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Historical and contemporary crop yield prediction models: Key lessons and innovations

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ABSTRACT

Crop yield prediction models (CYPMs) are essential for ensuring global food security and sustainable agricultural planning. This systematic literature review compared the overview of historical and contemporary CYPMs evolution, challenges, innovations, and key lessons learned from peer-reviewed literature. The study analyzed peer-reviewed papers published between 2015 and 2025, sourced from the Scopus, Web of Science, and PubMed databases, following PRISMA guidelines. Twenty-three studies met the inclusion criteria and were evaluated for methodological quality and risk of bias. Historical empirical and mechanistic models offered valuable theoretical foundations but were limited by data scarcity and scalability. Contemporary approaches, particularly those using machine learning, deep learning, and remote sensing, demonstrated superior predictive accuracy (R^2 = 0.85–0.93) compared with traditional models (R^2 = 0.60–0.75). Key lessons emphasize the importance of data integration, contextual calibration, and expert validation. Persisting challenges include computational demands and limited applicability in data-scarce regions. The review concludes that hybrid, interpretable, and resource-efficient models are critical for improving prediction reliability and achieving sustainable, equitable food systems.

1. Introduction

The UN report [1] demonstrates that the global population is projected to increase from 7.7 billion in 2019 to 8.5 billion in 2030 with (10 % increment), and 9.7 billion in 2050 with (26 % increment). Tilman et al. [2] suggested the global population is increasing at unpredicted rate and in 2050, additional 60 % food is necessary. Foley et al. [3] stated that there must be a significant change in agriculture like in crop yields, resource utilization, and sustainable farming practice because of the necessity to produce more food in the next 40 years more than the previous 8000 years farming practice. On the other hand, World Food and Agriculture Organization-FAO [4] reported that in 2050, an additional 70 % food is required. To achieve food security, it needs a great effort in improving agricultural innovations with science and technology to provide immediate agricultural solutions. Science and Technology innovations support building resilient agriculture that is not easily collapsed with climate change and other agricultural barriers. Climate variability greatly reduces food production and agricultural activity. Lobell et al. [5] estimated that climate change can reduce the food production by 10–25 % in 2050. The situation urges to ensure food security and provide accurate prediction of food accessibility around the world. Therefore, it is essential to provide yield models that help the agriculture prediction through early warnings, resource allocation, risk management, climate adaptation, integration of technologies (i.e., AI prediction models) to address food security. Yield prediction models are indispensable for modern agriculture, offering solutions to challenges such as resource scarcity, climate change, and food security. Jabed et al. [6] highlighted the role of Artif. Intell. Agric. for addressing food security and sustainability.

Crop yield prediction models have evolved significantly over the years. It evolved as a simple empirical process to advanced data-driven and machine learning approaches, recently. Models from pre-1980s era

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were based on basically uses historical types of simple statistical regression analysis and empirical crop yield modelling was done by integrating weather and soil factors. Fisher et al. [7] provided the earliest statistical approach to understanding a crop yield variability. After the 1980s the process based (Mechanistic) crop yield models have evolved and add more properties of crops like photosynthesis, respiration, and nutrient cycling. Computationally intensive data analysis models like DSSAT and APSIM were developed. Jones et al. [8] discussed about DSSATs interdisciplinary research application to solve problems in agricultural farming. After 1990s, remote sensing and GIS (Geographical Information System)-based large geographical area yield prediction models evolved by analyzing vegetation indices using satellite and drone imagery. Lobel [9] reviewed the use of remote sensing in yield prediction and crop yield gap analysis. After 2000s, the machine learning (ML) approach was developed to capture complex data and non-linear relationships with large datasets in crop yield predictions [10]. In 2010s, deep learning, big data and cloud computing revolutionized yield prediction used to process complex and high dimensional data with high accuracy and scalability [11]. Recently, precision agriculture and Internet of Things (IoT) have enhanced agriculture practice through data-driven decision making, advanced tools, and technologies to monitor, analyze, and manage agricultural practices [12]. IoT with smart sensors and drones enables real-time agricultural monitoring for yield predicts [13]. The historical details will be explained in (Section 3) of the review.

This review is aimed at systematically comparing historical and recent crop yield prediction models. The primary goal of this paper is to analyze the most typical approaches to the issue, and their strong and weak points, and hence, the paper intended to draw conclusions about the development of prediction models through history. Besides, it comes along the path of the next generation, and the different ways that this mathematical methodology may be useful to set up a world production system that is sustainable and less affected by food production are also demonstrated. The outcome of this systematic review is not focus on making new model like primary research, but a novel comparative framework and a synthesized knowledge base. The effectiveness of our review methodology will be demonstrated through its ability to delineate clear evolutionary patterns, extract transferable lessons, and identify critical, actionable gaps in the field of crop yield prediction.

While numerous reviews have examined either historical crop yield modelling approaches or recent advances in machine learning-based prediction, the paper presents a novel, systematic comparison that bridges these two eras. Unlike the existing literature that often treats historical and contemporary models in isolation, our work integrates empirical, mechanistic, remote sensing, machine learning, deep learning, and hybrid modelling paradigms within a unified analytical framework. We go beyond technical descriptions to extract cross-generating lessons, identify persistent challenges in low-resource contexts (e.g. Ethiopia), and evaluate how innovations such as real-time IoT integration, multimodal data fusion, and AI-driven scalability address (exacerbate) these gaps. Furthermore, this review is among the first to explicitly link model evolution to food security outcomes in data-scarce environments, advocating for context-sensitive, hybrid solutions that balance accuracy with accessibility. This integrative and equity-focused perspective constructs the core novelty of our contribution. Therefore, the study aims to address the following specific objectives:

- To systematically compare historical and contemporary CYPMs in terms of their methodological approaches, data requirements, scalability, accuracy, real-time adaptability, and technological integration,
- To identify the key lessons learned from both historical (empirical and mechanistic) and contemporary (machine learning, deep learning, remote sensing, IoT-enabled) models that can inform current and future agricultural modelling practices, particularly in scarce data regions,
- To synthesize recent innovations in CYPMs (including AI-driven architectures, multimodal data fusion, real-time sensing, and hybrid modelling) and evaluate their contributions to improving prediction accuracy, resilience to climate variability, and support for global food security,
- To critically assess the performance limitations and practical challenges of existing models across diverse agroecological and socio-economic contexts, with emphasis on data quality, computational demands, interpretability, and accessibility,

The study provides a scientific contribution such as:

i) Providing an overview of early and recent crop prediction models in general,
ii) Making a comparison between different measuring features of traditional and modern crop yield prediction models,
iii) The key lessons learned from both crop yield prediction models demonstrate an important insight or knowledge from an experience passed through successes and failures in crop yield prediction,
iv) Discussing the key innovations achieved towards accurate crop yield prediction for accurate yield predictions,
v) Identifying the key challenges faced in both crop yield prediction models in different measuring circumstances.

The remaining part of the paper is arranged as follows: Section 2 brings the systematic research approach applied in this study. Section 3 discusses the general overview of Historical and Contemporary Crop Yield Prediction Models. Section 4 reveals a critical review based on selected literature and a meta-synthesis of the studies to draw insight into crop yield prediction models. Section 5 deals with the conclusion which illustrates the role of the study, its significance, and limitations. Lastly, Section 6 indicates the future research consideration to improve crop yield prediction techniques.

2. Research methodology

2.1. Justification for research methodology selection

This study used a systematic review of literature approach, based on Charter and Kitchenhams' guidelines for the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach [14], to accomplish its objectives. The primary aim of this study is to synthesize and compare the vast and heterogeneous body of research on crop yield prediction models (CYPMs) across different technological eras. To achieve this objectively and comprehensively, a Systematic Literature Review (SLR) was identified as the most suitable research method. This choice is justified on both theoretical and practical grounds. First, SLR is designed to address broad, synthesis-oriented research questions like ours through a systematic, reproducible, and unbiased process for identifying, evaluating, and interpreting all relevant literature [14]. This is in direct contrast to traditional narrative review, which risks being non-comprehensive and influenced by author selection bias. Given our objectives to provide a balanced comparative overview, the rigorous structure of an SLR was imperative.

To ensure the highest standard of reporting and conduct, this SLR adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. PRISMA was selected because it provides a globally recognized and validated framework that enhances transparency, accuracy, and completeness of systematic reviews. The use of the PRISMA flow diagram (Fig. 1), for instance, is a critical tool for documenting the article selection process and ensuring reproducibility.

The literature search was conducted across three major databases: Scopus, Web of Science (WoS), and PubMed. This multi-database approach was taken to mitigate database coverage bias and ensure the most exhaustive retrieval of relevant literature possible. Scopus and

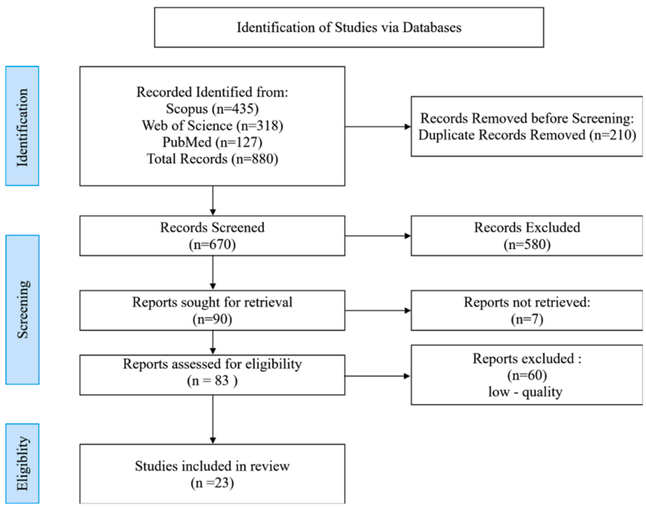

Fig. 1. PRISMA 2020 flow diagram illustrating the study identification, screening, and inclusion process:.

WoS are the leading multidisciplinary citation databases with extensive coverage in engineering, computer science, and agricultural sciences. PubMed was included to capture interdisciplinary studies at the intersection of agronomy, environmental science, and biology that might be missed by the other two.

Finally, the nature of the collected studies (geographical focus, specific models, publication type, time frame) precluded to analysis. Therefore, the data analysis was conducted through a structured narrative synthesis. This established qualitative methodology allows for the systematic organization of finding into thematic categories (e.g., comparison factors, challenges, innovations) to draw robust, evidence-based conclusions and identify overarching patterns in the field. This approach is uniquely suited to answer our "what", "how", and "why" questions regarding the evolution and lessons of CYPMs.

2.2. Research questions (RQs)

Research questions were designed to guide the whole review process in providing help in consistent, coherent, and structured synthesis and summary of works of literature. Hence, the following research questions developed to reach the objectives.

RQ1: What is the difference between the Historical and Contemporary crop yield prediction models in different measuring circumstances?

This question involves answering the detailed difference between the two models in different aspects like data requirement, scalability, prediction accuracy, methods it uses, and other related criteria.

RQ2: What are the main challenges of historical and contemporary crop yield prediction models in different measuring scenarios?

This question encompasses the main challenges faced during the application of crop yield prediction models. There were different tackling factors towards yield model application like environmental factors, technology, skill and techniques, data access and quality, adaptability, and other immutable field factors will be discussed

RQ3: What are the key lessons learned from historical and contemporary crop yield prediction models that inform current practices?

In this context, both crop yield prediction models have provided valuable insights, and lessons learned from their application in agricultural research and practice will be discussed.

RQ4: What are the innovations in crop yield prediction models, and how have they shaped the field for global food security?

This research question addresses the great revolutions in crop yield prediction due to its importance in accuracy, scalability, real-time prediction, and other factors used for agriculture for recent and future trend predictions. In addition to this, the role of these models towards global food security will be described.

2.3. Article search strategy

The article search strategy was planned based on the intent of systematic literature review and the research questions. The data for this review was sourced from the academic databases: Scopus, PubMed, and Web of Science. These databases were selected due to possessing high-impact factors related to technology and agriculture, broad search tools for academic publications, reliable resources for articles, and large databases for peer-reviewed literature. The key characteristics of the collected literature were defined by a focus on crop yield prediction models. The search queries combined general terms (e.g., "Crop Yield Prediction"), historical keywords (e.g., "Empirical", "Mechanistic"), and contemporary keywords (e.g., "Machine Learning", "Remote Sensing", "IoT") as described in (Table 1). The authors used two stage deduplication process. The first stage is performed automated deduplication reduction by using Rayyan AI tool. Then, the rest is manually verified by the research team.

2.4. Article selection criteria

The selection criteria for articles were defined to ensure the review was based on relevant and high-quality dataset. The primary characteristics of the included data were:

- Temporal Scope: Primarily recent works (2015–2025), with supplementary inclusions of seminal historical references (pre-1980s) to contextualize foundational modeling approaches.
- Publication Venue: Peer-reviewed journal articles, and conference proceedings from reputable sources.
- Model types covered: Empirical, mechanistic, machine learning (e.g., Random Forest, SVM), deep learning (e.g., CNN, LSTM), remote sensing-based, IoT, and hybrid models.
- Geographic Distribution: Studies originated from 18 countries, with a majority from high-income nations (e.g., USA, China, EU members); only limited representation from low-income regions such as Sub-Saharan Africa (including Ethiopia).
- Language: Exclusively English language publications.
- Content: Studies that provided empirical data, case studies, or comparative analyses of CYPMs performance, including discussions on challenges, lessons learned, or innovations.

The Boolean operators (e.g., OR, AND, and NOT) were used to enhance searches and combine related terms. The subsequent screening process based on titles, abstracts, and full texts, as illustrated in the PRISMA flow diagram (Fig. 1), ensured the final dataset adhered to these characteristics.

2.5. Exclusion, inclusion standards and prisma approach

The review included peer-reviewed journal article papers that analyzed both old and modern crop yield prediction models; papers across geography, datasets, and agricultural practices; studies that deal with crop yield prediction using modern technology or methods. Exclusion criteria applied in other cases did not focus on crop yield prediction; articles that do not satisfy the comparison between old and new methods; journals that are not peer-reviewed and lack methodological particulars that have general qualification check assessment as expressed in Table 2.

Time Frame: The search included relevant articles published from 2015 to 2025 for analysis. We will prioritize articles that were published during recent years for quality and accuracy. However, some papers that include historical crop yield modeling added to fill the historical data gap.

Language Restriction*:* The articles published in English language

Table 1
Search queries and database filters.

Databases	Search Query	Date Executed	Filters Applied
Scopus	TITLE-ABS-KEY ((“crop yield” OR “yield prediction” OR “yield forecast”) AND (“empirical model” OR “mechanistic model” OR “machine learning” OR “deep learning” OR “remote sensing”OR “IoT” OR “internet of things”) AND (“challenges” OR “lesson” OR “innovation” OR “comparision”)) AND PUBYEAR > 2014 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE, “English”)) AND (LIMIT-TO(DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”))	March 6, 2025	English Language
Web of Science	TS=((“crop yield” OR “yield prediction” OR “crop modeling”)) AND TS=((“empirical model” OR “mechanistic model” OR “DSSAT” OR “APSIM”) AND TS= ((“machine learning” OR “deep learning” OR “LSTM” OR “CNN” OR “random forest”)) AND TS=((“remote sensing” OR “Sentinel-2″ OR “MODIS” OR “IoT” OR “hybrid model” OR “big data” OR “evolution”)) AND DT=(Article OR Proceedings Paper) AND PY=(2015–2025) AND LA=(english)	March 8, 2025	English Language
PubMed	((“crop yield” [Title/Abstract] OR “yield prediction” [Title/Abstract] OR “yield forecast” [Title/Abstract]) AND (“empirical model” [Title/Abstract] OR “mechanistic model” [Title/Abstract] OR “machine learning” [Title/Abstract] OR “deep learning” [Title/Abstract] OR “remote sensing” [Title/Abstract] OR “IoT” [Title/Abstract]) AND (“challenge” [Title/Abstract] OR “lesson” [Title/Abstract] OR “innovation” [Title/Abstract] OR “comparison” [Title/Abstract])) AND ((“2015/01/01″ [Date - Publication]: “2025/03/10” [Date - Publication])) AND English [la] AND (journalarticle [pt] OR congresses [pt])	March 10, 2025	English Language

only considered to ensure consistency and accuracy in interpretation.

Screening: First, articles were searched. Then, titles, abstracts, and keywords were checked. After that, we read the full text to make sure we include only good and relevant papers. We also looked at the references of the chosen articles (snowballing) to find more studies that were not found in the initial search. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) 2020 guidelines [14], the article selection process was systematically documented to ensure transparency and reproducibility. The search was conducted in Scopus, Web of Science, and PubMed using predefined keywords and Boolean operators targeting studies published between 2015 and 2025. After removing duplicates, records were screened by title and abstract for relevance, and full-text articles were evaluated based on the predefined inclusion and exclusion criteria. Fig. 1 presents the detailed PRISMA 2020 flow diagram summarizing this process.

Table 2
Checklist provided for article Quality check.

No	Provided weighting Checklists	Description/Evaluation Focus
Q_1	Objective clarifications	Are the study’s goals clearly defined and aligned with the results?
Q_2	Methodological rigor	Does the study use clear and appropriate methods?
Q_3	Relevance to the review topic	Is the study directly related to CYPMs?
Q_4	Data transparency	Are data sources and assumptions clearly described?
Q_5	Analytical robustness	Are performance metrics (R^2, RMSE, MAE,) well defined and validated?
Q_6	Reproducibility & documentation	Are model codes, datasets, or workflows described for replication?
Q_7	Fills knowledge gap	Does limitations, challenges & innovations addressed?
-	Overall quality score	Total score (Yes=1, Partial=0.5, No=0); include cutoff ≥70 % for inclusion.

The flow chart summarizes the systematic selection of studies retrieved from Scopus, Web of Science, and PubMed databases between 2015 and 2025. Out of 880 initial records identified, 210 duplicates were removed, leaving 670 unique records for screening. After title and abstract screening, 580 records were excluded for irrelevance. Ninety full-text reports were sought for retrieval, with seven not accessible. A total of 83 articles were assessed for eligibility, and 60 were excluded for not meeting inclusion criteria (e.g., drawbacks seen such as insufficient methodological detail, and lacking comparative analysis). Finally, 23 studies were included in the systematic review and synthesis.

2.6. Article quality check criteria

A standardized data extraction and quality assessment process was employed. Two reviewers independently extracted data from each included study, capturing details on authors, year, objectives, methodology, and key findings. The methodological quality and risk of bias of each study were then evaluated using a pre-defined 7-point checklist adapted from Kitchenham and Charters [15] (Table). The checklist assessed clarity of objectives, methodological rigor, data transparency, analytical robustness, and reproducibility. Each item was scored as “Yes” (1), “Partial” (0.5), or “No” (0). Inter-rater reliability was substantial (Cohen’s k = 0.61–0.80) to almost perfect (Cohen’s k = 0.81–1.0), and all discrepancies were resolved through consensus. Studies scoring ≥ 5/7, a pre-specified threshold indicating acceptable methodological quality, were included in the synthesis.

In general, the search strategy aims to ensure a detailed, systematic collection of relevant literature, providing a comprehensive understanding of evolution, innovations, and lessons learned from both historical and contemporary crop yield prediction models.

3. Overview of crop yield prediction

The section provides a clear overview of Crop Yield Prediction and Crop Yield Prediction models. It deals with general history, components (such as technology, data source, and modelling approaches), different factors used for comparison, application, and introduction in historical as well as contemporary in crop yield predictions as shown in (Fig. 2). The section will be used further for discussion and analysis.

3.1. Crop yield prediction models (CYPMs)

Crop yield prediction has evolved over time through advancing

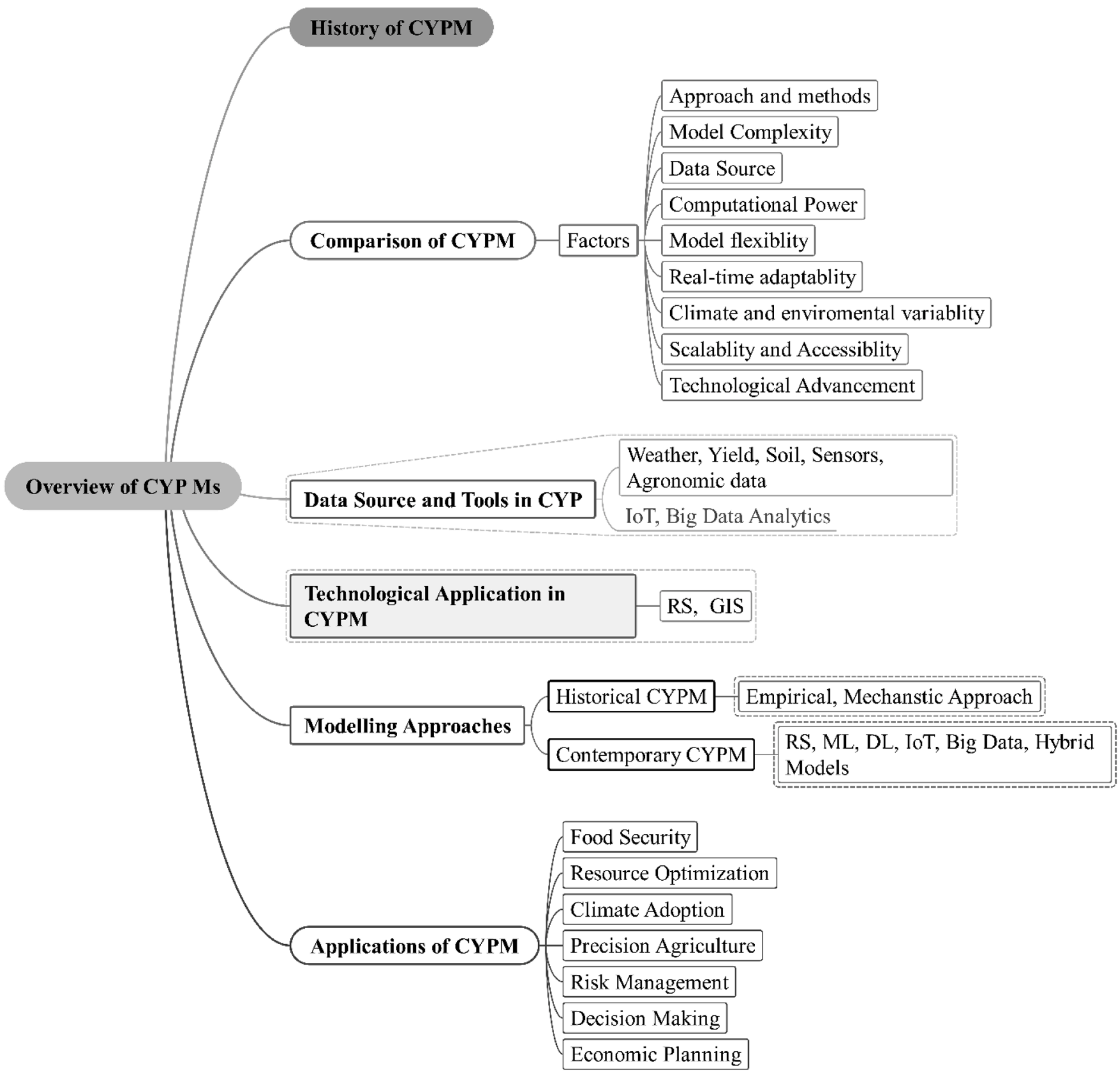

Fig 2. Overviews of Crop Yield Prediction Models.

statistical methods, computing power, data availability, and the growing need for predictive tools. Crop yield prediction modeling has its roots in the early 1900s, when scientists started relating crop yields to environmental variables like temperature and rainfall using simple statistical techniques. Simple regression models were created between the 1920s and 1950s to forecast yields from observed data. According to Jones et al. [16], the need to comprehend how crops react to environmental variability led to the advent of quantitative approaches in agriculture through this time. Although these early models were empirical with limited datasets and simple statistical methods, they laid the groundwork for more advanced predictive modeling. Crop yield prediction models became formalized in the 1960s to 1970s as both empirical and mechanistic methods were developed and gained popularity.

Based on monthly weather data, empirical models used regression techniques were proposed by Thompson [17] for crops like corn and wheat in USA, which is simple, data efficient, and used for specific regions. Subsequently, a mechanistic approach was proposed by Stewart et al. [18] using water stress model by including relationships like evapotranspiration and yield. After these the interest of modelling for crop management and climate impact studies, driven by advances in computing and data collection [19]. During the 1980s mechanistic crop yield models show a significant advancement in computing power and solving environmental challenges. Wen Guang et al. [20] proposed a soybean yield simulation model using thousands of equations to describe factors such as light interception, carbon partitioning, and nutrient uptake, representing a milestone in mechanistic modeling intricacy. In the 1990s remote sensing and geographical information system (GIS) used refining and validating crop yield prediction models. Baez Gonzalez et al. [21] explained how satellite-derived leaf area index (LAI) to reduce errors during calibration in observation, by using to improve empirical yield prediction for maize crop in Mexico. Empirical models also adapt advanced solving techniques including the nonlinear models. Schlenker et al. [22] developed empirical models to predict yield responses to temperature extremes in the USA, showing the non-linear effects of temperature on many crops. As Basso et al. [23] developed a mechanistic model which validated across diverse crops and regions, simulating daily variables like biomass and nutrient uptake to support accurate yield forecasting.

In 2000s the emergence of Machine Learning and Big Data which marked as a transformative period for a crop yield prediction model. You et al. [22] applied deep learning models, specifically LSTM and CNN, to predict soybean yields in the U.S using high resolution satellite and weather data gives a promising result over traditional approaches. In 2010s to present is characterized by a paradigm shift in crop yield prediction due to availability of diverse and real time data assimilation, technological advancements, high computational power, and integration of other interdisciplinary approaches. Filippi et al. [24] used real-time satellite and weather data, achieving higher accuracy in wheat crop yield prediction in Australia, by gaining continuous data update during growing seasons.

3.2. Comparison factors for crop yield prediction

These factors are used to evaluate how well a predictive model performs in terms of usability, reliability, and impact on agricultural decision-making. The criteria were selected based on technological modelling advancement, challenges in crop yield prediction (like environmental property, data availability), and practical applications. Among the main comparison criteria are model complexity, approach and methods used, data source, model accuracy, computational power, model flexibility, real-time adaptability, scalability and accessibility, climate and environmental variability, skill/expert dependency, and technological advancements.

3.2.1. Approach and methods

It includes a variety of techniques and strategies employed to predict yield outputs. These methodologies combine diverse data sources and analytical techniques to enhance yield prediction accuracy. Therefore, these approaches and methods collectively contribute to the development of robust models for accurate crop yield prediction, supporting informed decision-making in agriculture practice. In crop yield prediction approaches (i.e. Machine learning, Deep learning, hybrid models), and methods (i.e. data collection, feature selection, model training, performance evaluation) can create reliable models that predict crop yield.

3.2.2. Data source

Crop yield prediction needs diverse and high-quality data like metrological data, soil characteristics data, yield history data, and agricultural management practice data from different sources for building a robust yield prediction model. The ability to access and quality of these data influence the performance of predictive models [25], [26].

3.2.3. Model complexity

It is the sophistication of a predictive model, encompassing factors like number of parameters, model structure, and complexity of relationships that it can capture. Simpler models couldn't fully handle underlying data patterns, potentially leading to underfitting. On the other hand, complex models could signify intricate patterns in data but may also be prone to overfitting, where it may learn noise instead of identifying broader, generalizable trends. Engen et al. [27] indicated that used a hybrid large number of parameters of satellite images and weather data through Convolutional Neural Network (CNN) to enhance prediction accuracy. Due to model complexity during training, it used stochastic epoch sampling to mitigate overfitting during model training.

3.2.4. Computational power

The capacity of computing devices and systems to process and analyze vast and complex datasets using advanced algorithms (like machine learning and deep learning models) for yield prediction is very necessary. Recently, predictive models have become sophisticated, as a result it needs high computational resources to operate high dimensional data, perform calculations, and generate accurate and timely predictions. The advancement of computational power enhances crop yield prediction models, enabling the processing of large datasets and the application of complex algorithms. Jeong et al. [28] discussed combining deep learning models and process-based crop models as a hybrid model and emphasizing the computational demands associated with integrating these complex systems [28]. As a result, high computational power factors can develop efficient and scalable predictive models and allow timely and informed decision making in agriculture.

3.2.5. Model flexibility

The adaptability of reliable and accurate predictive models to support diverse crops, environmental conditions, and data inputs was essential. Filippi et al. [24] emphasized the advantage of building a machine learning crop yield prediction model that integrates many data layers (such as soil variation, terrain, weather, and satellite imagery) to make a prediction, thereby enhancing model flexibility [24]. The improvement of flexible models is so important in developing robust crop yield prediction approach capable of making decision making with in diverse agricultural circumstances.

3.2.6. Real-time adaptability

The need for dynamic adjustment of predictive models is based on ongoing changes in environmental conditions, crop development stages, and management practice in agriculture by integrating with real-time adaptability. The approach integrates advanced technologies such as machine learning, IoT, and remote sensing to improve the accuracy and timeliness of yield prediction [29].

3.2.7. Scalability and accessibility

These factors are essential in crop yield prediction models, due to their effectiveness and usability in different applications circumstances of agriculture.

Scalability indicates the ability of predictive models and systems to effectively handle increasing amounts of data which perform an analysis in large areas. D. Lobell et al. [30] developed a scalable satellite-based crop yield mapper model that was applied in large (extensive) area for estimating maize crop yield in Midwestern of United States. Accessibility shows the easiness of utilizing tools and the availability of necessary data in crop yield prediction. It encompasses user-friendly interfaces, affordable technologies, and open access data for safeguarding predictive insights are attainable for diverse users.

3.2.8. Climate and environmental variability

These factors had important application in crop yield prediction that the fluctuations in climatic factors (like temperature, precipitation, and humidity) and environmental conditions (soil properties and topography) that influence crop growth and productivity. Gardner et al. [31] demonstrated how temporal and spatial variations microclimate data affect climate suitability, providing better approximations of predicted yields and informing agricultural decision making.

3.2.9. Skill and expert dependency

In crop yield prediction, the extent of accuracy and reliability of predictive models relied on the expertise and specialized knowledge in the area of agriculture. These factors include the ability to select appropriate variables, preprocess data effectively, choose suitable modelling techniques, and interpret model outputs accurately. Van Klompenburg et al. [32] provided a machine learning based decision support tool for crop yield prediction supporting in crop growth and growing seasons. This explains the role of expert knowledge in effectively utilizing machine learning algorithms in decision making. Moreover, Jabed et al. [33] demonstrated the application of deep learning, machine learning remote sensing, and considering factors affecting crop yield prediction. These underscore the necessity of different expertise in integrating different technological approaches and data sources.

3.2.10. Technological advancements

The advancement of technology in crop yield prediction enables the analysis of complex datasets, encompassing environmental conditions, soil characteristics, and crop health indicators enabling precise and accurate prediction. Advanced integration of modern technologies (such as machine learning, remote sensing, IoT devices, and advanced data analytics) that enhance accuracy and efficiency of crop yield prediction. Jabed and Murad [33] reviewed the importance of machine learning and deep learning technology in yield prediction. Moreover, it emphasizes the role of remote sensing data integration with machine learning to observe critical insights in crop growth and growth estimation [33].

3.3. Technology application in crop yield prediction

The use of technology in crop yield prediction indicates that the application of scientific knowledge and tools to enhance efficiency in yields forecast. Several technologies and tools used to predict the crop yield prediction (such as remote sensing, Geographic Information System (GIS), IoT, Big Data analytics and other technology) are commonly used in crop yield prediction.

3.3.1. Remote sensing technology (RS)

RS indicates non-physical contact by covering large geographical areas with the use of satellite or drone imagery to collect data about a crop's health and growth for the estimation of yield by analyzing vegetation indices and other derived parameters for spatial and temporal information's with greater accuracy [34]. Remote sensing technology is comprised of sensors (which detect electromagnetic radiation emitted from earth surface), platforms (such as devices to carry satellite, drone or ground-based systems), and data processing systems (including software for analysis) [35]. Remote sensing is equipped with multi-function sensor technologies like thermal, optical (hyperspectral-*high resolution in specific area band* and multispectral-*moderate resolution over large area coverage bands*) [36], radar and microwave, LiDAR, Atmospheric sensors, and more functions with different satellite bands. *Remote atmospheric sensors* measure the atmospheric conditions and properties, such as humidity, aerosol levels, pressure, gas concentration, and temperature [37], [38]. Pantya et al. [39] provided a soyabean crop yield prediction by integrating remote sensing based atmospheric climate data, and vegetation indices. *Optical sensors* capture wavelengths of visible light, near infrared, and shortwave infrared that are reflected from the Earth's surface [40]. *Radar and microwave sensors* are remote sensing technologies which use microwave (wavelengths ranging 1 cm to 1 m) to observe the Earth's surface [41]. It detects light and dark conditions and applied in all types of weather conditions (i.e. effective in any cloud cover penetration, and extreme weather properties unlike optical sensors). *Thermal remote sensing* refers to the use of thermal infrared part of electromagnetic spectrum which measures the temperature of objects in a range of $3 - 14$ μm at a distant which emitted by the objects [42]. Ahmad et al. [43] reviewed the impact of water stress in crops by using a remote sensing based thermal sensing system in land surface temperature. *LiDAR remote sensing technology* in crop yield prediction uses laser pulses to measure distances and create high-resolution three-dimensional images on the Earth's surface [44]. It applied in crop canopy structures, crop height and biomass estimation, and yield prediction. Choudhary et al. [45] proposed a non-parametric grain yield estimation of wheat crop using thermal, microwave and optical remote sensing techniques in India.

3.3.2. Geographic information system (GIS)

GIS technology used to capture, store, interpret, analyze, manage, and demonstrate spatial data for the users by maps, reports and charts by using computer hardware and software applications. Sentil G.A et al. [46] provided a yield prediction mapping system with GIS technology helps accurate, real time, and effective decision makings. Li et al. [47] proposed a GIS based model focused on agricultural decision making and crop yield simulation. The proposed model effectively improved the crop yield prediction management.

3.3.3. IoT

IoT technology is the integration of technologies such as sensors, data analytics, and connectivity for real-time monitoring and decision making in crop yield prediction. IoT enhances accuracy, resource optimization, higher yields, and risk mitigation in crop yield prediction [48]. Galavarni et al. [49] proposed a smart irrigation system using IoT technology. Tzounis et al. [50]discussed the integration of IoT in agriculture, in the application of precision farming and yield prediction.

3.3.4. Big data analytics

This technology designed to access, store, process, integrate, analysis, and extract valuable insights from large and complex datasets in yield prediction [51]. Big data analytics basically performs huge tasks like data storage, data processing, data querying, data integration, data analytics, data visualization, data management, and decision support system. Oussous et al. [52] reviewed about various big data analytics technology features, advantages, limitations, and applications with different layers, including data storage, processing, querying, accessing, and management. Bibri et al. [53] examined the key data processing platforms and cloud computing technologies that are essential for big Data analytics. Chergui et al. [54] discussed the architecture of big data analytics systems in agriculture, focusing on data analysis layers, data types, sources, gathering techniques, and learning algorithms. Jharna Majumdar et al. [55] explored the application of Big Data in crop yield prediction through the data mining process.

3.4. Data sources and tools in crop yield prediction

Data sources in crop yield prediction include both historical and real-time data. There are common crop yield data sources like weather data, soil data, agricultural practice, remote sensing data, and historical yield data. Other agricultural data tools such as IoT sensors, Cloud computing system, and Big data analytics are tools for processing, collecting and handling data.

3.4.1. Weather data

Weather data are crucial in yield prediction. Weather data enables short term yield prediction, long term yield projections and risk assessment during yield losses. Weather data recorded hourly, daily and monthly in satellite or in station levels such as minimum and maximum temperature, wind speed, humidity, solar radiation, evapotranspiration, precipitation, wind pressure, and other data used for yield prediction. Kumar et al. [56] reviewed the importance of weather property data on crop yield prediction. Singh et al. [57] studied the effect of weather properties like temperature, rainfall, and humidity in crop yield prediction by using machine learning.

3.4.2. Soil data

Soils are important factors for growth and yield of crops. Fischer et al. [58] provided soil qualities for crop production. Soils have physical property such as soil structure, bulk density, soil texture (sand, silt, clay content), water holding capacity and drainage, soil depth and compaction, Chemical properties like soil pH, nutrient content (Nitrogen, Phosphorus, Potassium, and micronutrients), cation exchange capability, organic matter content, soil organic carbon, and salinity levels, and *Biological properties* like microorganisms, soil biodiversity, nitrogen fixation, and soil respiration that greatly influence the yield prediction [59–60]. K.Samundeeswari et al. [61] proposed a system to predict crop yield from soil data using decision tree and C5.0 algorithms, implemented using R software. Mahesh T R and Sindhu Madhuri G. et al. [62] employed a decision tree algorithm to predict crop yield based on soil moisture parameters, aiming to enhance agricultural productivity. Tziachris et al. [63] provide a soil property dataset from 2015–2019 in Greece, comprising 781 surveys. with 16 individual parameters. Depending on the crop type, these soil factors influence should be aggregated and optimized for better yield forecasting [64].

3.4.3. Agronomic practices data

Agronomic data refers to the collection and analysis of information using various techniques and methods related to crop yield prediction [65]. It is a vast use of data and information throughout agricultural practice. Some common data which consider agronomic practice includes soil and weather data. Others crop data like crop type and variety, plantation date, growth stage, seed quality, yield data, crop station schedules: fertilization application data, pest and disease data, weed management data, harvest data, environmental data are necessary for accurate yield predictions. S.Pereira et al. [66] studied water usage and irrigation data for efficient monitoring of resource and improve crop yields. Xing and Wang [67] performed practical research in tracking fertilizer application rates and nutrient uptake efficiency to minimize environmental impact. Jha et al. [68] provided weed management data and herbicide application principles.

3.4.4. Historical yield data

Historical yield data basically refers to the recorded information on the yields of crops over a specified period in the past. It serves as a basis for future predictions because it provides a quantitative record of past yield data. It helps to understand climate condition, technology uses, crop yield amount and distribution, and risk assessment in crop failure. Lobell et al. [69] used historical yield data to investigate the influence of climate change on global crop production. Generally, historical crop yield data have a great importance in making trend analysis, model calibrations, yield predictions and risk assessments [70].

3.4.5. Remote sensing data

Remote sensing-based yield data refers to the collection of information from several sensors attached in satellites or unnamed aerial vehicles, or ground-based vehicles to monitor crop health, growth stage, and environment conditions. Remote sensing gathers a lot of data by the equipped sensor technology. Among those data weather data (temperature, precipitation, humidity, etc.), soil data, crop physiology, soil moisture, crop structure and species, plant height and canopy structure, and other data collected with different remote sensing techniques. Using optical and multispectral based remote sensing crop yield data gathers vegetation indices like Natural Difference Vegetation Indices (NDVI), Enhanced Vegetation Indices (EVI), etc., can be identified. Mena et al. [71] developed an adaptive crop yield prediction model as Multiview gated fusion model that integrates a Sentinel-2 multi-spectral optical images, weather data, soil properties, and topographic information to predict crops like soybean, wheat, and rapeseed in Argentina, Germany, and Uruguay and gained better result from the conventional. M.Sanchis et al. [72] proposed by combining multisensory data in Enhanced Vegetation Index (EVI) from MODIS satellite, and Vegetation Optical Depth (VOD) from Soil Moisture Active and Passive (SMAP), to estimate crop yields. Cunha et al. [73] described a five-year crop yield prediction including remote sensing data, crop calendars, and weather forecast information to provide accurate pre-season and in-season yield through addressing cloud cover using a deep learning model. Joshi et al. [74] discussed a deep learning-based model as an effective tool for mapping and yield prediction from remote sensing data. Kumari et al. [75] also reviewed a crop yield prediction method by remote sensing, crop model, and crop assimilation to enhance crop monitoring and yield prediction at large-scale.

3.4.6. IoT in crop yield prediction

The use of smart sensors, wireless data communication, cloud computing, and Machine learning to make Decision Support Systems by examining environmental conditions and predict agricultural output is now possible using IOT [76]. The IoT architecture integrates sensors (e.g., soil pH, humidity, light), device (e.g., cameras within drones, satellites), and actuators (e.g., for spraying, dispensing fertilizer, or motor control) [77], connection or networking (i.e. data transmission with wireless Zigbee, LoRa or cellular data 4 G, 5 G or remotely communication using satellites), data processing(i.e. filter, clean and process raw data using cloud system like AWS IoT, stores data linking with data bases like SQL, etc.), data analysis application (i.e. machine learning for predictive analysis or decision support system in irrigation, fertilizer, etc.), decision making with agricultural systems, and security interfaces [78], [79], [80], [81], [82]. Research shows that the vast application of IoT in the field of agriculture with real data collection and making decision system with integrating other models. In the study [83] use devices like FC-28 sensor, DHT11 sensor, and JXBS-3001 sensors. The study collects data on soil parameters including soil composition, moisture, humidity, temperature, and for nutrient levels. In other studies, [84] provides an IoT system to access real time data in field like sunlight, relative humidity, temperature, and moisture with low-cost Arduino hardware and software integration. Moreover, IoT system has an application in crop growth and health monitoring system. M. Galaverni et al. [85] made a smart agriculture system using IoT system with a tomato plant in irrigation agriculture, denoted as *Irri-frame.* The proposed platform performs information evaluation, monitoring field parameters like water stress, soil plant analysis, and agronomic data collection on the plantation area. Generally, the IoT system in yield prediction plays a great role in improving yield accuracy, risk alleviation, resource management, and increase production efficiency [86].

3.4.7. Big data and cloud computing in crop yield prediction

In context of crop yield prediction, big data refers to the large, complex datasets collected from multiple data sources (i.e. IoT sensors, remote sensing data, historical yield data, and weather data) which are processed and analyzed using specialized tools to predict crop yield accurately [87]. Cloud computing refers to the use of a cloud-platform to store, manage, process, and analyze agricultural data (i.e. weather data, historical data, satellite data, yield data, management data. soil data) to predict crop yield accurately and make informed decisions for farming stakeholders [88]. Big data analytics reveal patterns and trends that improve prediction accuracy, while cloud computing provides scalable storage, computational power, and real-time data processing. These technologies improve timely decision-making in farming practices through data-driven insights.

3.5. Modeling approaches in crop yield prediction

According to data sources, computational approaches, technological advancement, and other factors crop yield prediction models classified as Historical and Contemporary crop yield prediction models

3.5.1. Historical CYPMs

Although no single traditional model exists, this section refers to early models that are limited in their capability to solve problems and basically laid the foundation for recent models, which existed before the 1980s. The section considers historical yield prediction models before the 1980s and grouped into two classes.

3.5.1.1. Empirical models. Empirical models basically use mathematical and/or that predict crop yield based on observed relationships between yield and environmental factors [89]. Observational estimation (used as indigenous knowledge) based qualitative approach to estimating crop yields with local knowledge in prior expertise and experience using specific crops, local weather patterns, and farming practices [90] in prior histories of crop yield prediction. This approach is a non-data-driven approach and depends on observationally based judgement. In the 1920s to 1950s, it is marked as a transition in crop yield prediction from qualitative to quantitative statistical approaches. Fisher [91] described one of the earliest works in statistical approaches that used correlation and regression analysis to quantify the relation between rainfall and wheat yield during 1920s. During the 1930s, Frank Yates [92] developed advanced statistical methods by using factorial experiments and analysis of variance to analyze crop yield data, correlating yields with fertilizer, soil type, and weather conditions. In the 1950s, Snedecor [93] provided a formalized statistical regression yield prediction technique based on soil fertility, weather, and management practices. In the 1960s to 1970s advanced empirical statistical modelling evolved by integrating optimizing yields for new high-yield varieties. Time series analysis yield prediction adopted to manage temporal and spatial variability. Thompson [17] widely used regression model by including multiple variables (such as weather, soil fertility, and technology adoption) to improve yield prediction accuracy. Even though there are improvements greatly after 1980s empirical models have many limitations. Empirical models experience issues like overfitting, a lack of biological insight, and difficulties in generalizing across various regions or conditions, tricky calibration and validation processes, and challenges related to scaling and temporal dynamics are among common ones. These issues emphasize the necessity for enhanced data collection, improved model integration, and a more profound understanding of local conditions and biological processes.

3.5.1.2. Mechanistic models. These models are mathematical representations of crop growth and development that simulate the effect of physiological and biophysical processes as a function of environmental conditions, genetic variations, and management practices [89], [94]. As Hammer et al. [94] explained these models describe the interactions between crop growth processes and environmental factors such as climate, soil characteristics, and farming practices. In 1960s deWit [95] introduced a mechanistic modeling of crop growth using photosynthesis and light interception further used as a foundation for WOFOST model. In the 1970s mechanistic approaches gain popularity when researchers developed a mathematical framework that describes crop growth and yield at various levels of sophistication. Kumar et al. [96] demonstrated that this era showed the prediction of yield under diverse conditions due to the development of models in climate and management practice. Patrico et al. [97] developed a model to simulate crop yield responses to water stress, by considering the mechanistic link between evapotranspiration and yield. During 1980s mechanistic approaches in yield prediction became more advanced and respond to emerging challenges like elevated CO_2 levels [97]. These models had limitations in data availability and quality limitation, model over fitting, and less integration of modern technologies.

3.5.2. Contemporary crop yield prediction models

Contemporary crop prediction models are defined as an advanced data-driven computational framework designed to predict future yields using modern technologies (such as machine learning, deep learning, remote sensing, IoT, Big Data analytics, or and hybrid approaches) which make integration and analysis of data for accurate and real-time yield prediction which have great application in precision agriculture, food security, and climate change adaption [29], [98]. Contemporary crop yield prediction models have equipped with recent agricultural technologies to provide more accurate and real time yield predictions [99]. These models have a great role for improved prediction accuracy, scalability and automation, better decision drawing, securing food demand and enabling sustainable agricultural practice. Key contemporary crop yield prediction models, which are gamechangers, include:

3.5.2.1. Remote sensing. Remote sensing can provide a repetitive observation without a non-destructive data acquisition in large geographical areas [100]. It creates maps, models, and other visual representations of the Earth's surface by integrating with emerging technologies [101]. Ali et al. [102] described remote sensing models can integrate with geographic information systems to monitor crop conditions and then predict yields through satellite or drone imagery in large geographical area [102]. This technique collects data from vegetation indices like natural difference vegetation indices(NDVI), weather data, soil data [103] and integrating with crop-specific models, to assess crop health, environmental stress, and climatic factors that impacting yields [104]. Khan et al. [105] provided a remote sensing based on a Corn yield prediction through vegetation indices and deep learning. The study also evaluated the effectiveness of remote sensing data by dividing into different growing seasons. Another study Nevavuori et al. [106] used Unnamed Arial Vehicles (UAV) high resolution images to apply on crop yield prediction model by image classification method integrating with convolutional neural network (CNN). Meshesha & Abeje [107] developed a crop yield prediction model for four major Ethiopian crops. The study used a 10-meter resolution and 5-days temporal coverage, satellite Sentinel-2, with 3 vegetation indices for yield of crops (like teff, maize, wheat, and rice) compared with ground yield data. The study used remote sensing and machine learning methods to provide a better level of yield prediction. As Tripathi et al. [108] described remote sensing technology gives a great offer such as real-time monitoring, large geographical area coverage, applied in different agroecological zones, it doesn't need physical crop samples, and scalability across various agricultural scales [108]. Previously done research demonstrated remarkable progress in crop yield prediction using remote sensing, machine learning, and hybrid modeling approaches. For instance, Nagiv et al. [109] integrated land-use policy and remote sensing data to improve agricultural monitoring. However, their study was limited by regional specificity and lacked dynamic temporal analysis, which reduces global scalability. More recently, Vafaeinejad, Sharifi et al. [110] integrated multi-sensor satellite data for near real-time crop monitoring, marketing a promising step toward operational systems but still constrained by cost and network infrastructure. However, the system is challenge-full in the need for data calibration, cloud cover interference, complex data interpretation, and resolution limitations [111]. Although the presence of many challenges, these models integrating with other models like deep learning and big data are considered a valuable tool for improving yield prediction accuracy [112].

3.5.2.2. Machine learning models in crop yield prediction. Machine learning (ML) is a branch of artificial intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to perform tasks without explicit instructions, relying instead on patterns and inferences from data [113–116]. Shawon et al. [98] used machine learning in crop yield prediction which has a significant value which trace and analyze large farm datasets like weather data, soil data, historical yield data, and crop management practices to predict future crop yield accurately [98]. Machine learning algorithms makes greater importance in crops yield predictions through analyzing complex data, enhance prediction accuracy, resource use optimization, risk management and early warning, climate change adaptation, and improve decision making [11], [117], [118]. Paudel et al. [119]used large dataset by combining agronomic principles of crop modeling with machine learning baseline (i.e. correct, modular and reusable data) to predict large scale crop yield. the research predicted the yield of 7 types of crops within 3 European countries namely France, Germany, and Netherlands. Another investigator Dey et al. [120] used machine learning based crop recommendation by integrating with Kaggle dataset (i.e. 10 horticultural crops and 11 agricultural crops) and evaluates the individual data sets for better prediction and accuracy. Studies showed Kumar et al. [121] that there are many types of machine learning models used in crop yield prediction [121] based on nature of data, model training and evaluation, and model selection used, there are many types of machine learning models available.

- *Linear Regression*: It is a simple model that predicts crop yield based on linear relationships between input features (e.g., rainfall, temperature, soil nutrients) and crop yield [122]. Research [123] used a linear regression machine learning model to analyze the relationship between environmental factors (i.e. area under cultivation, food price index, and annual rainfall) and yield outcome.
- *Decision Trees*: It is the one of powerful machine learning tree-based model that splits data into branches based on feature values to predict yield [124]. Research done [125] with crop predictive analytics

with tree-based ensemble machine learning model for the future in crop suitability and productivity prediction.

- *Random Forest*: It is an ensemble of decision trees that reduces overfitting and improves prediction accuracy [126]. The model offers high robustness and versatility. In the research [127], the random forest machine learning algorithm was employed to forecast maize yield and agronomic efficiency in Ghana, taking into account various factors such as soil characteristics, climatic conditions, environmental influences, and management practices, including the application of fertilizers. The research approved that there is a better suggestion in drivers of Maize yield and increased agronomic efficiency.
- *Support Vector Machines*: It is a machine learning model that is capable of handle high-dimensional and non-linear datasets [128]. The study M.Rajakumaran et al. [129] demonstrated the multi-attribute weighted tree based support vector machine approach used to enhance crop yield prediction accuracy through integrating multiple attributes effectively.
- *Gradient Boosting Machines (GBM):* It is an ensemble technique that builds trees orderly to correct errors from previous trees and have variants include XGBoost, LightGBM, and CatBoost, which are highly effective for crop yield prediction. Pavithra et al. [130] showed the performance of three gradient based machine learning algorithms: CatBoost Light Gradient Boosting Machine, and eXtreme gradient boosting for rice yield prediction. The models utilized parameters such as pesticide, rainfall, and average temperature. These algorithms show a promising result in their outputs.
- *k-Nearest Neighbors (k-NN):* These models are a non-parametric model that predicts yield based on the average of the k-nearest data points [131], [132], [133]. Farhat et al. [134] used proximal sensing data (such as soil moisture, normalized difference vegetation indices) applied k-NN among other algorithms to predict potato yields. The k-NN model demonstrated lower performance compared to others like Support Vector Regression with higher root mean square error values across many datasets. In contrary, Wilson et al. [135] research done in regard to rice yield prediction in Kerel, India, found k-NN regression outperform other models, achieving an accuracy of 98.77 %.

3.5.2.3. Deep learning in crop yield prediction. Deep learning models are advanced machine learning models that are capable of capturing complex, non-linear relationships (neural networks) in large agricultural datasets, making them adapted for s crop yield prediction analysis [136].

- *Convolutional Neural Networks (CNNs*): It is a powerful tool that is commonly used for processing image classification and processing for spatial data such as satellite or drone imagery vegetation indices (e.g., NDVI) to predict crop yield at regional or field-level [137]. Srivastava et al. [138] used a CNN based for winter wheat prediction by including the phenological and environmental data while Morales and Sheppard [139] used a winter Wheat early yield prediction with two-dimensional CNN architectures and gained a better yield result. Lei Wang et al. [140] on the other hand, provides a hybrid crop yield prediction model that with temporal and spatial by integrating deep learning frameworks like convolutional neural network (CNN), long short-term memory (LSTM), and graph attention network (GAT) modules to magnify the prediction accuracy. The proposed model demonstrates as the model shows increase the performance by 6 % from the previous model.
- Artificial Neural Network (ANNs) can model a crop yield prediction due to their capability to model complex, non-linear relationships between various influencing parameters [141]. Khaki and Wang et al. [142] a Deep Neural Network-ANN model to predict the maize yield using temporary dataset and environmental variables. The model exhibited with a root-mean-square-error (RMSE) of 12 % of the average yield from the existing model.
- Recurrent Neural Networks (RNNs): RNN model is an effective crop yield prediction by its efficiency in modelling temporal dependencies for time series data accurately [143]. Jiang et al. (2018) showed that a corn yield prediction with Long Short-Term Memory (LSTM) RNN model by using temporal weather data at county level, which got a promising result. Fan et al. [144] demonstrated a hybrid approach of Graph Neural Networks (GNN)-RNN for spatial and temporal data in crop yield prediction in USA showed a greater performance over the existing models.

3.5.2.4. Hybrid model approach in crop yield prediction. Hybrid crop yield prediction models are the integration of two or more models (from historical, contemporary or both) to achieve necessary solution of problems in crop yield prediction [11]. These models are crucial for enhancing agricultural outcomes by providing more reliable predictions based on complex interactions between environmental conditions and crop-specific traits [145]. Anikó Kern, et al. [146] used a hybrid approach of statistical model for crop yield by using climate data and remote sensing in Central Europe. The result gained an impressive resilient model for spatially yield forecast and future projections by integrating remote sensing and statistical methods. Hybrid crop yield prediction models integrate diverse data sources to capture the multi-faceted nature of crop yield. Huimin Zhuang et al. [147] proposed a hybrid model for crop yield prediction by integrating a data assimilated crop model with machine learning for the winter Wheat crop to improve yield prediction in the North China from 2009 to 2015. The research articulated that integrating various sources of crop enhance the crop model's ability to predict grain yields. Cerreta et al. [148] demonstrated that coupling remote sensing with process-based models improves yield estimation, but such mechanistic models often require extensive calibration and are computationally demanding for real-time applications. Sabas Patrick et al. [149] uses a hybrid model with ensemble techniques to combine banana plant future yield prediction from (1961–2020) yield data and multiple base models in Tanzanian Agriculture. The study used statistical time series models, state space, Long Short-Term Memory (LSTM) regression models, and ensemble models applying a weighted average approach to forecast yield of banana plant. Abdelouafi Boukhris et al. [149] used an integrated hybrid predictive yield model by including Sentinel-2 satellite imagery (such as NDVI, etc.), IoT (Raspberry Pi $B+$), big data, and deep learning techniques with mobile application in Morocco for wheat yield prediction. The research integrates both spatial and temporal crop yield data and enhances the yield of wheat crops by 14 % from the previous yield. Sharifi & Safari et al. [150] and Mahmoodi et al. [151] proposed explainable AI frameworks and spatiotemporal deep learning methods, respectively, yet both approaches remain limited by high computational requirements and dependency on large, labeled data datasets. Recent advances have employed deep learning and multi-sensor fusion to address these gaps. For example, Safari et al. [152] and Vafaeinejad et al. [153] applied CNNs to Sentinel-2 satellite data for large-scale yield estimation, achieving higher accuracy but still facing issues with data heterogeneity and explainability. These limitations underscore the need for hybrid, context-aware, and computationally efficient prediction models that balance accuracy with accessibility. Generally, these approaches have high acceptance due to having a combination solving ability of many models which provide accurate and reliable predictions.

Consequently, these models have improved accuracy, robustness, interpretability, handling complex data, sustainability, risk management, and resource optimization in crop yield prediction by combining the strengths of multiple modeling techniques through multiple data [11]. Even though the approach has an impressive result, but also it suffers with data quality, model complexity, less interpretability and other challenges.

3.6. Application of crop yield predictive models

The section provides a general importance of crop yield prediction models. These models offer significant benefits in agriculture like food security, economic planning, climate adaptation, resource optimization, decision making, precision agriculture, and risk management.

3.6.1. Food security

Food security is essentially very important to address around the world. For these reasons accurate crop yield prediction takes the great role. The estimation will be done with crop prediction models. Food security basically covers sufficient crop production, consistent food access overtime, and other dimensions. Therefore, to address these issues it's necessary to forecast food production levels, identification of scarce food regions, and take proactive measures to balance food production by adjusting food scarce and surpluses. Crop yield prediction models takeover the responsibility of building resilient food security system. Jabed and Murad [11] provided an important insight in the role of AI in ensuring sustainability in agriculture and food security.

3.6.2. Economic planning

The crop yield prediction models can accurately predict economic outcomes for decision-making. There are many methodologies employed in crop yield prediction models to support economic planning. Among these methods statistical models, remote sensing, machine learning or hybrid models are among those methods that are responsible for agricultural management, real-time monitoring of crop health and growth, and yield estimation**.** Liakos et al. [154] highlighted the role of machine learning in crop yield prediction and its significance for precision agriculture and economic planning.

3.6.3. Resource optimization

Resource optimization is essential in agriculture that increases the efficiency of farmers productivity, profit, and economic sustainability by optimizing fertilizers and pesticide, improving water management, enhance soil health, and reduce food waste. Chlingaryan [155] provided a review focuses on machine learning techniques for yield prediction and their application in optimizing nitrogen use. Morchid et al. [156] done research in smart irrigation by installing soil moisture sensors with IoT devices to ensure crops receive the right amount of water by adjusting the amount automatically.

3.6.4. Decision making

Crop yield prediction models can possibly be used to make decisions in agricultural activity like planting, harvesting and post-harvest activities, seed and crop varieties selection, Soil Preparation and irrigation setup through increasing profit by minimizing waste. Klompenburg et al. [2] highlighted how models like neural networks and support vector machines can reduce uncertainties by forecasting yields under varying environmental conditions, aiding farmers in decision-making for resource allocation and planning.

3.6.5. Climate adaptation

Climate adaptation indicates that the principle of adjustment to the actual or predictive climate change and its effects. Climate change is the main challenge for food security. Crop yield prediction models takeover risk management and resilience like early warning of crop failures, supporting climate smart agriculture, confirm economic stability, and integrate with emerging technologies. Wei et al. [142] provided a case study that explores resilient farming practices to mitigate flood risks in vulnerable agricultural regions. Kang et al. [157] provided a review discusses in the role of yield prediction in addressing food security under climate change.

3.6.6. Precision agriculture

Todays agriculture practice is integrated with recent technology tools (like GPS-guided tractors, drones, sensors, satellite imagery, etc.) to optimize crop production, reduce waste, and improve efficiency. These may refer to precision agriculture. Nyéki and Neményi [99] pinout that precision agriculture must be supported by technologies like remote accessing system, data analytics and management tools. play a great role in improving crop yield and quality. Moreover, big data in precision agriculture creates a comprehensive and long-term analysis of agricultural factors with various circumstances. Wolfert et al. [158] highlighted how data-driven approaches in precision agriculture can enhance yield forecasting, improve farm management, and support sustainable practices.

3.6.7. Risk management

Crop yield prediction models have invaluable insights, in giving a necessary measurement for farmers for better preparation in risk handling like frost, drought stress, flood, pest infestation, market fluctuation, weed propagation, disease breakout, or post-harvest losses. Taking proactive measures, yield predictive models play a great role. Klompenburg et al. [32] provided a comprehensive review of machine learning techniques for crop yield prediction, emphasizing their role in managing agricultural risks. Pantazi et al. [159] addressed the risk management in wheat crop by demonstrating how precise yield predictions can help farmers adjust inputs like fertilizers and irrigation, reducing the risk of overinvestment or crop failure in unpredictable conditions.

4. Results and discussion

The section presents a comparison, existing challenges, key lessons learned, and great innovations achieved on crop yield prediction models. A total of 23 documents, published between 2015 and 2025 and authored by researchers from 18 countries, were analyzed. The discussion flow structure is as shown in (Fig. 3) that deals with CYPMs in different comparison aspects.

4.1. Document analysis and risk-of-bias assessment

The 23 studies included in this review reflect a clear global and methodological trend in crop yield prediction research in (Table 3). First, geographic representation is highly skewed: 16 of the 23 studies (70 %) originate from high-income countries (e.g., USA, China, Austria, EU nations), while only 4 explicitly address low -income contexts (Ethiopia, Rwanda), highlighting a critical gap in context-specific validation for data-scarce regions. Secondly, model evolution is evident: all contemporary studies fully integrate advanced data sources such as sentinel-2, MODIS, IoT sensors and machine learning or deep learning techniques, with hybrid approaches (e.g., ML with APSIM, RS with statistical model) gaining traction in 9 of studies (39 %).

Thirdly, the performance metrics are consistently reported (R^2 ranging from 0.73 - 0.93 and RMSE/MAE is used where applicable) which provide empirical support for the superior accuracy of contemporary models over historical baselines (e.g., DSSAT R^2=0.62 vs. LSTM R^2=0.85 in Liu [153]). Finally, practical innovations are emerging, real-time systems such as *SMART-CYPS* (Kuradusenge et al. [170]), and scalable global datasets like *yield5min* Wu et al. [162] demonstrate a shift toward operational deployment. However, computational intensity, data dependency, and low interpretability remain persistent trade-offs, needs context adapted and light weighted solutions for the regions like Ethiopia.

According to the 23 reviewed studies, quantitative performance comparisons consistently show that contemporary models outperform historical ones. On average, deep learning models achieved R^2 values between 0.85–0.93, compared to 0.60–0.75 for traditional empirical and mechanistic models. Hybrid frameworks combining remote sensing with machine learning further reduced RMSE by 15–20 % relative to standalone approaches. These trends experimentally confirm the effectiveness

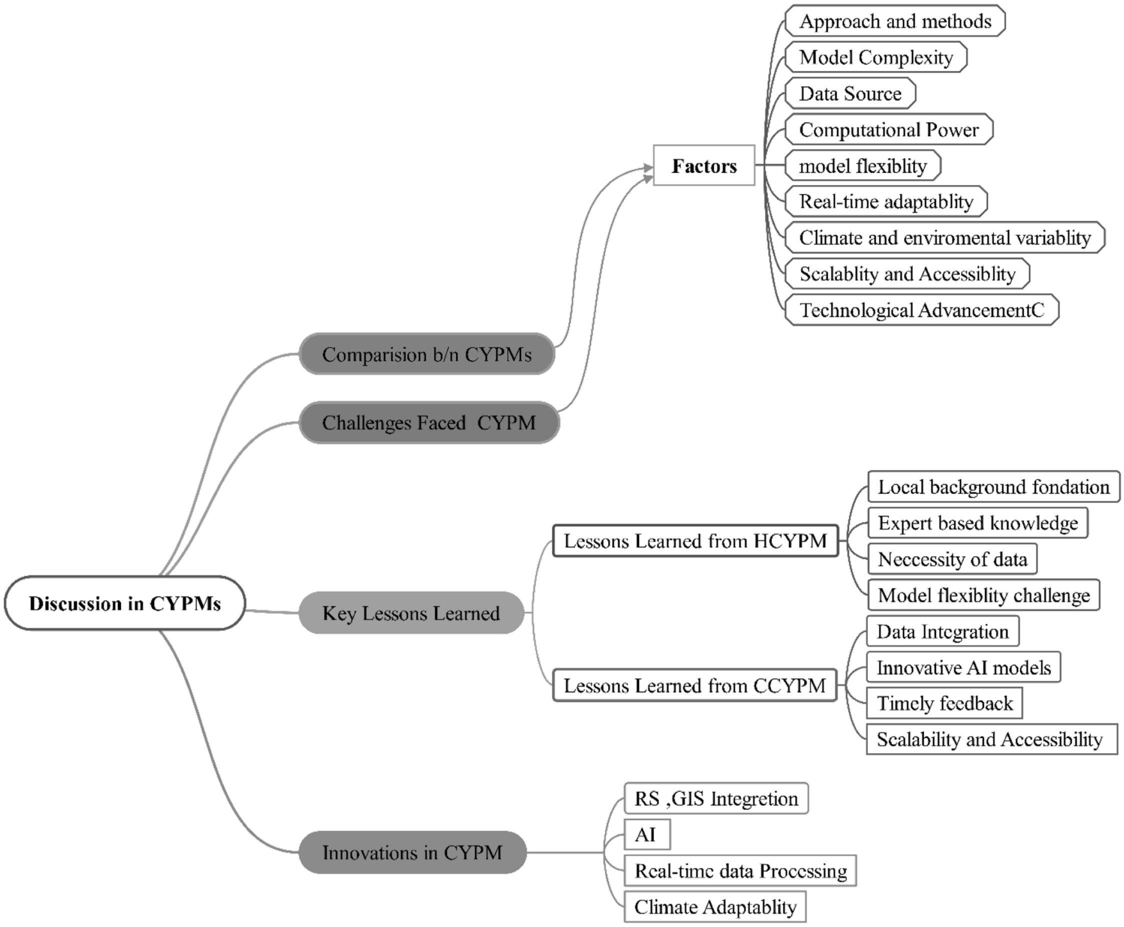

Fig. 3. Discussion flow chart in CYPMs.

and the robustness of contemporary CYPMs under diverse agroecological conditions.

4.2. Risk-of-bias and quality assessment findings

The consensus quality assessment revealed that the majority of the included studies were of high quality, with a mean score of 6.4/7. As detailed in Table 4, 19 studies (83 %), were rated as Low Risk-of-Bias, while the remaining 4 studies (17 %) received a score of 5, still meeting the inclusion threshold but with minor limitations, typically in performance metric limitation, reproducibility or detailed documentation of assumptions. The high overall quality scores strengthen the validity of the insights and conclusions drawn from this body of literature.

The inter-rater reliability, measured by Cohen's Kappa, was κ=0.78, (*calculated with R statistical software*), indicating substantial agreement. All discrepancies were resolved through consensus discussion.

4.3. Comparison between historical and contemporary crop yield prediction models

The section provides clear and concise comparisons between recent and historical crop prediction models as mentioned before in first Research Question, RQ1. Crop yield prediction models have their own strength and limitations. This comparison shows the strength of contemporary yield predictive models handling complex and real-time data, but traditional models remain relevant where simplicity and transparency are prioritized.

4.3.1. Approach and methods

Historical models relied on statistical methods (e.g., linear regression) or process-based crop yield models (e.g., DSSAT, APSIM) which simulate biophysical processes using predefined equations which lack complex, nonlinear relationships between yield variables. As Timlin et al. [163] describes that historical/traditional process-based models quantify the soil-plant-atmosphere continuum to anticipate yield responses to environmental changes, while empirical statistical models rely on historical correlations. On the other hand, contemporary crop yield prediction models use ML and DL to capture complex nonlinear relationships without predefined assumptions. Shahhosseini et al. [160] demonstrated that, regarding maize yield variance, the use of LSTM deep learning model exhibited better performance than process-based models by 73 % than traditional process based which performs 16 %, due to hold nonlinear relationships between soil and weather conditions.

4.3.2. Data availability

Historical models are characterized by limited, sparse, and localized data (such as yield record data, weather data) through manual collection, and often incomplete data with lack of spatial/temporal resolution. Timlin et al. [163] stated that process-based models depend on accurate quantification of physiological responses, which require comprehensive field data often unavailable at large scales or in data-scarce regions. However, contemporary crop yields predictive models leverage large, diverse datasets including IoT sensors, remote sensing, and availability of large global datasets which are characterized by real-time, high-resolution data crucial for accurate yield prediction. As Klompenburg et al. [164] described the integration of ML with remote sensing and

Table 3
Characteristics of studies included in the review.

S/N	Authors	Country	Model Type(s)	Data Source	Metric(s)	Key Finding
1	You et al. [22]	USA	DL (CNN, LSTM)	Sentinel-2, weather	$R^2 = 0.89$	DL outperformed process-based models by capturing nonlinear relationships
2	Meshesha & Abeje [108]	Ethiopia	ML (RF) + RS	Sentinel-2 (10 m), NDVI	$R^2 = 0.76$ (Teff)	Demonstrated feasibility of RS+ML in data-scarce SSA
3	Zhuang et al. [145]	China	HY (APSIM + ML)	LAI, weather, soil	RMSE = 0.32 t/ha	Hybrid improved accuracy by 18 % over standalone models
4	Filippi et al. [24]	Australia	ML + RS	MODIS, weather	MAE = 0.21 t/ha	Real-time updates enhanced in-season prediction
5	Liu et al. [154]	USA	DL (LSTM) vs. DSSAT	Weather, soil	$R^2 = 0.85$ (DL) vs. 0.62 (DSSAT)	DL better modeled temp extremes and nonlinear responses
6	Shahhosseini et al. [160]	USA	LSTM vs. APSIM	Weather, soil	RMSE reduced by 23 % with LSTM	DL showed 73 % better variance explanation than mechanistic models
7	Engen et al. [27]	Norway	DL (CNN hybrid)	Satellite, weather	$R^2 = 0.81$	Stochastic sampling reduced overfitting in high-parameter models
8	Jeong et al. [28]	South Korea	HY (ML + process-based)	Remote sensing, crop model	$R^2 = 0.88$	Integration improved realism but increased computational load
9	Lobell et al. [30]	USA	RS (satellite mapper)	MODIS, yield surveys	$R^2 = 0.78$	Scalable framework enabled large-area yield estimation
10	Kraaijvanger & Veldkamp [167]	Ethiopia	Empirical + field data	On-farm trials, management data	$R^2 = 0.56$	Local factors (fertilizer, altitude) explained over half of yield variance
11	Barrot et al. [168]	France	Expert-knowledge PerSyst	Agronomic rules, local data	Qualitative validation	Expert-guided calibration improved adaptability across farms
12	Darra et al. [169]	Greece	Review + case studies	Meta-analysis	N/A	Simpler models lack flexibility for spatiotemporal complexity
13	Kassa et al. [172]	Ethiopia	RS + climate data	NDVI, rainfall, temp	$R^2 = 0.73$	Cost-effective RS approach viable for Ethiopian food security
14	Kuradusenge et al. [161]	Rwanda	IoT + ML (SMART-CYPS)	Soil sensors, cloud	Accuracy = 92 %	Real-time dashboard improved accessibility for smallholders
15	Mena et al. [71]	Argentina/ Germany/ Uruguay	Multiview gated fusion (DL)	Sentinel-2, weather, soil	$R^2 = 0.91$	Multimodal fusion outperformed single-data models
16	Sanchis et al. [72]	Global	RS (MODIS + SMAP)	EVI, VOD	$R^2 = 0.79$	Microwave data compensated for optical cloud gaps
17	Cunha et al. [73]	Brazil	DL + RS	Satellite, crop calendar	RMSE = 0.28 t/ha	Cloud-cover mitigation via deep learning improved reliability
18	Nevavuori et al. [106]	Finland	DL (CNN) + UAV	High-res UAV imagery	$R^2 = 0.84$	UAV + CNN enabled field-level yield mapping
19	Paudel et al. [117]	Europe (FR, DE, NL)	ML baseline	Agronomic + weather	MAE = 0.41 t/ha	Modular ML framework scalable across crops/regions
20	Rajakumaran et al. [127]	India	ML (SVM + ensemble)	Soil, weather	Accuracy = 88 %	Multi-attribute weighting improved prediction robustness
21	Pavithra et al. [128]	India	GBM (XGBoost, LightGBM)	Temp, rainfall, pesticide	$R^2 = 0.86$	Gradient boosting outperformed RF and SVM
22	Wang et al. [138]	China	Temporal–Geospatial DL (CNN+LSTM+GAT)	Remote sensing, weather	$R^2 = 0.93$	Graph attention improved spatial dependency modeling
23	Kern et al. [144]	Europe	HY (statistical + RS)	Climate, NDVI	$R^2 = 0.82$	Hybrid statistical-RS model resilient for seasonal forecasting

**Q*=Quality score, DL=Deep Learning, GBM=Gradient Boost Method, HY=Hybrid, ML=Machine Learning, RS=Remote sensing, SVM=Support Vector Machine.

metrological data for yield prediction needs high quality, representative data for accurate prediction.

4.3.3. Model complexity

Historical crop yield prediction has simpler models with fewer parameters, relying on empirical or mechanistic assumptions. Process-based models require extensive calibration but were computationally less intensive. Feng et al. [165] presented process-based models can handle some complicated formula to describe crop growth leads to deviation in yield prediction, while statistical models are simple that limited to handle nonlinear relationships. Contemporary yield predictive models can run complex models with nonlinear relationships which requires significand computational resources and expertise.

4.3.4. Skills and knowledge dependency

historical models require domain-specific expertise in yield prediction and crop physiology for model calibration and interpretation. It requires fewer need for computational skills. However, it highly relied on manual parameters. As Tamlin et al. [163] stated that process-based models involve extensive parameter calibration, which requires specialized skill and knowledge of crop and environmental interactions. On the other hand, Contemporary crop yield prediction uses advanced computational skills (such as data science, programming, etc.) parallel to agronomic knowledge. Kaya [166] explained that intelligent systems integrating ML and IoT reduce human input by automating data processing and decision-making requires data science skills.

4.3.5. Technology advancement

Historical CYPM depends on basic computational tools and manual data collection. It has limited integration with advanced technologies such as IoT, remote sensing, which restrict scalability and precision. Feng et al. [165] noted that traditional models, such as empirical statistical models, developed using basic regression techniques and manual data collection, have limitations to integrate with modern technologies. Contemporary CYPM has integrated with advanced technological tools to automatic collect, process, and interpret large datasets for real time processing and accurate prediction. Salgado et al. [167] described that a cloud-based transformative crop recommendation model using ML, deployed on Amazon Web Service (AWS) Lambda for scalable, real-time crop recommendations, as showcasing of the integration of advanced

Table 4
Risk-of-Bias and Quality Assessment.

S/N	Authors	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q (/7)	Risk-of-Bias
1	You et al. [22]	✓	x	✓	✓	✓	✓	✓	6	Low
2	Meshesha & Abeje [108]	✓	✓	✓	✓	✓	✓	✓	7	Low
3	Zhuang et al. [145]	✓	✓	✓	✓	✓	✓	✓	6.5	Low
4	Filippi et al. [24]	✓	✓	x	✓	✓	✓	✓	6	Low
5	Liu et al. [154]	✓	✓	✓	✓	✓	✓	✓	7	Low
6	Shahhosseini et al. [154]	✓	✓	✓	✓	✓	✓	✓	7	Low
7	Engen et al. [27]	✓	✓	✓	✓	✓	✓	✓	7	Low
8	Jeong et al. [28]	✓	✓	✓	✓	✓	✓	✓	6	Low
9	Lobell et al. [30]	✓	✓	✓	✓	✓	✓	✓	7	Low
10	Kraaijvanger [167]	✓	✓	✓	✓	✓	✓	✓	5	Low
11	Barrot et al. [168]	✓	✓	x	✓	x	✓	✓	5	Low
12	Darra et al. [169]	✓	✓	✓	✓	x	x	✓	5	Low
13	Kassa et al. [172]	✓	✓	✓	✓	✓	✓	✓	7	Low
14	Kuradusenge et al. [170]	✓	✓	✓	✓	✓	✓	✓	7	Low
15	Mena et al. [71]	✓	✓	✓	✓	✓	✓	✓	6.5	Low
16	Sanchis et al. [72]	✓	✓	✓	✓	✓	✓	✓	7	Low
17	Cunha et al. [73]	✓	✓	✓	✓	✓	✓	✓	7	Low
18	Nevavuori et al. [106]	✓	✓	✓	✓	✓	✓	✓	6.5	Low
19	Paudel et al. [117]	✓	✓	✓	x	✓	✓	x	5	Low
20	Rajakumaran et al. [127]	✓	✓	✓	✓	✓	✓	✓	7	Low
21	Pavithra et al. [128]	✓	✓	✓	✓	✓	✓	✓	7	Low
22	Wang et al. [138]	✓	✓	✓	✓	✓	✓	✓	6	Low
23	Kern et al. [144]	✓	✓	✓	✓	✓	✓	✓	7	Low

*Legend: Q_1-Q_7 = Quality check parameters as shown in (Table 2), "✓" =Yes (1 points), "x" = No (0 points), "P" = Partial (0.5 points). *.
*Inter-rater reliability, measured by Cohen's kappa, was $k = 0.78$, indicating a substantial agreement. *.

technologies application.

4.3.6. Climate and environmental variability

Historical CYPMs struggle to account for extreme weather and climate variability due to rigid assumptions and limited data. In addition to this, process-based models often fail in under novel climate conditions. Tamlin et al. [163] emphasized that uncertainties in long-term climate projection and extreme weather events happen challenges for traditional models, which needs ensemble approaches to solve its variability. In other cases, Contemporary CYPMs can handle climate variability using ML and DL to model nonlinear interactions under climate changing conditions. Liu et al. [160] demonstrates that LSTMatt model maintains high accuracy during drought years, showed better performance than process-based models by adapting to metrological variability in the U.S. Corn Belt.

4.3.7. Real-time adaptability

Historical CYPMs mostly comprise static models and lack of real-time adaptivity due to reliance on historical data. As Feng et al. [165] noted that traditional models lack real-time feedback mechanisms, limiting their capability to adjust predictions during the growing seasons. In contemporary CYPMs is integrated with modern advanced technologies which support real-time adaptability for accurate dynamic predictions and recommendations. Kaya [166] described an intelligent greenhouse system that uses ML and sensors data for real-time environmental control, adapting irrigation and lighting to optimize crop growth.

4.4.8. Scalability and accessibility

Historical CYPMs have low adaptability due to data and computational constraints. It has also limited accessibility for the large farms with resources for field experiments and calibration. Tilmin et al. [163] articulated that the scalability of process-based models is constrained by data and calibration requirements, making them less accessible in resource-poor settings. While contemporary CYPM is highly scalable through platforms and open-access datasets. Wu et al. [162] introduced a global crop yield5min, a ML-based dataset for wheat, soybean, rice, and maize yields at 5 arc-min resolution, exhibits R^2 between 0.7–0.95, demonstrates scalability across the globe.

4.4. Challenges faced in both crop yield prediction models

This section provides a clear demarcation of challenges faced in Historical and Contemporary crop yield prediction models based on common selected comparison criteria as described in RQ2, previously. The criteria were selected based on key limitations and advancement of agricultural modelling. The criteria derived from fundamental aspects that influence the effectiveness and applicability of predictive models. Among these criteria; data availability (quantity and quality of data), model complexity, expert dependency (the need to rely on expert knowledge), technological constraints (role of technology in shaping model performance), climate and environmental variability (models ability to handle unpredictable environmental change), real-time adaptability (dynamically prediction update with timely data), and scalability and accessibility (models' level in application across different regions) which summarized in the Table 5.

The qualitative synthesis of (Table 5) reveals how challenges in CYPMs have evolved over years rather than disappeared. Historically, models were constrained by limited data and simple concepts, struggling with environmental variability due to inadequate information and computing power [165]. In contrast, modern models face challenges of data abundance and complexity, where ensuring data quality, integration, and interpretability has become more difficult than data collection itself [173]. A persistent accessibility gap is also evident. Although modern models are technically scalable, their use is limited by high costs, computational demands, and the need for specialized expertise (creating a digital divide that favors high-income regions and reinforces global inequality in agricultural predictions) [167]. Furthermore, there is a growing trade-off between predictive power and transparency. Older models were simple but interpretable, while current deep learning and hybrid systems are powerful yet opaque "black boxes," shifting expertise from agronomy to data science [170]. This highlights the need for Explainable AI to restore interpretability and user trust. Overall, the evolution of CYPMs represents a shift from scarcity to complexity, and future models must balance accuracy and scalability with transparency, affordability, and equity to achieve sustainable and inclusive agricultural forecasting.

Table 5
Summary of the challenges faced in both Historical and Contemporary CYPMs.

S/n	Challenges	Historical CYP Models	Contemporary CYP Models
1	Data Availability	Subjected to limited & localized data, manual gathering data leads to sparse information [168]	Vast data: limited to quality and integration [169], [11]
2	Model Complexity	Simple, Linear regression-based models: Based on experts' judgement [165]	Complex, non-linear models: Difficult to interpret [170]
3	Skill and knowledge Dependency	It depends on the expertise of model development and interpretation [171]	Skilled people need to develop, understand, and utilize; [172]
4	Technological constraints	Less computational power, Simple and rely on manual data, less accurate prediction [165]:	Demand of high computational resources and quality data: [173]
5	Climate and Environmental Variability	Inconsistent to environmental changes: [174]	Consistent with long-term climate trends: but vulnerable to extreme weather events: [170]
6	Real-time Adaptability	Provide static predictions limited to real-time adaption [165];	Integrates with real-time data: but suffers with data latency and gap; [167]
7	Scalability and Accessibility	Localized: limited to specific region predictions [164], [33]:	Highly Scalable: However, its cost, and infrastructure need is high [167];

4.5. Key lessons learned from both crop yield prediction models

The section provides important insights, best practices, opportunities and challenges, discovered throughout the development and use of crop yield prediction models as mentioned in RQ3 earlier. Clearly, for both Historical and Contemporary crop yield models which taught an important lesson in agriculture is described as a comparison.

4.5.1. Lessons learned from historical crop yield production model

Historical crop yield prediction models have been laid a foundation for contemporary crop yield predictive models' development. The adaptation principle of these models further helps to evolve over time to develop advanced technological crop yield predictive models. There are many key lessons that provide for the advancement of CYPM. These models provided critical insights for agriculture development, such as:

a) *Local background is vital*. These indicate that the necessity and importance of deep understanding of local factors affect crop yield prediction such as soil property, weather patterns, local agricultural management practices, and previous yield data. These historical crop yield models are crucial in development of local based crop yield prediction factors. The study by Kraaijvanger et al. [175] revealed the importance of local factors as about 56 % of grain yield variability was explained by management practice, altitude, and nitrogen fertilizer input, was conducted in Tigray, norther part of Ethiopia [175].
b) *Data availability is a key factor*. Reliable, high-quality data are critical inputs for accurate yield prediction [176]. Unlikely, historical yield prediction models limited with structured data leads to prediction inaccuracy. These limitations further learned to create recent approaches like artificial intelligence data models, IoT systems, Big Data, and others to integrate high dimensional complex nonlinear data analysis and processing.
c) *Expert-based knowledge remains valuable*. Incorporating expert-based knowledge in crop yield prediction develops effective models, enhances prediction accuracy and adaptability across various agricultural circumstances. Barrot et al. [177] used the PerSyst model with expert-based knowledge in parameterize factors such as reference yields, crop sequence variations, and crop management practices. The approach improves model application and reliability by adapting diverse farming conditions [177].
d) *Simplified models face flexibility challenges*. In Historical based prediction models, simplified approaches often lack the flexibility to account for the complex interactions among various factors influencing crop yields. Darra et al. [178] found there was a challenge in simpler models to fully capture spatial and temporal complex data like weather properties to predict in the outcome of crop yield, which indicates that simpler models have less flexibility and inaccurate in yield prediction. The finding briefs that the necessity of adaptable and comprehensive modelling techniques in crop yield prediction to effectively address the complexities characteristic in agricultural practice [178].

4.5.2. Key lessons learned from contemporary crop yield prediction model

i. *Data integration enhances yield accuracy*: Recent yield predictive models involve with the combining of multiple, diverse and complex datasets that provide complete and nuanced understanding the factors influencing crop yield prediction. By integrating data from various sources like remote sensing, weather data, soil data, farm management data, and yield data to predictive models can constitute complex interactions between environment as well as human factors. This temporal and spatial data holistic method leads to more accurate and reliable result for crop yield prediction.
ii. *AI Models are Innovative*: Artificial Intelligence (AI) has been increasingly employed to enhance yield prediction, using Machine Learning (Ml) and Deep Learning (Dl). These innovative models analyze diversified datasets like weather patterns, environmental factors, and soil conditions, to provide accurate yield prediction. Jabed and Murad [11] provided a comprehensive review about the application of AI in agriculture and its transformative potential improvement in crop yield estimation, agricultural planning, and resource management [11].
iii. *Immediate Feedback is Essential:* Real-time feedback has a great importance in crop yield prediction through immediate data gathering and analysis, which helps for timely decision-making process in crop yield prediction. Contemporary predictive models integrate advanced technologies tools like IoT, remote sensing, and AI significantly improved the reliability and accuracy of yield prediction system. Fatma M. Talaat [11] developed a crop yield prediction algorithm by integrating IoT techniques and climate data to support precision agriculture through real-time data with sensors to monitor environmental conditions, thereby enhancing accuracy of yield prediction. Yin et al. [161] studied a real-time corn yield monitoring and predicting Deep Neural Network (DNN) based prediction model system which facilitates a prompt adjustment in farming strategies to enhance productivity.
iv. *Scalability and Accessibility support for diverse agricultural needs:* Recent advancement in crop yield predictions focus on combining IoT, machine learning algorithms, and remote sensing technologies to address diverse agricultural outcomes in user friendly and applicable. Kuradusenge et al. [161] developed a combination of IoT and machine learning to facilitate real-time data gathering and visualization which deploys sensors in fields to continuously collect environmental data, transmitting to cloud systems for storage and analysis which is known as SMART-CYPS (Smart Crop Yield Prediction system). The user-friendly

dashboard allows the user to monitor crop conditions in real-time to enhance the *Accessibility*. On the other hand, the modular system design helps various crop types and farming practices which describes its *Scalability* in many agricultural circumstances.

v. *Underscores Critical Insights in Climate Change:* Contemporary crop yield prediction models have a critical impact of climate change in crop yield. These models can integrate IoT devices, remote sensing data, machine learning, Big Data analytics, and Cloud Computing to store, analyze, and interpret weather data to mitigate climate change in crop yield prediction through the analysis in forecasting extreme weather events, predict weather shifts in crop growing seasons, analysis of regional variability of weather, and integration of climate data [179].

4.6. Innovations in crop yield prediction

This part presents the new methods, advancement of technologies, or improvement that significantly enhances the way of crop yield prediction techniques, with referring to RQ4. Innovation in crop yield prediction, basically refers to the recent advancement of crop yield prediction models than Historical yield predictive models. It emphasizes the application and advancement of technologies, procedures, and data-driven approaches to predict yield accurately. Based on these concepts the key innovations in crop yield prediction are focused below.

a) *Remote Sensing and Geo-Spatial data integration:* Remote sensing and Geospatial data can provide timely, accurate, and comprehensive data (spatial detailed information's) about crop health, assessing environmental conditions and forecast crop yield effectively. The integration makes accurate information large geographical areas with cost effective way to assess climate change, pest infestation, soil analysis, crop monitoring, and other factors that help to predict yields accurately. Kassa et al. [180] studied the yield of corn and wheat crops by integrating remote sensing and climate data, in Ethiopia. Combining climatic factors with Normalized Difference Vegetation Indices (NDVI), researchers achieved more accurate yield prediction in cost effective way helps food security initiatives.
b) *Real-time data processing approach:* It is an innovative principle in crop yield prediction by integrating different advanced technologies like IoT sensors data, AI, RS, and Big Data analytics accurate timely, data driven decision making towards in crop yield prediction. It makes big difference by reducing risks, optimizing resource use, and enhancing crop yield prediction as well as the agriculture in efficient, sustainable, and resilient way [181].
c) *Artificial Intelligence (AI):* Artificial intelligence is an influential innovation that has effectively transformed crop yield prediction as well as the agriculture as a whole to the next step. integrates advanced tools like machine learning and deep learning method with data fusion techniques revolutionized the crop yield prediction. These innovations support precise, data-driven agricultural practices, enhancing productivity and sustainability [182].
d) *Climate Change Adaptability:* It indicates the process of using advanced tools, technologies, and strategies to mitigate the impact of climate change and building resilient, sustainable agriculture systems. Climate adaptability not only denotes climate change measures but also strives to foster an equitable and sustainable world. Hayman et al. [183] provided an innovative, spatially explicit frameworks for modelling the impacts of climate change on winter wheat crop yield prediction using remote sensing and crop models in United Kingdom. The research assessed climate change risks and designed climate-resilient agricultural systems [183].

5. Conclusion

In this systematic review, the evolution, lessons, innovations, and challenges of historical and contemporary CYPM are summarized, underscoring their critical role in improving global food security. Historical CYPMs, primarily empirical and mechanistic models developed before the 1980s, were based on fundamental principles but were limited by sparse data, observational data, low scaling of data, and static predictions. While historical empirical and mechanistic models provided essential insights, they were fundamentally constrained by data scarcity and simplistic assumptions. In contrast, contemporary models leveraging machine learning, deep learning, and IoT demonstrably achieve greater accuracy, with deep learning models consistently reporting R^2 values of 0.85–0.93, an important improvement over the R^2 range of 0.60–0.75 typical of traditional methods. Advance in yield prediction, real-time monitoring and climate-environmental frameworks have enabled precision agriculture and resilience to environmental challenges using geospatial data fusion. However, this advancement comes with significant computational demands. The high-dimensional data processing and complex algorithms underpinning contemporary models, particularly deep learning and hybrid approaches, create a substantial barrier to their adoption. These computational limitations directly impact scalability and processing efficiency, restricting access for users in regions with limited computing infrastructure or financial resources.

Despite this, ongoing issues such as data quality, computational demands, climate variability, and limited access in regions with low resources are necessitate for inclusive approaches. The development of hybrid modelling, edge computing, transfer learning, and explainable AI are necessary for future research to improve prediction accuracy and accessibility. CYPM can overcome these barriers and promote sustainable farming practices, contributing to food security for expanding global community.

Although this review may not exhaustively capture all modeling paradigms, it provides a reproducible and structured synthesis based on PRISMA 2020 principles, offering a methodological foundation for future meta-analyses.

The study, while offering a comprehensive systematic review of historical and contemporary crop yield prediction models, has limitations. The analysis is predominantly based on English-language peer-reviewed literature from high income countries (particularly USA, China, and European nations), with very limited representations from low-income regions such as Ethiopia and other Sub-Saharan Africa, potentially limiting the applicability of findings to data-scarce, resource-constrained settings. The reliance on secondary citations for historical models (pre-1980s) may omit nuanced methodological details from original sources. Additionally, the grey literature and non-English publication exclusion, though necessary for consistency, that may have overlooked good, localized insights. Due to high heterogeneity in crops, regions, model types, and evaluation metrics across the 23 selected studies, a quantitative meta-analysis was not feasible, limiting the synthesis to qualitative interpretation. Finally, incorporating articles after early 2025 not captured, that may include the recent CYPMs of AI and remote sensing publications.

6. Future research direction

Future research should consider the following key topics to reduce the challenges in crop yield prediction.

i. *Model Hybridism:* By combine multiple techniques from historical or/and contemporary yield predictive models to improve the accuracy and efficiency of yield prediction. These models can solve the limitation of standalone models by integrating many parameters and efficiency in crop yield prediction. The integration of models can enhance prediction accuracy, improve data-driven decision-making system, assess the ongoing environmental changes and adapt climate variability, improve resource use, enabling real-time monitoring, and more promising advantages can be found in through hybrid models/approaches.

ii. *Edge computing:* These approaches can address data dependency in cloud computing. It integrates edge devices (such as IoT sensors, drones, smart devices) to process data locally for real-time data analysis directly from the source site for analysis of crop yield prediction. These approaches can improve security, speed, efficiency, and reliability by processing data from source of data generated than storing to cloud.

iii. *Transfer learning:* In transfer learning uses in pretrained models for new agricultural datasets, when data is limited, and fast computational capability, with existing model of knowledge. These models help in addressing data shortages and reduce the need of high computational power demands, high accuracy, adaptability in many crop types across different regions, and reduce agricultural data collection.

iv. *Multimodal Data Fusion*: The integration of diverse data sources such as weather data, soil properties, remote sensing data, historical yield data, and farming practice to enhance prediction accuracy. By using models like machine learning and deep learning for analysis of data provides a comprehensive and reliable crop yield prediction through data fusion system.

v. *Explainable AI*: Beyond accurate prediction of yield, knowing how and why prediction process has permed, is very essential for direct decision making. The technique is used to understand the most influential factors (such as temperature, precipitation, nutrient level, or other factors) and helps for trusted, transparent, and clear decision making in agricultural practices.

vi. *Digital Twins:* These technologies improve predictions by enhancing accuracy, optimizing resources use, enabling scenario testing, supporting early detections, and driving data decisions by using virtual models. It simulates crop growth by using real-time data from sensors, weather, soil and agronomic practices.

By addressing these challenges, future research can pave the way for more accurate, efficient, adaptive, and universally applicable crop yield prediction models, significantly improving agricultural productivity and sustainability worldwide.

Ethical statement

The authors confirm the following ethical considerations for this study:

1. **Originality & Plagiarism:** This manuscript is an original work and has not been published elsewhere, nor is it currently under consideration by any other journal. All sources used are properly cited.
2. **Authorship & Contributions:** All listed authors have made substantial contributions to the study, including conceptualization, literature review, analysis, and manuscript preparation. No individuals who meet authorship criteria have been excluded.
3. **Data Integrity**: This study is a systematic review of existing peer-reviewed literature; no new experimental data involving humans, animals, or sensitive information was collected.
4. **Conflicts of Interest:** The authors declare no financial or personal conflicts of interest that could influence the research or its interpretation.
5. **Ethical AI Use:** While AI tools were used for grammar checks and citation formatting, all research insights, conclusions, and writing were independently developed by the authors.
6. **Compliance with Guidelines**: The study adheres to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for transparent and reproducible literature synthesis.

CRediT authorship contribution statement

Abebe Gatie Betew: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Girma Gebresenbet:** Writing – review & editing, Supervision, Methodology. **Geta Kidanemariama Gelaw:** Writing – review & editing, Supervision. **Daniel Ayalew Mengistu:** Writing – review & editing, Supervision. **Abdulkerim Mohammed Yibre:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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