)	Training samples (70 % of daily data); Testing samples (30 % of daily data)	1–6 hr	i. In this study, intra-day GHI (Global Horizontal Irradiance) was predicted using FY-4A satellite data	
					ii. The results showed that RF consistently outperformed SVM with high R ² value (0.9)	
					(105)	

Himawari-8	CNN + MLP	Convolutional + Feedforward DL model	Hourly global radiation: Training samples (90 stations); Testing samples (8 stations)	1 hr	i. The study developed a hybrid deep network combining CNN for spatial feature extraction and MLP to incorporate time/location metadata for hourly global solar radiation estimation (106) ii. The results demonstrated RMSE improvements over conventional ML models
MSG (Meteosat Second Generation)	DGM (Deep Generative Model) and U-Net	Generative and Encoder-Decoder DL model	Sample size not available	1–4 hr	i. The study used DGM and U-Net model for solar radiation nowcasting, wherein U-Net achieved lowest RMSE and MAE for majority of the months whereas DGM excelled in qualitative performance (107)
Cloud cover					
Meteosat	ConvLSTM and U-Net	Convolutional-Recurrent and Encoder-Decoder DL model	Overall samples: (2017–18 images)	1.5 hr	i. The study tested two DL architectures (ConvLSTM and U-Net) on Meteosat satellite imagery for binary cloud cover nowcasting (108) ii. Among the models, U-Net achieved best performance, surpassing the traditional NWP models with respect to MSE values at 90 min lead time
Aerosols					
MERRA-2	RF	Ensemble-based ML model	Overall samples: (266094 hourly observations)	1 day	i. The study used NASA MERRA-2 reanalysis satellite products to estimate hourly and daily surface PM _{2.5} concentrations in Thailand using an RF model (109) ii. RF achieved high correlation ($R = 0.95$) and near-zero mean bias when validated with the observed data
Multi variables					
ERA5 reanalysis (ECMWF)	Pangu-Weather	Foundation DL model	Training samples (1979–2017 years); Testing samples (2018 year)	7 days	i. The study used Pangu-Weather, a 3D vision transformer for global medium-range weather forecasting (94) ii. This DL model reported RMSE = 10 % lower than IFS and 30 % lower than FourCastNet

ML: Machine learning; DL: Deep learning; CHIRPS: Climate hazards group infraRed precipitation with station data; GPM: Global precipitation measurement; IMERG: Integrated multi-satellitE retrievals for GPM; GFS: Global forecast system; SEVIRI: Spinning enhanced visible and infraRed imager; PAUNet: Pyramid attention U-Net; ERA5: Fifth-generation European Centre for medium-range weather forecasts reanalysis; SAVP: Stochastic adversarial video prediction; ANN: Artificial neural network; MODIS: Moderate resolution imaging spectroradiometer; Sentinel: Sentinel satellite programme; RF: Random forest; LSASAF: Land surface analysis satellite application facility; MBE: Mean bias error; MAE: Mean absolute error; R^2 : Coefficient of determination; FY-4A: FengYun-4A; SVM: Support Vector Machine; GHI: Global Horizontal Irradiance; CNN: Convolutional Neural Network; MLP: Multilayer Perceptron; MSG: Meteosat second generation; DGM: Deep generative model; MERRA-2: Modern-Era retrospective analysis for research and applications, Version 2; NASA: National Aeronautics and Space Administration; PM_{2.5}: Particulate Matter with an aerodynamic diameter of $\leq 2.5 \mu\text{m}$; ECMWF: European Centre for medium-range weather forecasts; IFS: Integrated forecasting system; RMSE: Root mean square error; NWP: Numerical weather prediction; CSI: Critical success index.

Finally, farm-level adoption remains the most critical determinant of operational success. Importantly, participation, trust, credibility, timely delivery and multimodal communication are the major determinants of climate information service utilisation. Whereas poor infrastructure, difficulties in interpreting forecasts, local language limitations and insufficient attention to farmers' crop calendars result in reduced adoption of the technologies (114). Overall, the transition from research to operational deployment should follow a phased pathway rather than direct implementation of laboratory-developed models. Initially, the satellite-based AAS integrated with ML/DL models should undergo historical hindcasting and independent validation using standardised datasets (86), followed by multi-season and multi-location evaluation across India's contrasting agro-climatic zones. Later, models that demonstrate sufficient robustness should undergo local calibration and bias correction (117). Finally, the forecast performance, advisory quality, computational requirements, economic benefits and farmer acceptance are evaluated simultaneously based upon the pilot studies.

2. Conclusion

This review provides a conceptual framework that connects high-resolution satellite observations, Weather Research and Forecasting (WRF) Data Assimilation and artificial intelligence-driven forecasting within a unified agro-advisory architecture. Through bibliometric and systematic analyses, the study reveals a rapidly growing global research interest in the importance of remote sensing and artificial intelligence for addressing the agricultural challenges in a country like India, where diverse topography and climatic heterogeneity demand weather information at much finer spatial scales. Overall, the study illustrates how satellite products can be assimilated into numerical weather prediction systems to improve forecast accuracy and facilitate the generation of reliable block-level and village-level advisories. At the same time, it highlights the potential of machine learning (ML) and deep learning (DL) models to overcome the data latency constraint in satellite-based forecasting through data reconstruction. Furthermore, among the machine learning (ML) models, ensemble-based and kernel-based models emerged as the most promising tools for weather prediction and downscaling applications. Whereas, among the deep learning (DL) architectures, encoder-decoder models, generative models, feedforward models, foundational models and convolutional-recurrent models emerged as highly efficient for capturing complex spatio-temporal relationships and generating accurate forecasts. However, the future utilisations depend on the successful integration of computational infrastructure, skilled human resources, economic feasibility, institutional coordination and farmer acceptance. Ultimately, the future of satellite-based agro-advisory systems (AAS) lies in developing computationally efficient, economically sustainable and farmer-centric platforms that translate complex Earth

observation and forecast information into timely, understandable and actionable decisions. Such a transition can enable AAS to evolve from research oriented technological demonstrations into practical decision-support infrastructure for climate-resilient and precision agriculture.

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Authors' contributions

FP performed data curation, formal analysis, writing of the original draft and contributed to reviewing and editing the manuscript. SK supervised the study and contributed to reviewing and editing the manuscript. GD conceptualised the structural framework of the article. TR reviewed and edited the bibliometric analysis. KV reviewed and edited the tables. SD reviewed and edited the figures. DJ provided the statistical information on the significance of agrometeorological advisory services. KPR summarised the advantages and limitations of satellite based agrometeorological advisory services. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest

Authors do not have any conflict of interests to declare.

Ethical issues

None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude in order to summarise the articles for better understanding. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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