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Integration of artificial intelligence and remote sensing for crop yield prediction and crop growth parameter estimation in Mediterranean agroecosystems: Methodologies, emerging technologies, research gaps, and future directions

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ABSTRACT

Context: Crop yield prediction (CYP) along with crop growth parameter estimation (CGPE) recently gained prominence as essential means for optimizing agricultural resource use and addressing global food security challenges, particularly in regions with vulnerable climates and diverse agricultural systems, such as the Mediterranean one. Artificial intelligence (AI) and remote sensing (RS) play an important role in achieving such objectives.
Objective: To identify present methodologies and frameworks, emerging trends, research gaps and future directions in the integrated use of AI and RS in the Mediterranean area for CYP and CGPE.
Methods: We systematically reviewed the published scientific literature on the topic (106 studies) by means of the PRISMA methodology.
Result and conclusions: We found that integration of AI, particularly machine learning methods such as Random Forest, Support Vector Machine, and Artificial Neural Networks, along with satellite-based RS platforms such as Sentinel-2, Sentinel-1, MODIS, and Landsat-8, demonstrated strong potential to enhance monitoring and support adaptive agricultural decision-making. Deep learning models, such as Convolutional Neural Networks and Long Short Term Memories, are emerging tools for spatio-temporal modelling, although their use is limited, likely due to data and computational constraints. Wheat is the most frequently analyzed crop, alongside high-value perennial crops like olives and vineyards. Data acquisition relies predominantly on satellite imagery, though hybrid approaches incorporating unmanned aerial vehicle and ground-based data are promising in improving prediction accuracy. Despite these advancements, significant challenges persist, including uneven geographical research coverage, limited model transferability, and insufficient consideration of crop phenology. A critical lack of standardized validation datasets and the underrepresentation of North African and Middle Eastern countries further constrain progress.
Significance: To fully harness AI-RS integration for sustainable agriculture and food security in the Mediterranean area, and similar agroecosystems, future efforts should aim at i) prioritizing cross-regional collaboration, ii) focusing on hybrid AI-RS methods, iii) developing phenology-aware models, and iv) widening access to data.

1. Introduction

The agricultural sector is under mounting pressure to satisfy the growing global food demand driven by population growth (Miladinov, 2023) and various environmental challenges such as climate change, environmental degradation, and resource scarcity (Dlamini et al., 2023; FAO, 2019). These challenges are particularly acute along the Mediterranean rim (MED-rim), which is characterized by hot summers, water-limited areas, and soils that often have low organic matter and nutrient contents (Arfini, 2021; del Pozo et al., 2019; Rossetto et al., 2025).

Despite these vulnerabilities, the MED-rim is recognized as a global agricultural hotspot because of its high biodiversity and variety of agroecological zones it hosts (Migliorini et al., 2018). Its climatic and

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geographical features foster unique crop biodiversity and promote the development of resilient genetic diversity in crops (Médail and Quézel, 1999). Consequently, the MED-rim serves as a cornerstone of global agriculture, playing a key role in the production of important crops such as wheat, olives, grapes, and many others.

According to FAOSTAT data (2019–2023; Fig. 1), the main crop types in the region can be broadly categorized into cereal, perennial crops, oilseeds, root and tubers crops, vegetables, and fiber crops (FAO, 2023). Among these durum wheat holds particular importance, with MED-rim ranking the world's second largest after North America. Italy and Turkey are the leading contributors within the region, producing 4.3 and 3.7 million tons annually, respectively (Grosse-Heilmann et al., 2024).

The region is also renowned for its dominant role in global olive oil production, accounting for 82 % of the world's supply in 2023/24. However, MED-rim faces increasing threats from climate change, such as rising temperature, erratic rainfall patterns and prolonged drought along with secondary effect such as proliferation of emerging pests and diseases. These factors jeopardize both the quality and the quantity of agricultural production, posing a significant risk to global food security (Alrteimei et al., 2022; Baris-Tuzemen and Lyhagen, 2024; OTT, 2023).

To meet these challenges, there is an urgent need for more adaptive and data-driven agricultural practices that can operate at different spatio-temporal scales. Crop yield prediction (CYP) and crop growth parameter estimation (CGPE) have emerged as critical means for early warning systems, precision farming, and resource allocation (Chavan et al., 2024; Dlamini et al., 2023).

CYP refers to the process of forecasting the amount of crop yield per hectares based on various factors such as environmental conditions, crop type, and management practices. In contrast, CGPE involves estimating key parameters that describe crop growth and development, including biophysical parameters (e.g., leaf area index, biomass, plant height), phenological parameter, crop stress conditions (e.g., water availability, disease), soil properties (e.g., moisture, salinity, organic content) and environmental variables (e.g., rainfall, temperature, solar radiation). These parameters are essential for identifying risks to agricultural productivity, addressing yield gaps, and supporting data-driven decision-making in agriculture (Sandhu and Anand, 2024).

Conventional approaches to crop growth simulation and yield prediction include empirical, statistical, and process-based models, each facing its own set of challenges. Empirical and statistical methods often encounter issues such as co-linearity among predictor variables (e.g., rainfall and temperature) and assumptions of stationarity, which limit their adaptability to changing climatic conditions (Lobell and Burke, 2010). Process-based models, such as DSSAT (Jones et al., 2003), WOFOST (van Diepen et al., 1989), STICS (Brisson et al., 2003), EPIC (Williams, 1990), AquaCrop (Vanuytrecht et al., 2014), and APSIM (McCown et al., 1996) simulate crop growth and predict yields by accounting for complex environmental interactions. However, these models are highly data-sensitive and require numerous crop-specific parameters (Rossetto et al., 2019), and are computationally intensive often necessitating extensive calibration efforts (Pasquel et al., 2022).

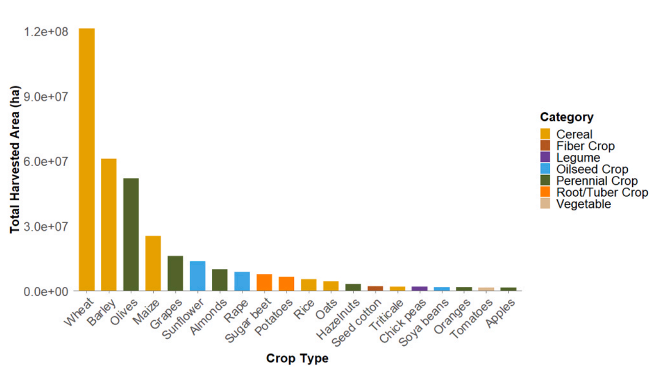

Fig. 1. Main cultivated crop types by area across MED-rim countries (average between 2019 and 2023. Source: FAO, 2023).

Furthermore, conventional methods often fail to adequately capture the complex interplay of biophysical and climatic factors at large-scale simulation such as regional, national, and continental levels, resulting in limited reliability and accuracy in crop growth and crop yield predictions (Dlamini et al., 2023; Hansen et al., 2006). Supplementary table 1 (ST1) outlines some of the most commonly used conventional approaches in crop modelling.

Emerging advanced technologies, such as remote sensing (RS) and artificial intelligence (AI), offer promising alternatives to address these limitations of traditional methods for estimating crop growth parameter and predicting crop yield. By leveraging the capabilities of RS and AI, it becomes possible to enhance the accuracy, reliability, and scalability of CGPE and CYP (Tsouli Fathi et al., 2020).

RS, through satellites and aerial platforms, is transforming agriculture by providing high-resolution spatial and temporal data on vegetation, soil, and climate conditions. This technology plays a fundamental role in monitoring crop physiological and environmental parameters (Ailian et al., 2020; Li et al., 2023).

RS-derived crop growth parameters are typically classified into physiological and environmental parameters. Physiological parameters include biophysical parameters (e.g., vegetation indices, such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), biomass accumulation, and plant height; Mridha et al., 2021; Tao et al., 2020), crop stress indicators related to water, nutrient, pest, and disease stress (Chakhvashvili et al., 2024; Dong et al., 2024), and phenological parameters, including crop growth stages, reproduction stage, and maturity timing (Dronova and Taddeo, 2022; Graf et al., 2023). Environmental parameters encompass soil stress indicators (e.g., soil moisture, soil nutrient content, water) (Abdulraheem et al., 2023), and weather parameters, including rainfall, temperature, and solar radiation (Chen and Tao, 2022).

RS enables the detection of spatial and temporal trends, anomalies, and shifts in biophysical and environmental conditions, which can be interpreted to assess vegetation health, soil dynamics, and climate-related impacts (Alqadhi et al., 2024; Rahimabadi et al., 2024). This capability enables the early detection of crop stress caused by drought (Roy et al., 2024), nutrient deficiencies (Futerman et al., 2023), or rising temperatures (Becker et al., 2023). Additionally, RS data facilitates continuous crop monitoring and yield prediction by integrating both real-time and historical datasets (Joshi et al., 2023; Kumari et al., 2024).

Agricultural monitoring and prediction have recently undergone significant advancements through the integration of AI (Kamilaris and Prenafeta-Boldú, 2018; Paudel et al., 2021). The subcategories of AI, machine learning (ML), and deep learning (DL), may play a pivotal role in modern agriculture by enabling early detection of diseases and pests, allowing prompt action to minimize crop losses (Delfani et al., 2024). In addition, AI models can integrate weather forecasts and soil sensor data to optimize irrigation strategies, thereby promoting soil health and improving water use efficiency (Alibabaei et al., 2021; Gera and Jain, 2023).

The integration of ML and DL models with high-resolution RS data may enables robust analysis and prediction of crop yields by evaluating vegetation indices, plant health, and growth patterns (Muruganantham et al., 2022; van Klompenburg et al., 2020). This synergy enhances scalability by enabling monitoring across diverse regions and improves adaptability by providing robust predictions in the context of climate variability and resource constraints (Liakos et al., 2018). Collectively, RS and AI form a dynamic and scalable framework that advances the precision and reliability of crop growth parameter estimation and yield prediction, contributing significantly to global food security challenges.

Two prior reviews have explored certain aspects of AI and RS integration in the MED-rim, but neither of the studies provided a systematic synthesis of their joint application for CGPE and CYP in this region.

Radočaj et al. (2022) reviewed that ML paired with RS data outperforms conventional interpolation for soil condition prediction in a Croatian case, with hybrid RS sources improving fertilization prescription mapping. Kganyago et al. (2024) reviewed recent advances in remotely sensed crop parameter retrieval driven by sensor innovations and machine learning, identified key uncertainties, and discussed implications for precision agriculture. Nonetheless, neither review systematically addressed the integrated use of AI and RS for CYP and CGPE, nor did they provide a structured synthesis of methodological choices, dataset types, model performance, or regional challenges. This gap underscores the need for a focused systematic literature review (SLR). To highlight this gap, Table 1 contrasts the present review with aforementioned studies.

By conducting a PRISMA-guided systematic review of 106 studies, this paper provides the first structured synthesis of AI and RS integration for CGPE and CYP specifically tailored to the Mediterranean agroecosystem. Beyond consolidating technological advances and model performance insights, the review provides a critical evaluation of methodological trade-offs, dataset limitations, and region-specific challenges that earlier reviews have not addressed. Given the rapid growth of AI and RS applications, persistent data scarcity, and urgent need for climate-resilient agriculture, this synthesis is both timely and essential, offering a dual role as scientific reference and practical roadmap for deploying integrated AI and RS strategies in data-constrained, climate-vulnerable agroecosystems.

To guide this synthesis, the following research questions (RQs) were formulated:

- RQ1- What are the prevailing methodologies and technological frameworks used in integrating RS and AI for CGPE and CYP in the MED-rim?
- RQ2- What are the current limitations and research gaps in applying RS and AI to agricultural productivity in the MED-rim agroecosystem?
- RQ3- What emerging trends and future directions are promising in using RS and AI applications in CGPE and CYP?

By addressing these RQs, this review aims to inform both researchers and practitioners, advancing sustainable agricultural practices and improving the management of scarce resources in Mediterranean agroecosystems and comparable dry, warm agroecosystems worldwide.

2. Material and methods

2.1. Review protocol

This SLR adopts the "Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA)" framework, an evidence-based process designed to improve reporting quality (Page et al., 2021). Fig. 2 illustrates the stepwise flowchart of the review process, which consists of three main steps: (1) planning the review, (2) conducting the review, and (3) reporting the review, each with its respective internal sub-steps.

During the planning step, research questions (outlined in Section 1) were carefully formulated, and a review protocol was developed. Predefined search strings, inclusion and exclusion criteria, and selection standards were established to guide the process. Systematic searches were then conducted in the selected databases using predefined search strings to identify relevant studies. This was followed by data extraction, bias assessment and synthesis aligned with the research objectives. Finally, results were systematically documented in the reporting step, incorporating thematic analyses and detailed summary tables to enhance clarity and ensure reproducibility.

2.2. Search strategies

The SLR includes articles retrieved from two main scientific databases: Scopus and the Web of Science (WoS). The choice of the two databases ensures that all included studies have undergone peer review, as both were selected for their comprehensive and reputable coverage across diverse scientific disciplines (Martín-Martín et al., 2018). The search strategies involved designing search queries and selecting appropriate databases for execution. Search queries were developed using keywords and Boolean logical operators ("OR" and "AND") applied to the title, abstract, and keywords fields in both databases. Keywords included terms such as "remote sensing", "artificial intelligence", "agricultural productivity", and "Mediterranean region", along with synonyms to maximize relevance. After iterative testing and refinement of the search syntax, the final logical search queries were developed and are presented in ST2.

2.3. Eligibility criteria

To ensure scientific rigor, thematic relevance, and geographic focus, a set of eligibility criteria was applied. These criteria guided the selection process to include studies that meaningfully contributes to understanding the integration of AI and RS for CGPE and CYP with in MED-rim agroecosystems. The eligibility criteria consist of two main components (Table 2): inclusion criteria (IC) to identify relevant studies, and exclusion criteria (EC) to filter out irrelevant, redundant or insufficiently detailed records.

2.3.1. Definition of the MED-rim

Defining the MED-rim for agricultural studies perspective is complex due to its diverse and heterogeneous environmental characteristics. These include climate diversity (Lionello et al., 2006), geographical boundary (Blondel et al., 2010), topographical complexity (Grove and Rackham, 2003), and the multifaceted impacts of climate change (Iglesias et al., 2012).

This study adopts the definition by Noce and Santini (2018), as shown in Fig. 3. The MED-rim encompasses the area adjacent to the Mediterranean Sea and is distinguished by unique geographical and climatic features. Geographically, it includes all territories directly bordering the Mediterranean Sea, sharing distinct environmental and

Table 1
Comparison of present study main aspects with previous review articles.

Aspect	Present study	Kganyago et al. (2024)	Radočaj et al. (2022)
Scope	Systematic review of AI and RS integration for CYP and CGPE in the MED-rim	Review of RS and ML advances in crop parameter retrieval globally	Comparison of conventional and ML-based methods for soil parameter prediction
Geographical focus	Mediterranean agroecosystem	Global (with Mediterranean case insights)	Croatia (as case study)
Review methodology	PRISMA-guided systematic review of 106 studies	Narrative literature review	Narrative literature review
AI techniques covered	ML, DL and hybrid AI methods	ML and DL methods	ML methods
RS platforms	Satellites, Unmanned Aerial Vehicles (UAVs), ground-based sensors, and hybrid platforms	Satellite, UAVs, and ground-based platforms	Satellites and UAVs

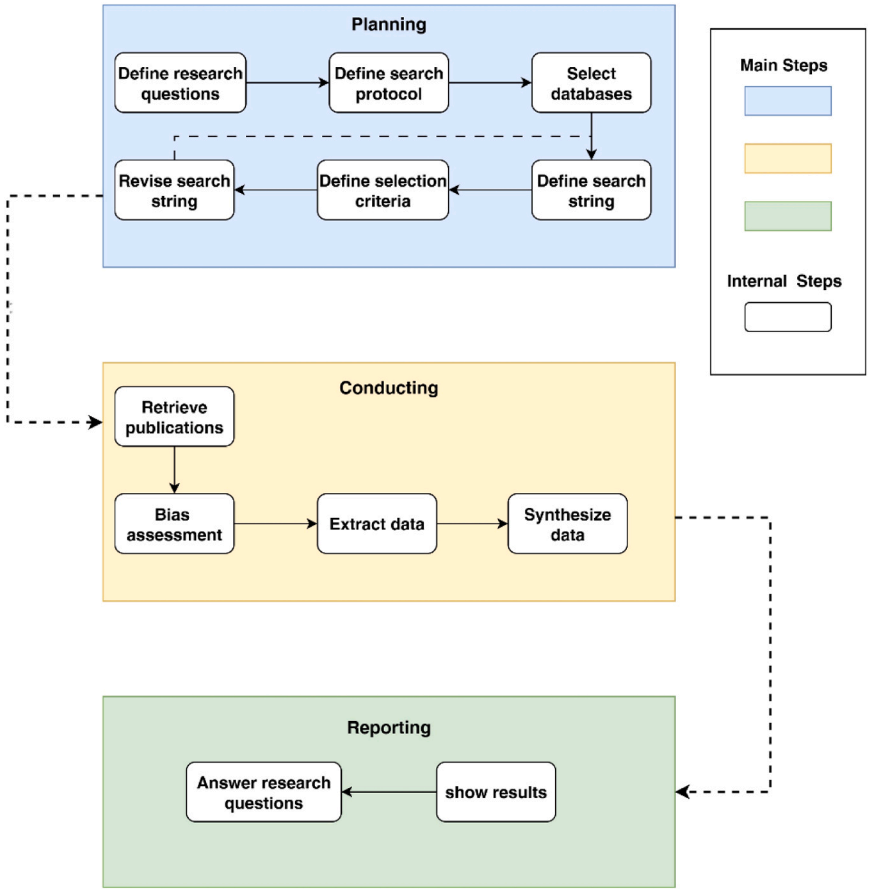

Fig. 2. Main and internal steps of SLR (adapted from Koutsos et al., 2019).

Table 2
Summary of inclusion and exclusion criteria.

Dimension	Inclusion criteria (IC)	Exclusion criteria (EC)
Duplicate check	Unique entries across databases (IC1)	Duplicate records (EC1)
Meta data completeness	Complete bibliographic information (IC2)	Missing title or author (EC2)
Language	Publication in English or French language (IC3)	Publication in other languages (EC3)
Publication type	Journal articles, conference papers, books and book section (IC4)	Review articles and data and erratum paper (EC4)
Geographical scope	Studies within/near the MED-rim bioclimatic region (IC5)	Studies conducted outside the MED-rim region (EC5)
Thematic focus	Direct or indirect relevance to CGPE and CYP using AI and RS (IC6)	Studies not addressing CGPE/ CYP or not integrating AI and RS (EC6)

biogeographical features. For analytical purpose, the region was divided into three sub-regions: Euro-MED (Europe Mediterranean; Spain, Gibraltar, France, Monaco, Greece, Italy, Mata, Croatia, Slovenia, Montenegro, Albania, Cyprus, Bosnia and Herzegovina), NA-MED (North Africa-Mediterranean; Morocco, Algeria, Libya, Egypt, and Tunisia), and ME-MED (Middle East-Mediterranean; Türkiye, Israel, Palestine, Lebanon, and Syria) (Fig. 3).

Beyond geography, a climatic classification was applied to refine the document selection process. To achieve this, the Köppen-Geiger climate classification (Kottek et al., 2006) was applied to delineate the Mediterranean climate. According to this classification, the Mediterranean climate is categorized as a mid-latitude temperate climate with dry summers, characterized by either warm (Csb) or hot (Csa) summer conditions. Based on this definition, documents featuring case studies within the established bioclimatic limits, or near the marginal boundaries of the Mediterranean climate zone were considered relevant for inclusion in this review.

2.4. Risk of bias assessment

A bias assessment was conducted to minimize the risk of including studies outside the scope of this review. The assessment was carried out by organizing the screened data in Microsoft Excel® and scoring each publication on a five-point Likert scale (1 = lowest, 5 = highest) for agricultural research type, study design, and evidence quality (i.e., the degree to which findings are supported by rigorous, transparent, validated methods, as detailed in Table 3). An average percentile score was then calculated for each study, and only those meeting or exceeding the 75 % threshold were retained, thereby ensuring a high-quality, relevant synthesis.

In addition to methodological screening, we recognize the potential for publication bias and language bias. Publication bias may arise because studies were retrieved primarily from Scopus and WoS databases, potentially overlooking relevant gray literature or studies published in less-ranked journals. Language bias may also be present since the review primarily included studies published in English and French, which could limit the representation of research conducted in Mediterranean regions where local languages (e.g., Italian, Spanish, Arabic, Greek) may be often used. While these limitations could not be fully eliminated, acknowledging them provides transparency and contextualizes the scope of our findings. Future works may benefit from incorporating non-English databases and additional low-ranked sources to further mitigate these risks.

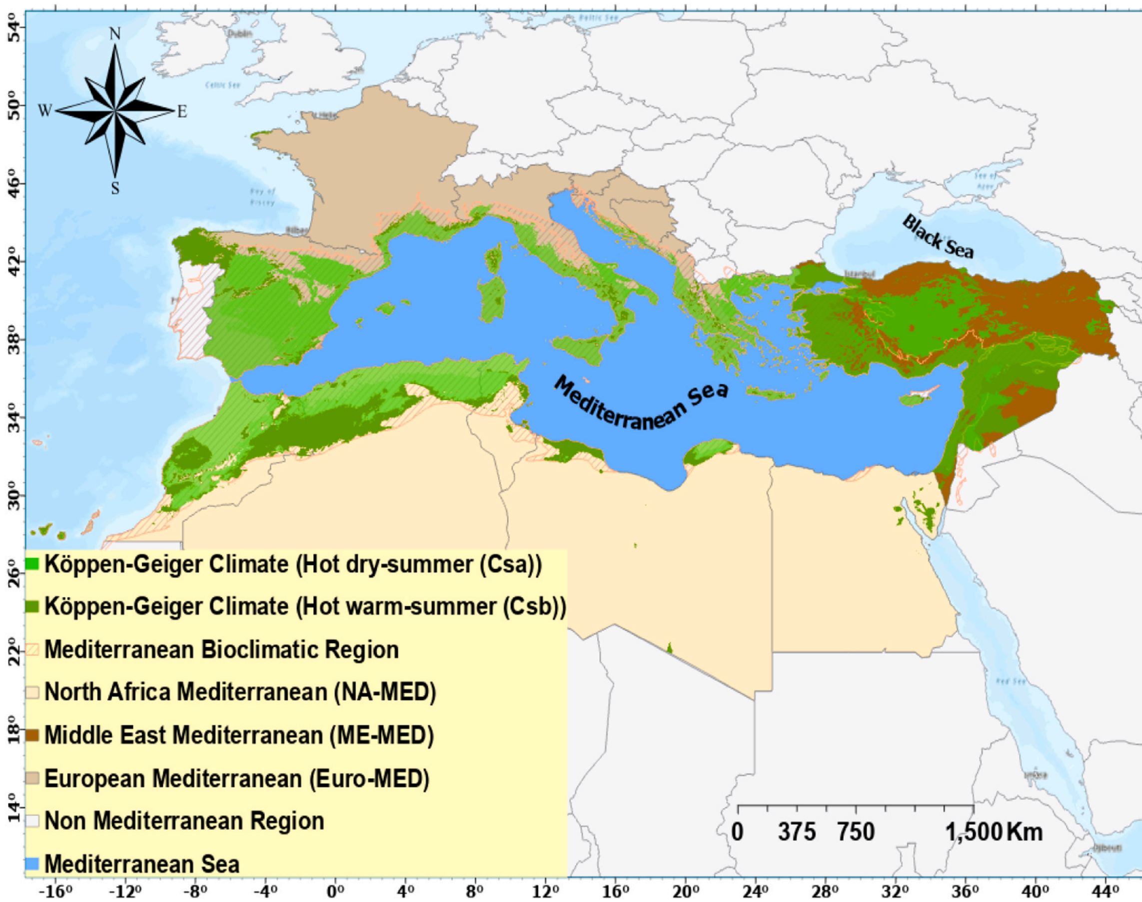

Fig. 3. Geographical domain under investigation.

Table 3
Ranking strength of evidence of publications (adapted from Koutsos et al., 2019).

Strength of evidence	Type of agricultural research	Study design	Evidence quality
Strong (5)	Applied research, adaptive/farm-level research, strategic research	Experiments, field trials,	Strongly substantiated (documented evidence)
Moderate (4)	Case studies, modeling/ simulation	Case studies and simulations	Well substantiated (evidence under conditions)
Weak (3)	Opinion pieces, conference papers, and workshop papers	Qualitative papers, reports of experts, opinion paper	Weakly substantiated

2.5. Data extraction and synthesis

Following the bias assessment and final selection, a structured data extraction matrix was iteratively developed to systematically extract and synthesize evidence information from selected publications, ensuring consistency and reproducibility.

Prior to full-scale implementation, a pilot validation was conducted on a random subset (20 % of the selected) to refine the architecture of the matrix (ST3) and ensure its robustness in capturing critical variables. The matrix attributes the data primarily into two categories: 1) general metadata, including bibliographic details (titles, authors, journal and publisher name, publication year, DOI), article type, journal impact metrics (SCImago Journal Rank (SJR) quartile), 2) thematic and methodological data, including, crop type, methodology frameworks used for CGPE and CYP, data acquisition platforms, vegetation indices, model training approaches, scale of study, and model evaluation metrics. This iterative refinement process, conducted in accordance with PRISMA guidelines, ensured consistency and facilitated cross comparative analysis, which facilitates the synthesis of heterogeneous evidences into actionable insights.

3. Results

3.1. Literature search

The search strategy identified a total of 551 publications: 195 from WoS and 356 from Scopus database. After removing duplicates (EC1; n = 171), excluding irrelevant documents (EC2; n = 6) and filtering publication by language (EC3; n = 4), 370 publications remained.

The remaining documents were then assessed by eligibility criteria (EC4, EC5 & EC6). Each publication's relevance using a 5-point Likert scale, where 1 indicated the lowest and 5 the highest relevance (as shown in Table 3). For each study, an average score was calculated, and those meeting or exceeding the 75 % threshold were selected for inclusion in the literature synthesis. This screening process resulted in a final selection of 106 publications: 35 from Scopus, 8 from WoS, and 63 indexed both databases. The selection process is detailed in Table 4 and summarized in the PRISMA flowchart (Fig. 4).

3.2. Literature analysis

3.2.1. Dataset overview

Fig. 5a illustrates the annual number of selected publications on MED-rim up to November 2024. Selected publications demonstrate a noticeable increase since 2020, likely driven by advancements in RS

Table 4
Distribution of publications type and source database before and after exclusion criteria (EC). *Review papers were not included in the review, and discussed in the Introduction.

Type of publication	Databases						
	Scopus only		WoS only		Scopus & WoS		Total
	Before	After	Before	After	Before	After	Final selected
Journal article	100	19	18	7	276	61	86
Conference proceeding paper	65	15	5	1	50	3	19
Review paper	3	-	1	-	12	2	*
Data & erratum paper	2	-	-	-	2	-	-
Book & Book chapter	9	1	-	-	2	2	1
Unlabled data	6	-	-	-	-	-	-
Total	185	35	24	8	342	63	106

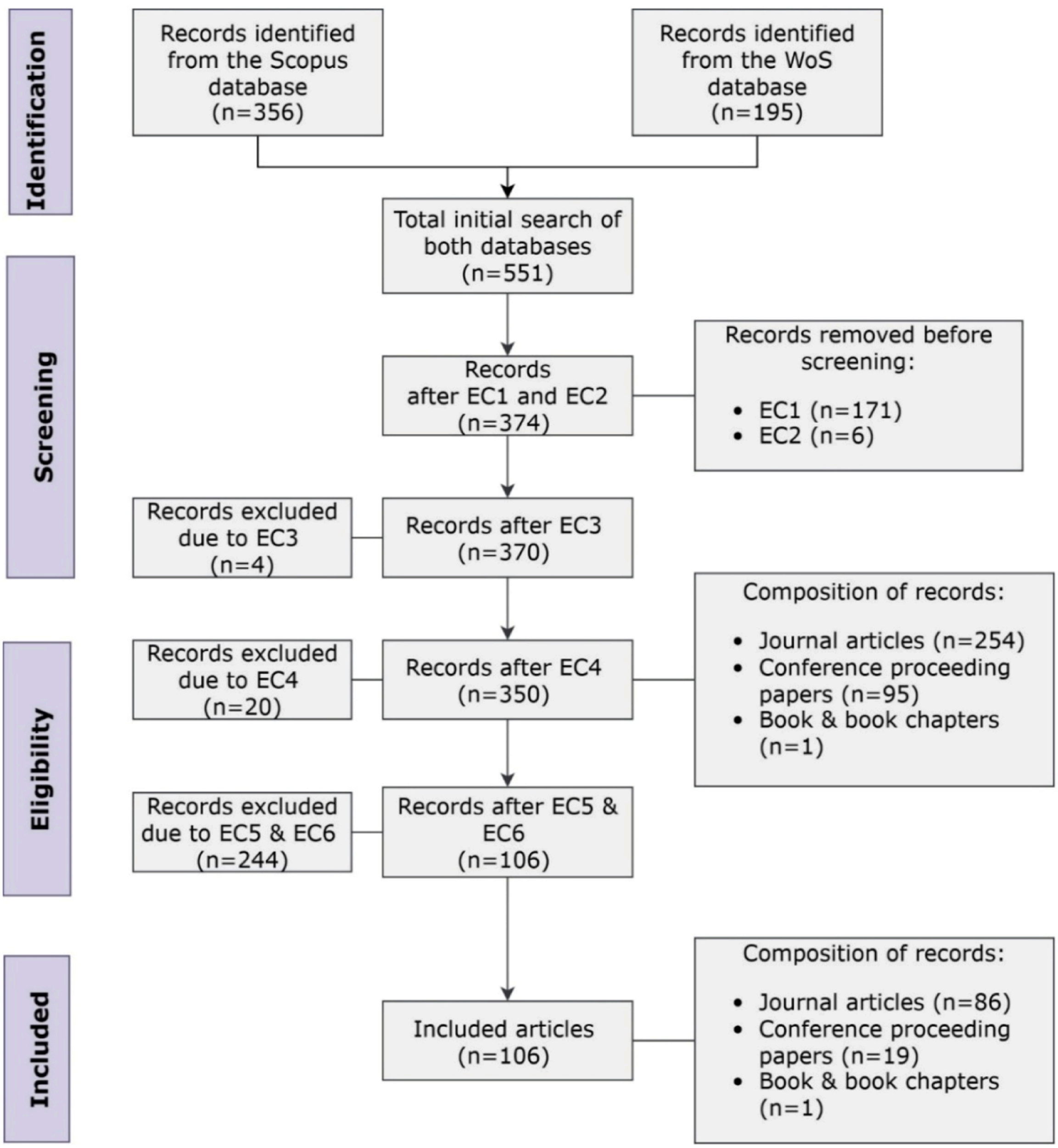

Fig. 4. SLR flowchart, adapted from Page et al. (2021), illustrating the key stages and outcomes of the review process, including identification, screening, eligibility assessment, and final inclusion of studies. The full list of the analysed papers along with processed data (exclusion criteria) is reported in Supplementary Material file mmc2.xls

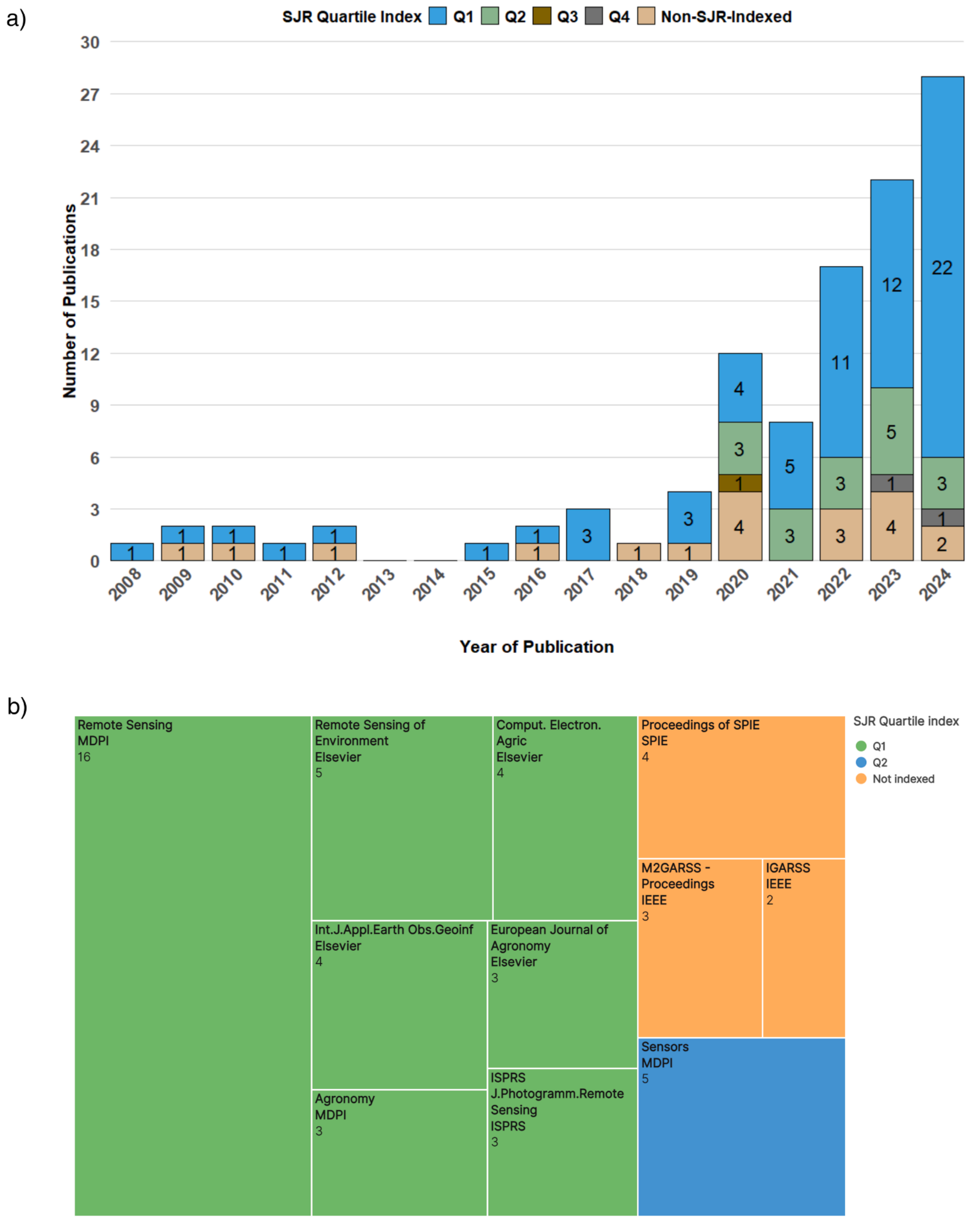

Fig. 5. a) Temporal distribution of selected publications and SJR Quartile index (Note: prior to 2008, in 2001 only one Q2 document was found, which is not included in this plot). b) Distribution of top 17 % of the most frequently utilized journals and conference proceedings in the SLR.

data acquisition platforms, such as improvements in spatio-temporal resolution that enable more detailed and frequent observations. These technological advances, coupled with the increased computational power of computers through large-scale GPUs and AI-specific hardware, have facilitated the processing and analysis of massive datasets generated by RS technologies (Zhang and Zhang, 2022). We acknowledge the impact of COVID-19 pandemic on agricultural research and publication process (Mafruchati et al., 2021; Trentin et al., 2024), which may explain the observed dip in academic output during 2021. These finding highlights the domain is emerging and experiencing growing activity.

According to SJR ranking, most publications are published in Q1 journals (62 %), followed by Q2 journals (17 %). A smaller portion appeared in lower-impact journals (Q3:1 % and Q4:2 %). Additionally, 18 % of documents were in non-SJR-indexed, primarily conferences proceedings. The SJR indicator is widely recognized as a robust measure of journal prestige, as it accounts not only for the number of citations but also for the influence of the citing sources, thus providing a field-normalized assessment of journal impact (Guerrero-Bote and Moya-Anegón, 2012).

The included studies were published in 45 different journals and 13 conference proceedings. Fig. 5b illustrates the top 17 % most frequently used journals and conference proceedings in AI and RS integration for CGPE and CYP studies. Among these, 8 are peer-reviewed journals, while two are conference proceedings (IEEE, and SPIE). Although most conference proceedings are not indexed by SJR, they were included in the review as they provide valuable and updated insights into AI and RS applications for CGPE and CYP.

Among journals, Remote Sensing (n = 16) and Sensors (n = 5) ranked first and second in publication output respectively. These were followed by top-tier Q1 journals, such as Remote Sensing of Environments (n = 5), International Journal of Applied Earth Observation and Geoinformation (n = 4), and Computers and Electronic in Agriculture (n = 4). The remaining journals contributed two or fewer publications.

This analysis highlights the diversity of publication outlets in the field, which is essential for mapping the research landscape, identifying collaborative opportunities, and tracking emerging trends in CGPE and

CYP for sustainable agricultural management.

3.2.2. Geographical distribution of case studies over MED-rim

Fig. 6a reveals a significant disparity in research activity across EURO-MED, ME-MED, and NA-MED countries. Several studies were conducted across multiple locations, with experiments carried out in one region while validation and testing in another (Astaoui et al., 2021; Baghdadi et al., 2018; Ezzahar et al., 2024; Ozalp, 2020; Paloscia et al., 2020; Ramat et al., 2023).

The Sankey diagram (Fig. 6b) reveals strong research linkages between first-author affiliations and case study locations, highlighting regional and international collaborations. Most countries exhibit a self-focused pattern that is first author's affiliation matches the study location, reflecting national research priorities. In contrast, Italian-based researchers demonstrate notable research collaboration with work spanning EURO-MED (Malta, Slovenia, Spain, Greece, Cyprus, Croatia), NA-MED (Algeria, Egypt, Tunisia) and ME-MED (Israel). Additionally, researchers from non-MED nations such as Germany, the Netherlands, Austria, Australia, China, Jordan, and Japan also contributed to MED-rim studies, indicating global interest in the region.

3.2.3. Crop type analysis in the MED-rim

Fig. 7a depicts the crop-specific distribution for CYP and CGPE studies. In CYP studies, cereal crops dominate: wheat (15 studies) was

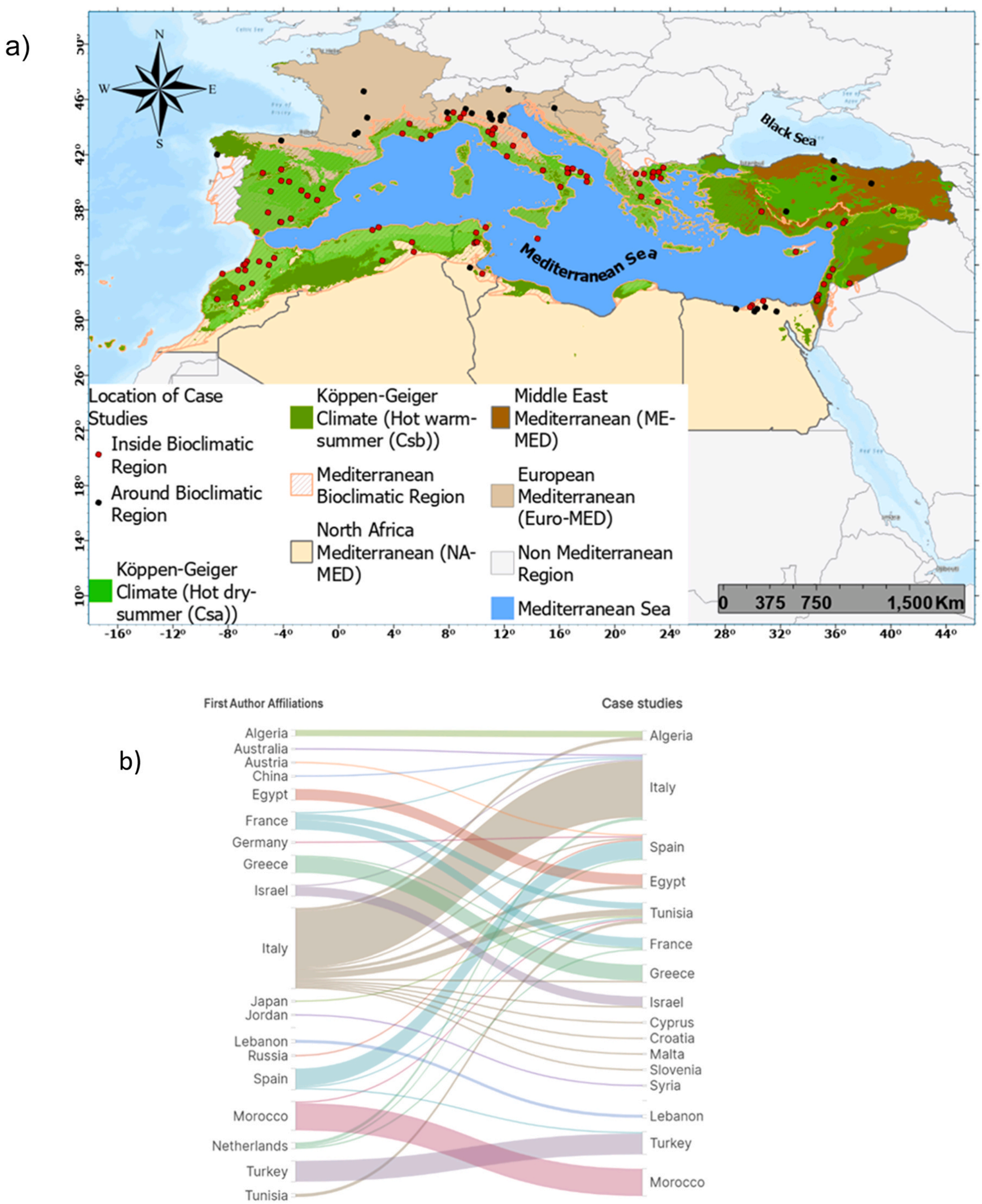

Fig. 6. a) Geographical distribution of case studies over the MED-rim b) Sankey diagram of first author affiliations with case studies.

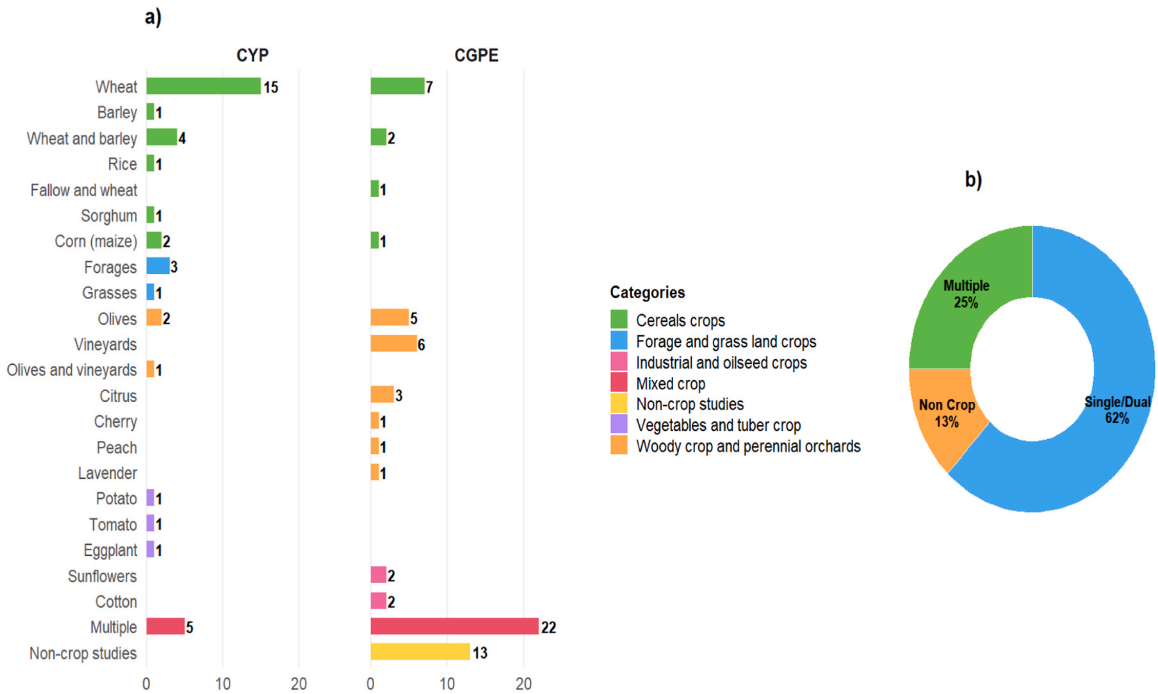

Fig. 7. a) Crop-specific study distribution for CYP and CGPE, and b) Study categorization based on the number of investigated crops over MED-rim.

the most common, followed by mixed wheat-barley systems (4 studies), corn (2), barley (1), rice (1), and sorghum (1). CGPE studies also examined cereal crops such as wheat (7) but featured more woody and perennial crops including vineyards (6), olives (5) and citrus (3). Industrial crops like cotton (2) and sunflower (2) are also present. Notably, mixed cropping systems were more prevalent in CGPE (22) than in CYP (5) studies.

The reviewed publications highlight the agricultural diversity of the MED-rim agroecosystem. As shown in Fig. 7b, most studies (62 %) focus on one or two crops, while 25 % examined multiple crops without distinguishing between crop types. The remaining 13 % were non-crop-specific focused, addressing factors that indirectly influence crop growth through soil conditions such as soil salinity (Klibi et al., 2020), soil organic carbon and matter (Angelopoulou et al., 2023), soil moisture (Yahia et al., 2021) and soil degradation (Samarinas et al., 2024).

Wheat emerges as the most studied crop in both CPGE and CYP studies, underscoring its importance as a staple cereal in MED-rim agriculture. Other commonly analyzed cereals include barley, corn (maize), and sorghum, which are vital for both human nutrition and livestock feed. Conversely the study reveals that perennial woody crops (olives and vineyard), the backbone of the MED-rim agriculture (De Ollas et al., 2019), have been more broadly investigated in CGPE studies. Additionally, fruit crops such as citrus, cherries, and peaches, along with vegetables like potatoes, tomatoes, and eggplants, are also investigated.

3.3. Prevailing methodologies in RS and AI in MED-rim agroecosystems

A diverse range of methodologies and technological frameworks were employed to estimate crop growth parameters and predict crop yield. Data acquisition was conducted using a variety of RS platforms, including satellites, UAVs, aerial, ground-based and hybrid systems.

3.3.1. Data acquisition platforms

RS platforms provide critical, non-destructive data for monitoring crops and environmental conditions over various scales. Based on the platform, RS is commonly divided into satellite-based, aerial (manned aircraft), and UAVs, with ground-based proximal sensors often considered a separate category. Each platform type offers distinct spatial resolution and temporal coverage, and they may carry different sensor types (e.g. optical, radar, thermal) that capture information across the electromagnetic spectrum (EMS). In agricultural applications, these platforms enable continuous spatial and temporal monitoring from field to regional scales. In Mediterranean agroecosystems, satellite imagery has been the predominant data source (~69 % of studies), followed by UAVs (~13 %), whereas manned aerial surveys (~2 %) and ground-based measurements (~2 %) play smaller roles; ~14 % of studies employ hybrid combinations of multiple platforms (Fig. 8). Below, we discuss each platform category (satellite, UAVs, aerial, ground-based, and hybrid) comparing their performance and use in CGPE versus CYP, along with their advantages, limitations, and Mediterranean specific challenges.

Table 5 summarizes the data acquisition platforms used in MED-rim for CGPE and CYP studies. The comparison highlights differences in spatial resolution, revisit frequency, advantages, and limitations across satellites, UAVs, aircraft, ground-based sensors, and hybrid approaches. While satellite systems provide broad coverage and historical archives, UAVs and ground-based platforms enable ultra-high resolution and flexible timing at local scales. Manned aerial surveys offer an intermediate solution, and hybrid integration leverages multiple sources to

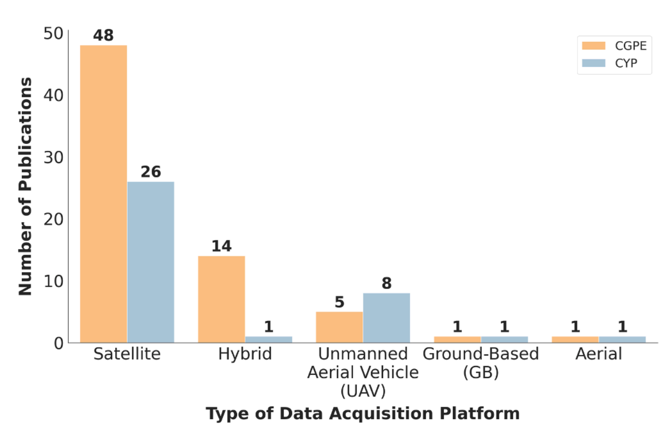

Fig. 8. Commonly used data acquisition platforms.

Table 5
Summary of data acquisition platforms used in MED-rim studies for CGPE and CYP, outlining their spatial resolution, revisit frequency, key advantages, and limitations.

Platforms	Spatial resolution	Revisit frequency	Key advantages	Key limitations
Satellite - Optical (Multispectral)	~10–30 m (Sentinel−2: 10 m; Landsat−8: 30 m; MODIS: 250–500 m)	Sentinel−2 ~5 days; Landsat ~16 days; MODIS daily	Broad area coverage (regional/national scale); open access missions; multi-spectral data for vegetation indices and crop mapping; long historical archives (decades) for trend analysis	Misses field level detail; cloud cover disrupts optical data; fixed revisit schedule (timing may not align with critical crop events); requires atmospheric corrections (dust, cloud and haze which are common in MED-rim climate)
Satellite - Radar (Microwave)	~3–20 m (Sentinel−1: ~10 m; TerraSAR-X: 3 m; RADARSAT−2: 5–25 m)	Sentinel−1 ~6 days; TerraSAR-X: ~3 days; RADARSAT−2: ~4 days	All-weather capability (penetrates clouds); complements optical data by capturing crop canopy structure and soil moisture dynamics; provides unique information on conditions such as flooding and surface wetness	Speckle noise and complex processing; data interpretation less intuitive; typically lacks colour/spectral information; some radar data not freely available or have tasking delays
Satellite - Thermal Infrared	~100 m - 1 km (Landsat−8 TIRS: 100 m; MODIS thermal: 1 km)	Landsat ~16 days; MODIS daily	Direct measurement of land surface temperature proxy for crop water stress and evapotranspiration; can identify water deficits before visible symptoms; enhances drought monitoring when combined with optical sensor indices	Coarser spatial resolution (fields may contain mixed signals); high-resolution thermal data acquired infrequently; measurements influenced by atmospheric humidity; limited number of thermal sensors leading to gaps in time series
UAVs	~2–10 cm (at typical flying altitudes)	On-demand (flexible flight timing)	Ultra-high resolution reveals fine crop details (plant gaps, disease spots, weed patches); user-controlled timing (capture critical growth stages or rapid changes); can deploy diverse sensors (RGB, multispectral, thermal, hyperspectral) at low cost; data immediately available for analysis	Limited coverage (not feasible for very large areas); requires skilled operation and favourable weather; regulatory restrictions on drone flights in some areas; data processing (ortho mosaicking) is time-consuming for large datasets; repeated flights needed for time-series (labour intensive)
Aerial	~0.1–1 m (depending on flight altitude and sensor)	On-demand (campaign-based)	Covers larger area than UAVs with high resolution than satellites; ability to carry advanced sensors (large hyperspectral, thermal scanners, LiDAR) that drones cannot easily lift; useful for regional surveys and capturing data when satellite passes are infrequent	High operational cost (piloted aircraft, fuel, sensor rental); infrequent data collection (usually one-time or annual flights, not continuous monitoring); requires specialized processing (georeferencing, calibration of imagery); subject to aviation regulations and weather constraints for flying
GB (Proximal)	Millimetres to single plant scale	Continuous or scheduled sampling	Very high accuracy and specificity (direct measurements of plant or soil parameters); can capture variables not observable remotely (e.g. leaf nutrient content, exact soil moisture, stem sap flow); high temporal frequency possible (e.g. hourly sensor readings); critical for calibrating and validating remote sensing models	Extremely limited spatial representativeness (point data may not reflect whole field variability); deployment and maintenance can be labour-intensive and costly on large scale; data often require manual collection (if not automated sensors); not a standalone solution for broad monitoring due to sparse coverage
Hybrid (multiple platform integration)	Multiple scale	Multiple timing	Synergistic use of multiple data sources compensates for individual platform weaknesses; enhanced prediction accuracy by providing multi-resolution, multi-modal inputs for models; robustness in variable conditions; multiple scale insights (regional context and local detail); facilitates cross-validation of data (one sensor cross-checks another)	High complexity in data management and fusion; requires careful co-registration and normalization between datasets; increased cost and coordination (multiple platforms to deploy); potential model overfitting or inconsistency if one data type dominates; expertise needed in multiple sensing modalities

overcome individual weaknesses. This overview illustrates the trade-offs that researchers must consider when selecting or combining platforms for agricultural monitoring in Mediterranean environments

3.3.1.1. Satellite based platforms (optical, radar, thermal). Optical (multispectral) satellites imagery forms the backbone of RS in MED-rim agriculture, providing broad coverage and free accessibility of multiple datasets. Multispectral optical sensors (from visible to near-infrared bands in EMS) on satellites like Sentinel-2, Landsat and MODIS have been extensively used both in CYP and CGPE studies. These sensors capture vegetation reflectance and indices (e.g. NDVI) that are crucial for assessing crop health, phenology and yield.

Sentinel-2 satellite has emerged as the predominant multispectral source for yield prediction in the region (used in 14 studies), followed by MODIS (5 studies) and Landsat-8 (3 studies) platforms (ST4). The popularity of Sentinel-2 is due to its 10–20 m resolution and 5-day revisit, enabling detailed vegetation monitoring. For example, Kayad et al. (2019) used Sentinel-2 NDVI imagery combined with ML algorithm to assess the field-scale spatial variability of corn grain yield in Northern Italy over three growing season (2016–2018), supporting precision farming decisions. Landsat-8 (30 m, 16-day) has been employed to derive drought indices including vegetation condition index (VCI), temperature condition index (TCI), and vegetation health index (VHI) that serve as early warnings of yield losses under drought (Kefi et al., 2022). Similarly, moderate-resolution MODIS data (250–500 m,daily) have been integrated with climate data to monitor drought impact on agricultural productivity in multiple provinces in Morocco (Bouras et al., 2021).

In CGPE studies, multispectral sensors have been even more widely utilized, with Sentinel-2 (30 studies), Landsat-8 (13 studies), Landsat-7 (6 studies), and MODIS (6 studies) being among the frequently utilized (ST4). These sensors have been applied across various agricultural contexts to assess crop growth parameter components. For instance, Rouault et al. (2024) used Sentinel-2 data to derive critical biophysical parameters, including leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR), and fraction vegetation cover (FVC), as well as phenological parameters like crop development stage across large-scale agricultural farms. Building in this capacity, Cetin et al. (2023a) integrating Sentinel-2 with Landsat-7/8 imagery markedly improves the estimations of actual evapotranspiration (ETa) in irrigated systems. This improvement arises from the complementary strengths of the sensors: Sentinel-2 offers high-resolution, frequent-revisit data for precise crop classification, while Landsat provides a long-term historical archive and thermal bands essential for surface temperature assessment. Such synergies enhance the reliability of ETa estimates, thereby informing water-management strategies in semi-arid regions.

Beyond general monitoring, Sentinel-2 has also proven effective in precision agriculture (PA) applications. Farbo et al. (2024a) integrated Sentinel-2 multispectral bands (B6, B7, B8, and B3) with machine learning models to evaluate the effects of plastic cover technology on crop ecophysiological parameters in vineyards. Despite potential spectral interference from the plastic cover, Sentinel-2 achieved strong predictive performance, with root mean square error (RMSE) values below 7 % for intercepted solar radiation (ISR) and below 0.14 MPa for stem water potential (Ψ). These results highlight the platform's sensitivity to subtle variations in crop health under advanced PA systems.

Similarly, Souissi et al. (2022) employed MODIS-derived vegetation indices (MOD13Q1) and potential evapotranspiration products (MOD16A2) within an artificial neural network framework to predict root-zone soil moisture (RZSM) in regions where surface and subsurface moisture show weak correlation. While the method demonstrated substantial predictive potential, the authors noted that persistent cloud cover in temperate and tropical climates can constrain model accuracy.

Microwave (radar) sensors, operating in the microwave range of the EMS, provide all-weather monitoring capabilities, making them invaluable for continuous agricultural observation, particularly under cloudy days. These radar sensors transmit and receive pulses via antenna, analyzing backscattering signals to reveal information such as target distance, direction, shape, size, roughness, and dielectric properties of the Earth's surface (Janga et al., 2023).

The analysis of the selected document showed that various types of radar sensors were utilized for CYP studies, with the most common being Sentinel-1, RADARSAT-2, TerraSAR-X, and COSMO-SkyMed (CSK) (ST4). For instance, Pancorbo et al. (2023) demonstrated the use of Sentinel-1 data to predict winter wheat yield at the field scale, highlighting its capacity to provide essential parameters for CYP such as biomass, crop growth dynamics, soil moisture, and vegetation water content during cloudy winter seasons. Similarly, Fieuzal and Baup (2017) combined TerraSAR-X radar imagery with SPOT 4/5 and FORMOSAT-2 optical data to forecast wheat yield. In their study, TerraSAR-X played a key role by capturing backscattering coefficients linked to crop structure and moisture, thereby enabling all-weather monitoring of vegetation dynamics and supporting accurate yield prediction.

Various radar sensors have been utilized for CGPE studies in the MED-rim. For instance, Chauhan et al. (2020) used RADARSAT-2 and Sentinel-1 to estimate the biophysical parameter (crop angle of inclination (CAI)), enabling crop lodging assessment and monitoring. For environmental parameter estimation, such as surface soil moisture (SSM), Abdikan et al. (2023b) integrated multiple radar sensors such as Kompsat-5, RADARSAT-2, Sentinel-1, and ALOS-2 with Landsat-8 imagery to estimate large-scale SSM, which is crucial for agriculture, drought assessment, and ecological studies.

Thermal infrared (TIR) sensors uses passive remote sensing to measure the radiant flux emitted by ground objects within TIR wavelength ranges, typically 3–35 μm. Capturing energy in the thermal infrared spectrum with devices such as thermal cameras and radiometers provides valuable information on the emissivity, reflectivity, and temperature of target objects (Ishimwe et al., 2014).TIR-based satellite products, particularly from MODIS sensors, have been effectively utilized to estimate near-surface air temperature by integrating variables such as land surface temperature (LST), normalized difference vegetation index (NDVI), atmospheric water vapor, and atmospheric stability indices. These parameters, when combined through statistical or hybrid machine learning models, have demonstrated strong predictive power for estimating air temperature at 2-meter height in agricultural regions. Such approaches are especially valuable in data-scarce areas, where insitu observations are limited, yet environmental parameters remain critical for crop monitoring and growth modeling (Khesali and Mobasheri, 2020, 2023).

In crop yield prediction (CYP) studies, MODIS TIR sensors have been frequently applied to capture thermal signals relevant to vegetation performance. For example, Bouras et al. (2021) employed the MODIS MOD11A1 product to calculate the temperature condition index (TCI), enabling the assessment of vegetation thermal stress and its correlation with cereal yield during sensitive growth stages. Similarly, TIR data have played a significant role in crop growth parameter estimation (CGPE). Karahan et al. (2024), for instance, combined Landsat-9, Landsat-8, and MODIS-derived LST images to analyze daily actual evapotranspiration across irrigated and rainfed agricultural fields, demonstrating the potential of thermal sensors to capture key processes in water use efficiency and crop growth dynamics.

While some of these satellites are frequently used, others have been explored in specific case studies based on their spatial resolution, revisit frequency and sensor capabilities. Other satellites have been employed in CYP studies, including the European-based SMOS (Ozalp, 2020) and SPOT-4/5 (Castaldi et al., 2015; Fieuzal et al., 2017; Fieuzal and Baup, 2017), the US-based Quickbird (Elmetwalli et al., 2022), the Taiwan-based FORMOSAT-2 (Fieuzal et al., 2017; Fieuzal and Baup, 2017).

Similarly, various satellites have been applied in CGPE studies, such as Kompsat-5 (Abdikan et al., 2023b), VENμS (Arun and Karnieli, 2021), ALOS-2 (Abdikan et al., 2023b), FORMOSAT-2 (Ndikumana et al., 2018), SAOCOM (Gentile et al., 2024), Quickbird (López-Granados et al., 2010), CHRIS/PROBA (Verger et al., 2011) and PlanetScope (Campi et al., 2024; Garofalo et al., 2023).

3.3.1.2. UAVs platforms. Recently, the agricultural sector has shown a growing interest in utilizing UAVs for monitoring and retrieving agricultural information. UAVs changed the farming practice by offering cost savings, improving operational efficiency, and maximizing return on investment (Rejeb et al., 2022). Most field-scale agricultural studies utilized UAVs for retrieving high spatial-temporal resolution agricultural information, which enables to visualization of detailed information such as crop overlaps by flying at low altitudes closer to the agricultural field (Zhang et al., 2021).

Across the MED-rim, UAVs have been increasingly applied in both CGPE and CYP studies. For CGPE, UAVs platforms are mainly deployed at the field scale to identify and monitor crop biotic stressors such as diseases (Di Nisio et al., 2020; Navrozidis et al., 2023; Vélez et al., 2023) and weeds (Saad El Imanni et al., 2023), as well as abiotic stressors including water status (López-García et al., 2022) and soil nutrient levels (Fiorentini et al., 2024b). UAVs data have also been used to assess wheat lodging (Chauhan et al., 2019).

For CYP, UAV-based vegetation indices have been employed to predict durum wheat yield (Badagliacca et al. 2023; Fiorentini et al., 2024a). Safonova et al. (2021) used UAVs imagery to estimate olive tree yield via biovolume, while Impollonia et al. (2022) applied UAVs multispectral imagery for crop trait estimation and breeding-oriented spatiotemporal yield predictions.

The analysis of selected studies also indicates that UAVs platforms were widely utilized for CYP. For example, Badagliacca et al. (2023) and Fiorentini et al. (2024a) UAV-based vegetation indices were used to predict the durum wheat yield on a field scale. Safonova et al. (2021) employed UAVs images to estimate the yield of olive trees in terms of biovolume. Impollonia et al. (2022) used UAV-based multispectral images to estimate crop traits using biophysical parameters and modeling parameters for crop breeding to develop spatiotemporal yield predictions.

3.3.1.3. Aerial platforms. Aerial platforms have played an important role as precursors to UAV-based applications, offering early insights into the potential of high-resolution remote sensing in agriculture. For instance, Gutiérrez et al. (2008) employed airplane photography to develop a regional-scale crop stress mapping system associated with weed presence, demonstrating how aerial imagery could support field management decisions beyond the plot scale. More recently, Milewski et al. (2022) applied hyperspectral airborne data to estimate grain yield in relation to soil degradation at the field scale, highlighting the capacity of aerial platforms to capture detailed spectral information linked to soil and crop interactions. Together, these studies underscore how aerial systems laid the groundwork for the current shift toward UAVs, bridging the gap between satellite observations and fine-scale field monitoring.

3.3.1.4. GB platforms. In agricultural studies, different GB platforms are primarily used for collecting field ground truth data, which serve as observational data for model training and testing. These platforms play a key role in CGPE and CYP studies.

For instance, GB hyperspectral imaging has been utilized to assess the genotype response of crops in relation to nutritional and water status Raya-Sereno et al. (2024). Additionally, a handheld spectroradiometer is also used for obtaining high-resolution vegetation indices and environmental parameters for precise estimation of eggplant yield at the field scale Taşan et al. (2022).

3.3.1.5. Hybrid platforms. Utilize heterogeneous data acquisition platforms, including satellite, aerial, UAV, and GB, to enhance data acquisition techniques. In agricultural studies, these platforms are widely used to enhance the efficiency, accuracy, and sustainability of CGPE and CYP by providing multiple input datasets for model training and testing.

For instance, Brook et al. (2020) integrated Sentinel-and UAV imagery to explore soil water availability, plant water flow, and efficiency, linking plant water status and vegetation indices across SWIR, VIS, and NIR regions. The study also used ground-based spectrometer measurement and independent UAV imagery to confirm the findings. To quantify crop yield, grain protein content, and net nitrogen consumption at field scale agriculture, Pancorbo et al. (2023) used hyperspectral aerial photos and satellite imagery from Sentinel-1 and Sentinel-2 on the same date.

3.3.2. AI approaches

We systematically categorize the AI methodologies used in the selected CYP and CGPE studies across MED-rim agroecosystems. Three main categories emerged as: ML (88 studies), DL (10 studies) and hybrid methods (8 studies).

The distribution reflects the current dominance of ML methods in operational agricultural activities, the emergence role of DL in handling complex spatio-temporal tasks, and the strategic adoption of hybrid method to integrate complementary strengths. The following sections critically examine each category, highlighting model-specific strengths, weaknesses, and suitability to MED-rim contexts.

3.3.2.1. Machine Learning. ML, a subset of AI, enables algorithms to learn from data, identify patterns, and generate predictive models for performing specific tasks (França et al., 2021). In agricultural research, ML is applied across four key managements areas: soil, water, livestock and crop (Liakos et al., 2018). The following section presents the application of ML methods in crop management, particularly in CYP and CGPE studies over MED-rim agroecosystem. The analysis of ML model (89 studies) used in this study suggest that 46 % of the studies used single model for CGPE and CYP. While 18 % of the studies used two different models, 10 % used three, and 26 % used more than four models. Among the reviewed studies, Random Forest (RF), Artificial Neural Networks (ANNs), and Support Vector Machines/Regression (SVM/SVR) were the most prevalent ML methods, with RF accounting for 19.7 %, followed by SVM/SVR (16.1 %), and ANN (13.8 %), as illustrated in the Fig. 10.

Random Forest

RF is an ensemble method, enhances prediction accuracy by averaging multiple decision trees trained on different random subsets of data, reducing correlation among trees, and simplifying tuning using conventional linear regression (LR) models (Hastie et al., 2009; Williams, 2011a). Owing to its capacity to integrate heterogeneous inputs, handle high-dimensional datasets, and rank variable importance, RF has become one of the most widely applied ML algorithms for CYP and CGPE in Mediterranean agroecosystems.

In CGPE studies, RF has been particularly effective in crop stress detection and physiological monitoring. Garofalo et al. (2023) predicted olive stem water potential (Ψstem; R^2=0.78) from remote sensing-based vegetation indices, while Navrozidis et al. (2022) using Sentinel-2 imagery, RF achieved the strongest performance among tested ML models

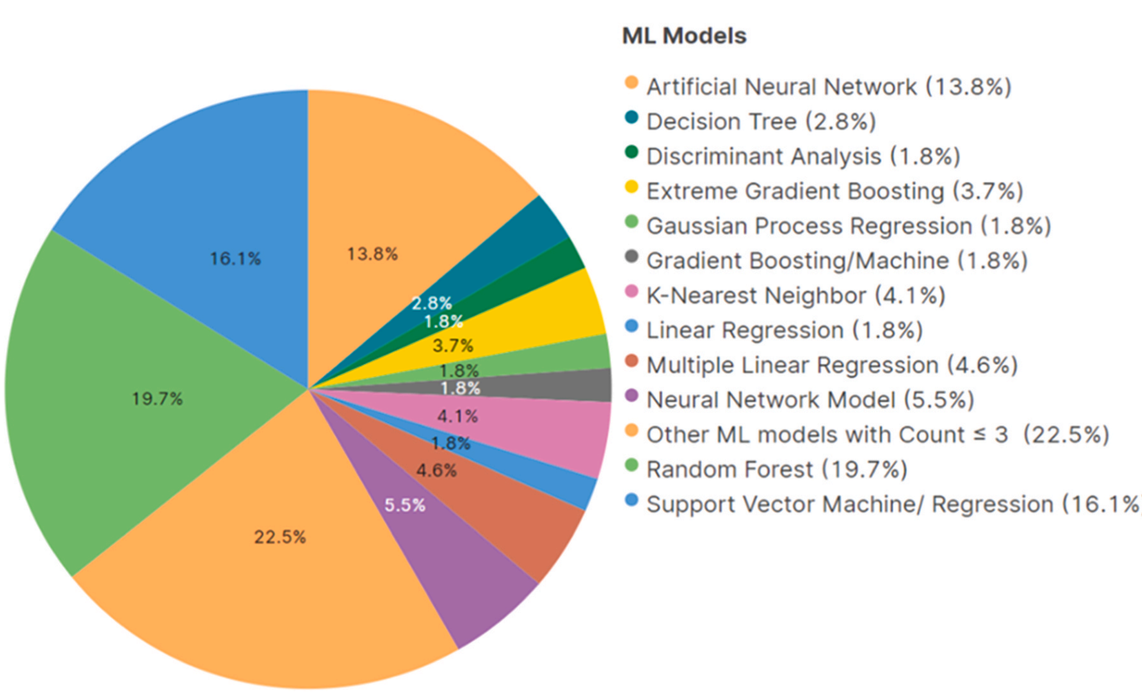

Fig. 9. ML models used in research studies for CYP and CGPE over MED-rim agroecosystem.

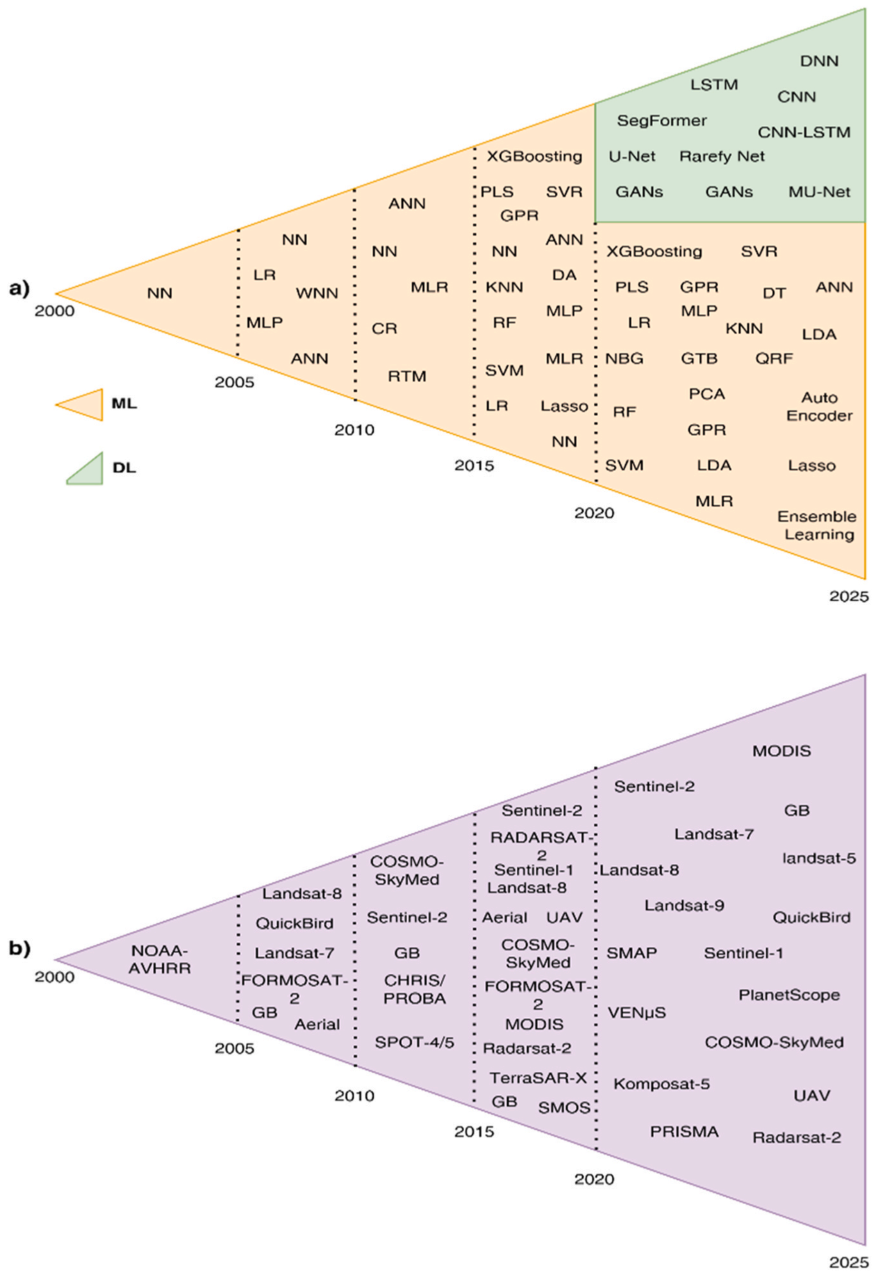

Fig. 10. Temporal evolution of (a) AI techniques, including Machine Learning (ML) and Deep Learning (DL) and (b) RS platforms used in CGPE and CYP studies over MED-rim agroecosystems from 2000 to 2025.

(AUROC=0.76; sensitivity=0.67) for olive orchard stress detection. However, accuracy dropped at fine stress thresholds (510 %), highlighting RF's difficulty in distinguishing subtle stress levels despite robust ensemble learning. Extending this work, Navrozidis et al. (2023) used UAV hyperspectral data further improving ML (RF, XGBoost) model performance. RF achieving (AUROC=0.977) slightly outperforming XGBoost (AUROC=0.955), and feature selection enhanced both models to AUROC= 1.0, underscoring its adaptability for precision agriculture. Similarly, Ayari et al. (2024) used RF to estimate NDVI from Sentinel-1 SAR data, achieving useful accuracy across phenological stages but with signal saturation during crop maturation.

Beyond stress monitoring, RF has been widely used in vegetation and weed mapping. Saad El Imanni et al. (2023) employed multiple ML models for classifying the weed affected within and between citrus trees using UAV and DEM data as input. The finding reported that RF outperform other ML model with overall accuracy of 98.05 %, marking the benefit of AI and RS application in early detection of weed-affected regions and effective application of herbicides. Similarly Lebrini et al. (2021) mapped Moroccan agricultural changes over two decade using MODIS phenological metrics, achieving 93–97 % accuracy and demonstrating RF's suitability for long term climate-resilient monitoring and land-use planning.

RF proved to be a reliable and efficient tool for integrating UAV based data to predict yield of crops. Impollonia et al. (2022) applied RF algorithm to estimate crop traits and predict the yield of Miscanthus using UAV-based vegetation indices (VIs). The time series vegetation indices were collected over the growing season, providing temporal information on crop phenological stage. With the functionality of RF for voting peak descriptors derived from VIs it was possible to estimate the crop traits and predict yield with good accuracy (RMSE for yield; 2.3 Mg DM ha-1), demonstrating its capacity to capture phenological and support agricultural decision making. Similarly, Vanli et al. (2020)

integrated satellite imagery with multiple ML models to classify wheat area during anthesis stage. The findings demonstrated that RF outperformed other ML methods, achieving high accuracy (R^2=0.97) in classifying the cultivated areas. Subsequently, the study combined classification with statistical regression to successfully forecast crop yield.

Collectively, these studies illustrate RF's robustness across scales, from UAV-based phenotyping to regional satellite monitoring. However, its deployment at scale remains constrained by computational demands, relatively slow prediction, and susceptibility to overfitting in noisy or unbalanced datasets (Trentin et al., 2024). These limitations highlight the importance of balancing predictive gains with feasibility and exploring hybrid approaches for Mediterranean agriculture.

Support Vector Machine/Regression

SVM and their regression variant SVR are second most widely applied ML approaches over MED-rim. By using kernel functions to project input data into higher-dimensional feature spaces, SVM/SVR excels at modeling complex, nonlinear, and high-dimensional relationships (Brereton and Lloyd, 2010; Williams, 2011b).

In CGPE, SVR has been employed to model crop structural traits. Chauhan et al. (2020) estimated crop biophysical parameter such as crop angle of inclination (CAI) and crop height by using Sentinel-1 and RADSAST-2, enabling spatio-temporal estimation of crop lodging. The study introduced a novel approach to quantitively estimating the CAI, a key structure for estimating crop lodging severity, through application of SVR modelling. Among the evaluated SAR dataset, RDARSAT-2 FQ8 (low incidence angle) yielded the best performance, achieving RMSEcv= 8.89° of and R^2cv = 0.87, illustrating the potential of SAR data and SVR in quantifying lodging severity and reducing harvest-related yield losses. For identifying the soil conditions, Elshewy et al. (2024) found a quadratic SVM model outperformed alternatives ML models (R^2=0.86, RMSE=175.98) in mapping salinity from Landsat-8 imagery by capturing nonlinear interactions among spectral bands and total dissolved solids, thus supporting salinity mitigation strategies.

SVM/SVR has also shown strong predictive ability in yield forecasting. Meroni et al. (2021) compared ML models for predicting cereal yields in Algeria using NDVI and meteorological data. SVR with radial base function and linear kernels outperformed LASSO and RF, achieving RMSE of 0.14–0.2 t/ha (13–14 % of mean yield). Remarkably, SVR models showed better accuracy, particularly in low-yield years, important for developing early warning systems. Even in data scarce setting, a well-calibrated SVR provided reliable season forecast. Overall, the findings notice that the developed framework have a potential of replicability in other regions facing similar data constraints, offering a scalable solution for crop yield prediction in food-insecure areas. Similarly, Darra et al. (2023) applied an Auto-ML framework combining SVR with ARD regression to predict tomato yields from Sentinel-2 vegetation indices. The hybrid model improved robustness (R^2adj=0.67 ± 0.02, RMSE=1.03 ± 0.03), leveraging SVR's strength in capturing nonlinearities while ARD reduced noise and irrelevant features.

Together, these studies highlight SVM/SVR's strengths in handling complex feature spaces and delivering robust predictions under data limitations. However, their performance is highly dependent on kernel selection and hyperparameter tuning, which can increase computational cost. Moreover, SVM/SVR models often lack transparency and can struggle with very large datasets compared to ensemble or deep learning methods, underscoring the need for careful calibration and hybridization in operational agricultural applications.

Artificial Neural Networks

ANNs is inspired by the way architecture of biological neural systems and have become increasingly popular for regression, classification, and clustering tasks. Their adoption in agricultural studies has grown substantially, as they provide flexible frameworks capable of capturing nonlinear interaction between biophysical, spectral and climatic variables for classification and prediction tasks (Kujawa and Niedbała, 2021). This review identified ANN as the third most frequently applied ML model in MED-rim CGPE and CYP studies.

In CGPE studies, ANNs have been used to improve classification and monitoring of crop and soil conditions. Cetin et al. (2023a), (2023b) employed ANNs with Sentinel-2 imagery and field data to generate crop type classification maps, which were subsequently used to estimate crop water stress index (CSWI) and leaf area index (LAI). These outputs provide valuable indicators for irrigation management. Similarly, Boudibi et al. (2020) compared several regression and ML methods for mapping soil salinity. A feed-forward multilayer perceptron ANNs achieved the highest performance (R=0.95 for field data and R=0.97 for environmental covariates), demonstrating the model's ability to capture complex nonlinear relationships and deliver accurate salinity predictions to guide precision farming in salt-affected regions.

In CYP studies, has shown strong potential when integrating multi-source RS data. Fieuzal et al., (2017) applied a three-layered feed forward ANNs integrating a multi temporal optical (FORMOSAT-2 and SPOT 4–5) and radar (TerraSAR-X and Rasdarsat-2) with agronomic data to predict corn yield in southwestern France. The model achieved R^2= 0.77 and RMSE= 6.6 qha^{-1} using red reflectance and enabled early-season prediction R^2= 0.69 and RMSE= 7.0 qha^{-1} when combined with CHH radar backscattering coefficients. However, radar-only inputs performed poorly (R^2<0.15) due to noise from soil moisture and surface roughness, underscoring the need for sensor integration. Extending this work, Fieuzal and Baup, (2017) applied a similar ANNs approach to large-scale wheat prediction during the stem elongation stage. Incorporating radar data improved accuracy to R^2= 0.76 and RMSE= 7.0 qha^{-1}, while optical sensors were more effective during earlier stages, highlighting complementary sensor contributions across phenological phases.

Collectively, these studies demonstrate ANN's robustness in handling diverse and nonlinear agricultural datasets. They are particularly effective when fusing optical and radar data, capturing temporal dynamics across growth stages. Nonetheless, ANNs require careful calibration to avoid overfitting, and their "black-box" nature limits interpretability. Despite these challenges, ANN-based approaches remain powerful tools for advancing precision agriculture in Mediterranean agroecosystems by enabling timely stress monitoring and reliable yield forecasting.

3.3.2.2. Deep Learning. DL is the subset of ML models, which enables to model the pattern in data as multi layered and complex networks, enabling to solve complex problems such as computer vision and natural language processes (Gopinath, 2023). In agricultural studies DL revolutionize the agricultural sector by enhancing accuracy and efficiency of CGPE and CYP (Waqas et al., 2025). Compared to traditional ML, which often relies on handcrafted features and limited predictive capacity, DL can automatically extract spatial and temporal features directly from raw inputs. However, these advantages come at a cost: DL methods generally require large, high-quality training datasets, advanced computational infrastructure (e.g., GPUs/TPUs), and careful hyperparameter optimization. According to our review, only 10 MED-rim studies explicitly employed SL models (6 with single model, 2 with dual architecture and 2 with triple models) indicating that adoption limited relatively to ML approaches. This imbalance likely reflects challenges in data availability, computational demand, and interpretability, but also underscores DL emerging promise.

Convolutional Neural Networks

CNNs inspired by the human visual cortex, revolutionize image identification, recognition, classification, and segmentation. Their convolutional and pooling layers capture local spatial dependencies, making them particularly effective for RS imagery.

In CGPE applications, CNNs have shown strong capacity to enhance crop monitoring through both temporal and spatial feature extraction. Fontanelli et al. (2022) demonstrated that 3D-CNN models, trained with multitemporal COSMO-Sky radar imagery in Tuscany, outperformed 1D-CNN by jointly capturing spatial and temporal dynamics, achieving accuracies above 80 % in 2020 and 90 % in 2021. This spatial awareness allowed superior detection of vegetation dynamics in heterogeneous landscapes, particularly where optical imagery was limited. Complementing this, Mazzia et al. (2020) applied a lightweight CNN (Rarefy Net) to refine Sentinel-2 NDVI maps with UAV data, producing super-resolution vegetation indices with statistically significant improvements in Vigor classification ($p < 0.001$). While effective, the model's crop-specific focus on vineyards highlights generalizability constraints. Together, these studies underscore CNNs' potential in data fusion, bridging multi-scale satellite and UAV datasets, and enabling scalable, cost-effective tools for improving biophysical parameter retrieval in precision agriculture.

CNNs have increasingly shaped CYP research by enabling advanced image classification and segmentation from diverse remote sensing inputs. Kalopesa et al. (2023) demonstrated this potential in grassland monitoring in Greece using Sentinel-2 imagery, where 3D-CNN models outperformed 2D-CNN (OA = 87.96 % vs. 86.29 %) by capturing both spatial and temporal dependencies. This highlights the importance of integrating temporal features alongside spectral indices for continuous pasture productivity and environmental monitoring. Beyond classification, CNN-based segmentation has shown promise for tree-scale yield estimation. Safonova et al. (2021) conducted a study in Spain, using instant segmentation model of CNN called Mask R-CNN and UAVs imagery to segment olive tree crowns and shadows, enabling accurate estimation of biovolume for yield prediction. The model achieved near-perfect accuracy (F1 = 100 % for RGB, 95 % for multispectral), with further gains (F1 = 98 %) through RGB-multispectral data fusion. Estimated biovolumes aligned closely with field measurements (94.5 % accuracy for RGB), underscoring CNNs' scalability for monitoring scattered tree crops. However, while such approaches excel with high-quality, crop-specific datasets, their performance may not generalize across heterogeneous landscapes. This limitation was evident in Sabo et al. (2023), where 1D and 2D CNNs trained on regional NDVI and climate time-series data underperformed relative to simpler ML models such as SVR, LASSO, and MLP. Despite optimization efforts, the CNNs struggled to capture spatial and climatic variability due to limited training data, illustrating the sensitivity of DL models to dataset size and diversity. Collectively, these studies reveal CNNs' dual potential: high precision in crop-specific, data-rich contexts, and vulnerability to underperformance when data are scarce. Thus, while CNNs offer transformative opportunities for scalable and accurate yield estimation, their success hinges on data availability, multi-source integration, and careful model selection tailored to regional conditions.

CNNs have proven to be highly effective tools for both CGPE and CYP, offering powerful capabilities in spatial and temporal feature extraction, image segmentation, and multi-scale data fusion across satellite and UAVs platforms. Their strengths lie in delivering high precision for crop-specific and data-rich contexts, where they outperform traditional ML approaches and enable novel applications such as tree-level yield estimation. However, their performance is strongly dependent on training data quality and diversity, with limited generalizability in heterogeneous or data-scarce regions. This underscores that the transformative potential of CNNs in agricultural modeling is maximized when combined with multi-source data integration and regionally tailored model design.

Long-Short Term Memory

LSTM networks, a variant of recurrent neural networks (RNNs), were designed to overcome the vanishing gradient problem that limits traditional RNNs in modeling long sequential data (Hochreiter and Schmidhuber, 1997). By incorporating memory cells with gated mechanisms, LSTMs can selectively retain or forget information, enabling them to capture long-term dependencies essential for tasks involving sequential or temporal dynamics (Gers et al., 2000; Yu et al., 2019). This architecture makes LSTM particularly suited to agricultural applications, where time-series data such as vegetation indices, phenology, and climate variables play a central role.

Recently LSTM models have gained widespread use in agricultural and environmental time-series analysis due to their ability to effectively capture temporal dependencies and dynamics. According to the analysis result of the study they have been used for long-term sequential pattern recognition in vegetation indices fluctuations (Farbo et al., 2024b), crop phenology analysis (Arun and Karnieli, 2021; Stergioulas et al., 2023) and water stress indicators (Bounoua et al., 2024). These studies demonstrate the potential of LSTM models in modelling sequential data for enhancing prediction accuracy and supporting decision making process in precision agriculture.

Recent studies highlight the growing relevance of LSTM in CGPE and yield CYP. Farbo et al. (2024b) demonstrated the model's predictive strength by using a bi-directional LSTM to forecast NDVI in Italian maize fields, achieving low RMSE values (0.028–0.058) when combining Sentinel-2 indices with meteorological data. Although performance declined at continental scale (RMSE 0.062–0.105) due to climatic heterogeneity, the results showcased LSTM's scalability potential. Similarly, LSTMs have been applied to crop phenology studies, where temporal sequence modeling is critical. Arun and Karnieli (2021) embedded LSTM into VCapsNet to capture phenological transitions, enhancing resilience against noise and variability. Stergioulas et al. (2023) found that CNN-LSTM variants outperformed simpler LSTM models in lavender bloom detection, reflecting the added benefit of incorporating spatial convolution for spatiotemporal learning.

Beyond crop phenology, LSTM have been used in water stress modeling. Bounoua et al. (2024) evaluated LSTM variants (i.e., ConvLSTM and CNN-LSTM) for forecasting the temporal pattern of water stress on citrus farms in Morocco. The findings suggest that CNN-LSTM performed well for long-term predictions, while ConvLSTM showed better performance in short-term predictions. This finding highlights how model architecture and input design influence predictive performance in different agricultural contexts.

LSTM offer a robust framework for modeling agricultural time-series by effectively capturing spatiotemporal relationships. Yet, their performance remains contingent on model architecture, input quality, and domain context, suggesting that careful adaptation and hybridization with other deep learning models are key to maximizing their utility in precision agriculture.

Beyond CNNs and LSTM, recent work points to the promise of attention-based models and Transformers. Maimaitijiang et al. (2023) demonstrated that Transformer architectures, applied to weekly UAVs multispectral imagery, outperformed conventional CNN and LSTM models in predicting corn yield and grain composition, with attention mechanisms further improving model accuracy. Crucially, models trained on multi-date time series surpassed those using single-date imagery, underscoring the value of dense temporal monitoring. While the study developed outside the MED-rim, these findings suggest that adopting attention-augmented and Transformer models, particularly with frequent UAVs or satellite observations, could significantly enhance CGPE and CYP in MED-rim agroecosystems.

3.3.2.3. Hybrid Methods. The integration of Machine Learning (ML) and Deep Learning (DL) methods has emerged as a widely adopted strategy in agricultural modeling, as these approaches complement each other by leveraging their respective strengths. In this review, eight studies combined ML and DL models for crop yield prediction (CYP) and crop growth parameter estimation (CGPE). Notably, seven of these studies employed more than four distinct models, while one relied on three, reflecting the growing emphasis on hybrid approaches to enhance predictive robustness.

Hybrid strategies are particularly common in CGPE studies (Abdikan et al., 2023a; Ezzahar et al., 2024; Kokkas et al., 2023; Mirzaei et al., 2024). For instance, Abdikan et al. (2023a) integrated DL and ML models for analyzing sun flower height estimation using Sentinel-1 and Sentinel-2 datasets. The study highlighted that different models excelled at different phenological stages: ANN performed best during stem elongation, CNN during inflorescence development and flowering, and XGBoost during ripening. This finding underscores the value of hybrid methods in capturing stage-specific crop dynamics.

Similarly three studies applied hybrid approaches to CYP (Boukhris et al., 2024; Idrissi et al., 2023; Kheir et al., 2024). Kheir et al. (2024) demonstrated this through a large-scale experiment using 22 hybrid models within the H2O AutoML platform for wheat yield prediction in Egypt. By integrating remote sensing vegetation indices with topographic and weather data, the study constructed stacked ensemble models that outperformed individual ML and DL algorithms. The best ensemble achieved an R^2 of 0.51 and a Wilmott's agreement index of 0.82, surpassing standalone models. Importantly, this approach illustrates the potential of hybrid modeling as a scalable and cost-effective solution for yield prediction in data-scarce regions, where accurate forecasts are critical for agricultural planning under climate uncertainty.

The evidence shows that integrating ML and DL into hybrid frameworks has become a powerful strategy for both CGPE and CYP, as it capitalizes on the strengths of diverse algorithms across different crop stages and data types. By combining multiple models, hybrid approaches consistently deliver greater predictive robustness than single methods, with stacked ensembles in particular demonstrating strong potential to enhance yield forecasting accuracy in data-scarce and climate-sensitive regions.

3.3.2.4. Comparative analysis of AI models for CGPE and CYP in MED-rim agroecosystems. We selected 12 representative studies and summarize in Table 6, according to the most common AI methodologies applied in Mediterranean agroecosystems, the spatial scale of analysis (field, large, or country level), and their primary application to either CGPE or CYP studies. This structured selection enables a comparative perspective on how different AI approaches perform across contexts. ML models, particularly RF, SVM, and ANN, continue to serve as the backbone of most applications. Their enduring appeal lies in robustness under moderate data conditions, relative computational efficiency, and partial interpretability through feature importance analysis. However, their transferability remains limited, as models calibrated in one region or season often underperform when applied elsewhere, underscoring a need for continuous recalibration.

DL methods, including CNNs, LSTM, and hybrid variants (e.g. CNN-LSTM), demonstrate clear advantages in capturing spatiotemporal patterns, especially when dense, multi-source datasets are available. These models achieve notable gains in early classification and yield forecasting accuracy, yet their benefits are offset by heavy computational demands, reliance on large, annotated datasets, and limited interpretability. Unlike ML, which offers generalizable insights across heterogeneous conditions, DL excels in data-rich contexts but struggles to scale across the Mediterranean's diverse agroecological zones.

Hybrid approaches such as AutoML frameworks have emerged as a promising middle ground, achieving strong predictive performance by combining complementary algorithms. Nevertheless, they often act as "black boxes," raising questions about transparency and operational utility. Importantly, the literature reveals a geographic imbalance: Euro-MED studies dominate, while NA-MED and the ME-MED remain underrepresented due to persistent data scarcity. This skew constrains the generalizability of findings and highlights the urgent need for more inclusive, regionally balanced research collaborations.

The comparative evidence underscores the promise of AI and RS integration while highlighting systemic biases in interpretability, data availability, and regional representation. Addressing these through cross-regional collaboration, phenology-aware models, and transparent benchmarking will be essential to ensure equitable and scalable applications in Mediterranean agriculture.

3.4. Trends in AI and RS platforms in MED agroecosystems

The analysis of selected documents shows the evolution of AI techniques from 2000 to 2025, a significant shift from traditional ML models to more complex DL architectures (Fig. 10a). Early applications (2000–2010) primarily used models such as ANNs, LR, and MLP. By 2010, more diverse ML approaches emerged, including RF, SVM, and Regression Tree Models (RTM). After 2015, the focus shifted toward ensemble methods (e.g., XGBoost, Gradient Boosting) and dimensionality reduction techniques, reflecting a need for better scalability and performance. Post 2020, DL models like CNNs, LSTM, and Generative Adversarial Networks (GANs) began to dominate, especially in tasks requiring high-level feature extraction from large datasets. Recent years have seen the rise of hybrid models such as CNN-LSTM and advanced architectures like SegFormer and MU-Net, indicating a trend toward tailored solutions for complex spatiotemporal data analysis in both CYP and CGPE studies.

On the RS side, the platforms evolved from early satellite missions like NOAA-AVHRR, QuickBird, Landsat-7/8, and aerial imagery to more advanced satellite constellations and ground-based sensors (Fig. 10b). By 2010, platforms such as Sentinel-1/2, COSMO-SkyMed and RADARSAT-2 expanded the scope of observation with higher resolution and frequency. The post-2020 era introduced cutting-edge systems like Landsat-9, PlanetScope, PRISMA, and Komposat-5, which offer improved spectral capabilities and more flexible data acquisition. UAVs also gained popularity for high-resolution, field scale monitoring. The simultaneous advancement in RS platforms and AI methodologies has enabled highly detailed, timely, and scalable agricultural monitoring solutions. Together, these trends reflect a powerful convergence, making AI and RS integration increasingly central to applications in CYP and CGPE studies.

3.5. Technological frameworks supporting the integration of RS and AI

The integration of AI with RS in agricultural and environmental studies relies heavily on robust technological frameworks that support data acquisition, pre-processing, modeling, and decision-making outputs. These frameworks can broadly be categorized into cloud-based platforms and ML and DL libraries, each offering distinct advantages.

Cloud-based platforms such as Google Earth Engine (GEE) (Gorelick et al., 2017) provide scalable environment for handling large volumes of RS data, thus simplifying the deployment of ML and DL workflow. For example, Farbo et al. (2024a) leveraged GEE for Sentinel-2 image processing and derivation of vegetation indices and precipitation datasets, while executing ML analysis in Python. In contrast, Saad El Imanni et al. (2023) applied ML models (RF and KNN) directly with in GEE after uploading UAV imagery, showcasing its flexibility for repository-based and user-provided data. These cases illustrate how cloud-based platforms streamline image processing and model development by offering accessible, centralized infrastructure.

ML and DL libraries, on the other hand, form the computational backbone of AI and RS application. Over the past three decades, numerous libraries have been developed across programming languages (Python, R, MATLAB, C, JavaScript, etc.) to enable flexible analysis pipelines (Jovic et al., 2014; Nguyen et al., 2019). Commonly used ML libraries include *caret* (Kuhn, 2008), *randomForest* (Liaw and Wiener, 2001), *Scikit-learn* (Pedregosa et al., 2011), and *MATLAB* (Demuth and Beale, 2004), while DL studies frequently adopt *TensorFlow* and *Keras*. Notably, most studies combine multiple libraries, given that no single tool addresses all research needs. Table 7 below presents the most mentioned ML and DL frameworks in both CGPE and CYP studies.

In summary, cloud platforms provide the scalability and accessibility required for large-scale RS data processing, whereas ML and DL libraries offer customizable analytical depth. Together, they constitute complementary technological pillars that enable the integration of AI into CGPE and CYP.

Table 6
Comparative overview of selected studies on AI applications for CGPE and CYP across Mediterranean and related agroecosystems, highlighting study scope, datasets, model strengths, limitations, and trade-offs. Scale of study is defined on SM-Section 1 as: field-scale (<10 ha), large-scale (10–10,000 ha), and country-scale (national or district level).

Author	Study area; crop type, and scale of study	Scope of study	Datasets	AI models	AI model strength	AI model limitations	Tradeoffs (AI model)
Abdikan et al. (2023a)	Türkiye; sunflower; field-scale	CGPE: crop height estimation at phenological stages	Sentinel−1; Sentinel−2; insitu data	Hybrid (SLR, MLR, ANN, CNN, XGBoost)	Captures linear and nonlinear patterns; fuses SAR and optical indices to improve accuracy; balances interpretability and performance; stage specific strengths: ANN at stem elongation, CNN at flowering, XGBoost at ripening	SLR/MLR limited by linear assumptions and multicollinearity; ANN prone to overfitting on small datasets, less interpretable; XGBoost and CNN require careful tuning and are less transparent; Coherence features improved some models but degraded others.	Complex models improve accuracy but reduce interpretability; SAR + optical fusion requires heavy preprocessing; no single model works across all stages
Kheir et al. (2024)	Egypt; wheat; country level	CYP: yield prediction & climate scenario forecasting	Sentinel−2; DEM; soil grid; ERA5 weather data; climate forecast; insitu crop yield data	Hybrid (AutoML consist of 22 ML/DL models)	Automated model selection & tuning; ensemble models robust to diverse datasets; scalable framework training 20 + models; fast training with minimal manual effort; deployable for RS-only yield mapping and climate change forecasting.	Require large, high-quality datasets; limited transparency in decision-making; prone to overfitting; weak cross-regional transferability; high computational demand; limited incorporation of agronomic knowledge	AutoML saves time but reduces user control; ensembles improve accuracy but hinder interpretability
Fontanelli et al. (2022)	Italy; wheat, maize, sunflower, sorghum, vineyards, olive trees, and legumes; field-scale	CGPE: early-season crop classification	COSMO-SkyMed SAR HH/VV	1D & 3D CNNs	3D-CNN ensemble captures spatiotemporal dynamics, enhancing prediction accuracy and robustness across crop growth stages	Requires large, well-annotated datasets and high computational resources for training and deployment	1D CNN offers efficiency but less accuracy; 3D CNN improves precision at higher complexity
Brook et al. (2020)	Italy; vineyard; field-scale	CGPE: crop monitoring and water use efficiency	Sentinel−2; UAVs RGB+RedEdge; in-situ plant traits	CNNs	Effectively fuses Sentinel−2 and UAVs data, reconstructing high-resolution spatial-spectral data that improve vineyard monitoring accuracy	Requires long training time, large datasets, and computational resources; spectral-spatial balance may cause scaling distortions of ground features	Higher depth enhances spectral-spatial fidelity but increases training cost; skip connections reduce time but risk losing residual learning capacity.
Arun and Karnieli (2021)	Israel; Wheat and Barel; field-scale	CGPE: crop classification using phenological curves	VENμS NDVI time-series	LSTM–VCapsNet	Learns crop-specific growth patterns; robust to noise and missing data; effective with limited samples	Needs high computing power, careful parameter tuning, and may lose detail in reconstruction when penalty values are set too high	Architecture choice depends on dataset size; deeper networks boost accuracy but at higher cost; multi-sized kernels balance speed and robustness
Boukhris et al. (2024)	Morocco, wheat, large-scale	CYP: yield forecasting with NDVI and weather data	MODIS; Sentinel−2; Landsat−8 NDVI; weather data; yield records	LSTM, Bi-LSTM, Stacked LSTM	Bi-LSTM captures both forward and backward temporal dependencies, improving yield prediction accuracy when combining NDVI, temperature, and precipitation data	Requires large training datasets, long training time, and fine-tuning to avoid overfitting or unstable performance	Bi-LSTM offers higher accuracy but requires more preprocessing; captures temporal trends well but sacrifices explicit spatial modeling
Fieuzal et al. (2017)	Southwestern France; corn (maize); field-scale	CYP: yield estimation (diagnostic vs real-time)	Formosat−2; SPOT−4/5; TerraSAR-X; RADARSAT−2; yields data; soil data	ANNs	ANN captures nonlinear relationships between multi-temporal optical (red reflectance) and radar signals, enabling accurate and early corn yield forecasting.	The model works best when it gets many satellite images across the crop season; radar data alone are less accurate; The model's performance can drop if image quality is poor or if weather/soil conditions vary too much.	Optical data give high accuracy but depend on cloud-free conditions; radar adds timeliness and complementarity but less precise; combining both balances accuracy and earliness
Mourad et al. (2020)	Lebanon; multi-crop (wheat, maize, potato,	CGPE: LAI estimation	Harmonized Landsat−8 & Sentinel−2 (HLS),	ANNs	ANN in SNAP biophysical processor automates LAI	Often underestimates LAI, especially at high values; less accurate	Provides generalizable, quick estimates but

(continued on next page)

Table 6 (*continued*)

Author	Study area; crop type, and scale of study	Scope of study	Datasets	AI models	AI model strength	AI model limitations	Tradeoffs (AI model)
	vegetables, herbs, tobacco); large-scale		SNAP NN, THEIA SeLI; 451 fields		retrieval from Sentinel−2, enabling fast, large-scale crop monitoring without manual calibration	than tailored VI models; requires quality inputs from multiple bands	sacrifices crop-specific precision
Lebrini et al. (2021)	Morocco: various farming systems (fallow, rainfed, irrigated annual/ perennial); large-scale	CGPE: phenology mapping	MODIS NDVI; CHIRPS rainfall	RF	RF effectively classified farming systems with high accuracy (90–96 %), robust to noise, outliers, and large input datasets	Struggles to separate rainfed vs. fallow due to similar NDVI patterns; model performance depends on ground-truth quality and data availability	Very high in-year accuracy but reduced transferability; long time-series allows scalability but reduces fine detail
Devkota et al. (2024)	Morocco; wheat; large-scale	CYP: yield and yield gap prediction	Sentinel−2 VIs; soil and management information	RF	Random Forest used Sentinel−2 vegetation indices to predict crop yields with high accuracy; identifies the most important yield-driving variables	The model requires large, labelled datasets and fine-tuning; its decision process is less interpretable, and vegetation index saturation limits accuracy in dense crop canopies	Robust, scalable ensemble vs lower transparency; multiple VI inputs boost accuracy but add preprocessing; per-season hyperparameters balance precision and effort.
Meroni et al. (2021)	Algeria; cereals; country-scale	CYP: yield forecasting with small data	MODIS NDVI; CHIRPS; ECMWF; national yield stats	LASSO, RF, SVR, GBR, MLP	ML models improved accuracy over peak NDVI, handling nonlinear climate and yield relations even with small datasets	Require extensive calibration, sensitive to small training samples, and not always superior to simple benchmarks in practical terms	Model accuracy improves after extensive tuning, but simpler models often perform competitively
Elshewy et al. (2024)	Egypt; non-crop (soil salinity); field-scale	CGPE: soil TDS prediction	Landsat−8; soil samples	SVM, Trees, GPR, Ensembles	SVM with Blue, Red, and SWIR2 bands achieved best accuracy, showing strong ability to capture salinity spectral relationship	Requires careful parameter tuning and quality ground-truth; performance varies by band selection; GPR models risk overfitting with noise	Linear models are simpler but less accurate; quadratic SVM gave the best balance

3.6. Performance evaluation metrics

Evaluation metrics are essential in both quantitative and qualitative studies, as they provide a systematic means to assess the performance and effectiveness of learning model outputs (Rashid et al., 2021). The metrics used in the MED-rim for evaluating the performance of AI models in estimating the CGPE and CYP revealed several patterns. Among them, 7 % used single evaluation metrics (e.g., Santi et al., 2012; Stergioulas et al., 2023; Verger et al., 2011), 28 % used dual (e.g., Chakhar et al., 2024; Metwaly et al., 2024b), and 25 % used triple evaluation metrics (e.g., Awad, 2016; Metwaly et al., 2024a). By contrast, 39 % of studies utilized four or more evaluation used four or more methods (e.g., Nabil et al., 2024), while one Idrissi et al. (2023) exceptionally applied 11 metrics for evaluating the performance of the model employed.

Regression metrics dominated, with root mean square error (RMSE;75 studies) and coefficient of determination (R^2; 67 studies) being the most frequently used. These were followed by classification metrics, particularly overall accuracy (OA; 26 studies) and confusion matrix (22 studies). Other widely adopted metrics included mean absolute error (MAE; 18studies), producer accuracy (PA:18 studies), user's accuracy (UA; 16 studies), Pearson's correlation coefficient (r;14 studies), Kappa coefficient (k; 11 studies) and normalized root mean square error (nRMSE; 10 studies). In addition, more than 50 other metrics were used sporadically across fewer than 10 studies, further illustrating the heterogeneity of evaluation practices 10 studies as depicted in Fig. 11.

Various evaluation metrics were used to assess model performance and accuracy for specific crop types; however, it is difficult to compare the performance and accuracy of CGPE and CYP when using dissimilar evaluation metrics for similar crops (Rashid et al., 2021). Therefore, it is recommended to standard systematic approach should be used while comparing crop specific yield prediction and growth parameter estimation.

4. Discussion

The analysis suggests there is an increasing trend towards to high-impact journals. This is probably due to the globalization of research and collaboration networks (Adams, 2013). The geographical distribution of case studies and first author affiliation indicates that the research is mainly driven by EURO-MED countries (Italy, Spain, France and Greece), while ME-MED and NA-MED contributions differ significantly, influenced by national research capacity, infrastructure, and socio-economic and political stability. These findings underscore the need for enhanced collaboration with resource allocation to underrepresented regions. Addressing these disparities is critical to fostering balanced research efforts across the MED-rim agroecosystem, enabling a more comprehensive approach to shared agroecosystem and environmental challenges. Both CYP and CGPE studies have extensively investigated MED-rim cereal crops, particularly wheat, highlight its importance as staple crop. CGPE studies investigated diverse crop types, especially perennial woody crops like olives and grapes, which are the crucial to ME-rim agriculture. However, the limited representation of fruit and vegetables crops and under exploration of mixed cropping systems in CYP studies points to a narrow research focus that may not fully capture the complexity and resilience strategies of MED-rim farming. Additionally, non-crop studies affecting CYP are not investigated, despite their crucial role in soil health and long-term sustainability.

This review identifies diverse methodologies integrating RS and AI to estimate crop growth parameters and predict crop yield in MED-rim agroecosystems. Satellite-based RS platforms dominate (69 %), followed by UAVs (13 %) and hybrid systems (14 %). Multispectral sensors

Table 7
Most mentioned ML and DL frameworks in literature.

Library	Programming language	ML/DL/ Hybrid algorithm	Tasks performed	Number of retrieved studies
Scikit-learn (Pedregosa et al., 2011)	Python	ML (SVM, SVR, Lasso, MLP, RF, NN, DT, GBM, KNN, RR, AB, ANN, XGBoost, HR)	ML tasks (classification, regression, clustering, dimensionality reduction, model selection, preprocessing)	16 studies (7: CYP and 9: CGPE)
Neural Network toolbox (Demuth and Beale, 2004)	MATLAB	ML (ANN)	Supervised classification task	16 studies (1: CYP and 15: CGPE)
Caret (Kuhn, 2008)	R	ML (SVM, SVR, Lasso, MLP, RF, NN, DT, GBM, KNN, ANN, LM, PCA, GPR, CR, PLSR, MLR)	ML tasks (classification, regression, training, prediction, dimensionality reduction)	11 studies (7: CYP and 4: CGPE)
randomForest (Liaw and Wiener, 2001)	R	ML (RF)	Classification and regression based on a forest of trees using random inputs	8 studies (5: CYP and 3: CGPE)
TensorFlow (Abadi et al., 2016)	Python/R/ JavaScript	DL (1D-CNN, 2D-CNN, RafefyNet)	Open-source library capable of performing ML and DL tasks using CPU and GPU	5 studies (4: CYP and 1CGPE)
Keras (Chollet, 2015)	Python/R/ JavaScript	DL (LSTM, CNN, Bi-LSTM)	High level deep learning API to facilitate debugging and modeling process running on top of TensorFlow	4 Studies (2: CYP and 2: CGPE)
Auto-sklearn (Feurer et al., 2020)	Python	Multiple ML models	Automated ML toolkit for algorithm selection and hyperparameter tuning (Bayesian optimization, meta-learning and ensemble construction)	1 CYP study
H20 Auto ML (LeDell and Poirier, 2020)	R/Python	Hybrid (DL and ML models)	Automated ML and DL toolkit used for algorithm selection, feature generation, hyperparameter tunning, iterative modelling and model assessment.	1 CYP study

like Sentinel-2, MODIS, and Landsat-8 are widely used for capturing vegetation indices essential for monitoring crop growth and yield prediction. Microwave (radar) and thermal sensors complement multispectral data, offering capabilities in all-weather monitoring and evapotranspiration estimation. UAV platforms enable high-resolution field-scale monitoring of biotic and abiotic crop stressors. AI methodologies are dominated by ML, with RF, SVM/SVR, and ANN as the most prevalent models. DL methods like CNNs and LSTMs, although less common, are gaining traction for handling complex and sequential agricultural data. Hybrid methods combining ML and DL models improve prediction accuracy, particularly under varying crop phenological stages and in data-scarce regions. Overall, integrating heterogeneous RS platforms with AI methodologies enhances the precision, scalability, and robustness of agricultural monitoring and prediction efforts in the Mediterranean, supporting climate-resilient farming practices.

4.1. AI and RS integration strategies to faces challenges in the Med-rim

The integration of RS data with AI is currently revolutionizing CGPE and CYP in agricultural studies in the MED-rim by addressing challenges of spatial heterogeneity, climate variability, fragmented land use and management practices. This synergy requires rigorous data processing, temporal alignment, and dimensionality reduction to align heterogeneous datasets which often involve multi-source, multi-temporal and, in general, multi-dimensional challenges. Four key strategies are emerging: (1) multi-source data fusion; (2) temporal modelling frameworks; (3) data pre-processing pipelines; and (4) dimensionality reduction techniques.

4.1.1. Multi-source data fusion

In MED-rim agroecosystem characterized by diverse microclimate and fragmented farming fields landscapes (Mekki et al., 2018), single-source RS data often struggle to capture the full spectrum of relevant agroecosystem variables. Multi-sources data fusion, combining heterogeneous data acquisition platforms to enhance the robustness of AI models (Himeur et al., 2022), is a prominent strategy to overcome this issue. Multi-source data fusion addresses this limitation by integrating complementary capability of various RS platforms. Notably, satellite mission from ESA (Sentinel-1 and Sentinel-2) and NASA (Landsat-8 and Landsat-7) have been fused in a number of studies together with ground-based platforms to support more effective and robust estimation crop growth parameters and yield predictions.

AI models, primarily ANN, plays a central role in this integration, as they may handle complex, nonlinear relationship between diverse input features, constituting an ideal tool for fusing multi-source data. At the same time, the fusion of diverse data source strengthens ANN model, providing richer, more complementary information enhancing their accuracy, generalizability and robustness.

For instance, Yahia et al. (2021) developed a novel weight-based fusion system to estimate soil moisture content by integrating Sentinel-1 and Landsat-8 satellite imagery. The system applied feature-level fusion (input level fusion before AI model) and decision-level fusion (fusion after AI model) using Landsat-8 based vegetation indices with Sentinel-1 derived parameters. ANN effectively learned from these diverse inputs, resulting in significant performance gains. The study also compared the fusion systems with single-source models and found that both multi-source data fusion methods outperformed the single-source method, while decision-level fusion proved to be superior achieving lowest RMSE of 1.34 % and stronger corelation coefficient of R= 0.93.

Similarly, Fieuzal et al. (2017) employed ANN as core data-driven fusing tool for developing a hybrid approach for predicting corn yield by combining muti-temporal optical (Formosat-2 and Spot-4/5) with radar (TerraSAR-X and Radarsar-2) satellite. The integration of these diverse satellite modalities enables the authors to develop full crop season prediction by exploitation of complementary information: optical satellites providing multiple vegetation indices, while radar satellites contributed data related to crop structure and soil moisture related insights. Two data fusion strategies were evaluated: a diagnostic approach (all season data for post-harvest prediction) and real-time approach (progressive update of yield prediction through crop cycle). Notably, the real-time approach demonstrated superior performance, enabling early

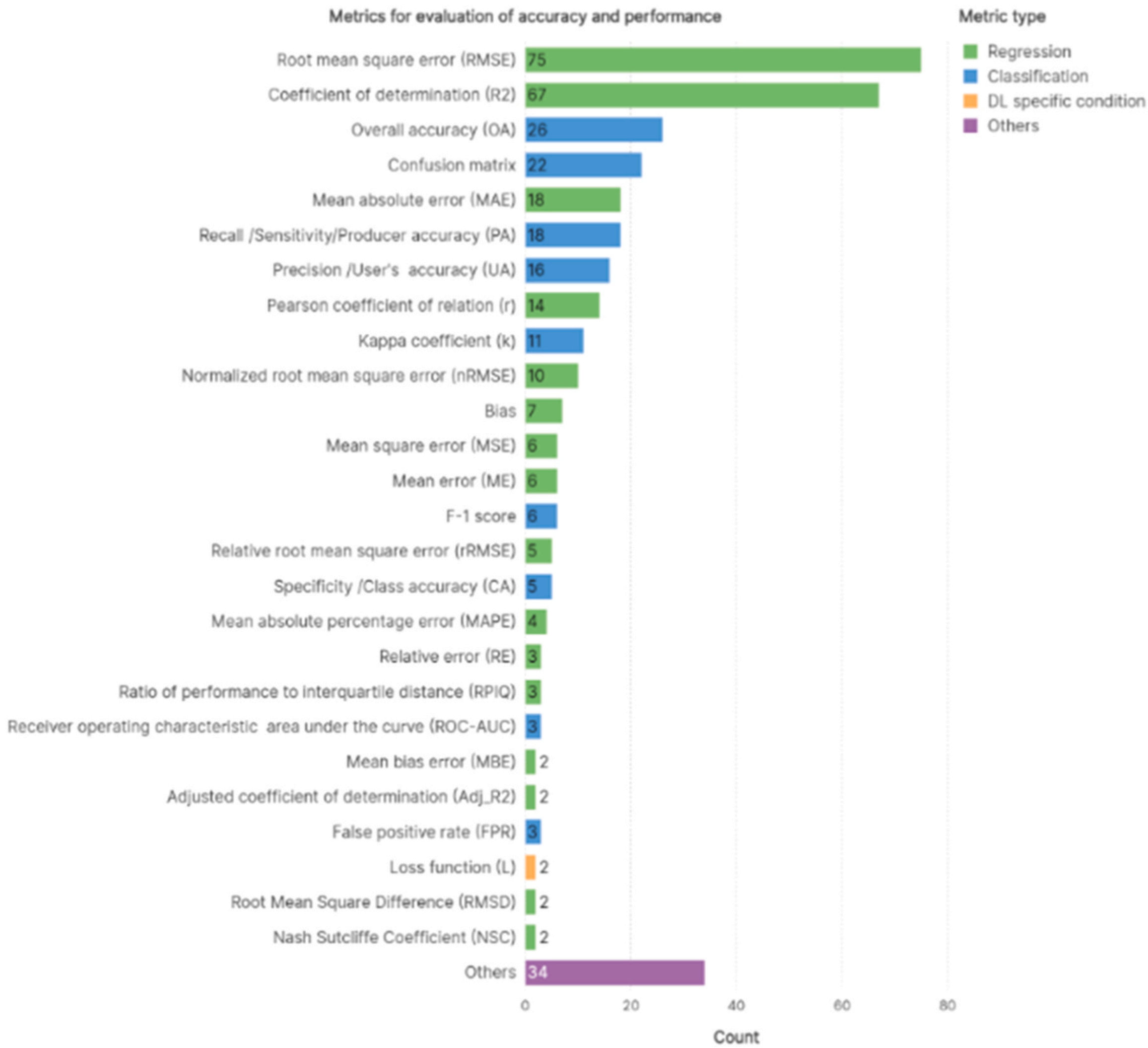

Fig. 11. Metrics for evaluation of performance and accuracy.

crop yield. The finding demonstrates the potential of ANNs model to deliver timely, resilient and localized predictions.

4.1.2. *Temporal integration and data assimilation*

Crop growth is a dynamic and time-sensitive process, requiring temporal data integration for accurate CGPE and CYP. The advancement in temporal frequency of satellites enable the capture of key phenological stages such as greening, flowering and senescence. They also help in identifying stress events, which may be missed by single-data observations (Zhang et al., 2009; Zhao et al., 2012). In such cases AI models offer a powerful tool for handling such temporally rich data by stacking and grouping vegetation indices from multiple observation dates to form multi-temporal input features, which significantly enhance the model prediction accuracy. Do Nascimento Bendini et al. (2024) estimated the crop biomass using RF model and Sentinel-2 imagery as input data. The study showed that the model using multiple observation data far outperformed the single snapshot observation, with prediction accuracy increasing from R^2= 0.55 (single-date) to 0.75 (multi-data).

Similarly, Castaldi et al. (2015) demonstrated the advantage of ANN model in managing multitemporal RS data for CYP. The study employed ANN-based inversion radiative transfer model for effectively retrieving key biophysical parameters from SPOT satellite imagery across multiple phenological stage. The integration of multi-temporal data enabled the identification of crop elongation stage as the optimal period for yield prediction. Furthermore, the application of ML models such as MLR and Cubist regression, enhanced predictive accuracy, particularly when high resolution SPOT data (10 m) was used (Castaldi et al., 2015).

Another way AI handles temporal integration of multi-temporal RS data is through sequential models that ingest multi-temporal data as ordered series. Two class of DL models CNN and LSTM as well as hybrid of the two (ConvLSTM, CNN-LSTM) are particularly used in in handling sequential data. CNN excels at extracting spatial features from spatial images, while LSTM excels at modeling multi-temporal data. Bounoua et al. (2024) conducted comparative analysis of ConvLSTM vs CNN-LSTM for forecasting crop water stress using multi-temporal satellite data. The ConvLSTM integrated the convolutional layer and LSTM layer in the same platform which effectively handle short sequential data by simultaneously managing short term spatial and temporal dependency. However, as the model sequence level increases the model performance slightly declines, probably due to its tendency to smooth over finer spatial details. In contrast CNN-LSTM model, which extract the spatial dependency by CNN model and handle the sequential temporal dependency using LSTM independently, showed superior performance while handling long-term sequential data. The finding of the study remarks model selection should consider the sequence length and computational efficiency. Even though the CNN-LSTM model showed higher performance than ConvLSTM in handling long term sequential data require, higher cost in terms of computational resources.

4.1.3. Dimensionality reduction

RS data integration often leads to high-dimensional features spaces. For instance, combining several bands across multiple dates plus additional sensor data can result in hundreds of predictors for a single field. Such high dimensionality poses challenges for analysis and interpretation. AI techniques, particularly dimensionality reduction methods enable the extraction of essential features from vast and heterogenous datasets, enhancing applications like CYP and CGPE. Badagliacca et al. (2023) used PCA for differentiating the spectral response of 30 wheat cultivars captured by UAVs based vegetation indices, enabling to enhance the subsequent ML model. Besides reducing the dimensionality, they also reduce noise and redundancy in the data. Similarly, Habyarimana et al. (2019) used PCA-DA for simplifying the multicollinearity of Sentinel-2 based fAPAR time series data, enabling accurate biomass yield predictions.

4.1.4. Data pre-processing pipelines

To operationalize the above strategies, rigorous data pre-processing pipelines are required. The MED-rim RS datasets often come from multiple satellites over many dates and may suffer from issues like cloud cover (common in winter cropping months), varying resolutions, and sensor noise (e.g. Saharan dust affecting optical imagery). AI plays a pivotal role in addressing these challenges by efficiently handling large datasets and extracting robust patterns, thereby strengthening the reliability of RS inputs for CGPE and CYP. Key pre-processing steps where AI provides significant advantages include radiometric and atmospheric corrections, geometric alignment and resampling, cloud-shadow masking, and data gap filling.

4.2. Limitations, research gaps and future scope

The synergy between AI and RS, although promising, still present some limitation and research gaps. Araújo et al. (2021) stratified the five levels (device, data, network, application, and system) of challenges in transformation to Agriculture 4.0. Building on this framework, we derived six categories deeming particular attention Table 8 summarizes these categories, providing an overview of the main limitations, research gaps, and future research directions identified across the reviewed studies.

5. Conclusions

Our review consists in a comprehensive synthesis of current research integrating AI and RS for CYP and CGPE across Mediterranean agroecosystems. By examining 106 studies, we identified prevailing trends, technological frameworks, methodological approaches, and research gaps that shape the integration of AI-RS in the region. Together, these technologies may enable dynamic and high-resolution monitoring, supporting informed agricultural management decisions. We then provide a critical baseline for guiding future research and policy initiatives aimed at enhancing food security, climate resilience, and sustainable resource use in Mediterranean agroecosystems and similar regions worldwide.

Research confirms AI and RS technologies offer transformative potential for enhancing agricultural monitoring, particularly in regions like the MED-rim that experience pronounced climate stressors such as heat, drought, and erratic rainfall. AI may efficiently analyse large, multi-temporal datasets generated by RS platforms, especially from satellites like Sentinel-2, MODIS, and Landsat, to extract patterns related to crop phenology, growth, and productivity.

ML methods, such as RF, SVM/SVR, and ANN dominate the landscape across both CGPE and CYP studies. These models are preferred for their relative ease of implementation, strong performance with medium-sized datasets, and ability to handle nonlinear relationships. RF was the most frequently applied model due to its ensemble learning strengths and robustness in varied conditions. Deep learning models, such as CNNs and LSTM networks, are increasingly explored for their capacity to simulate temporal sequences and spatial features, although their adoption remains limited due to high data and computational requirements.

A distinctive feature of Mediterranean-focused research is the crop-specific application of these technologies. Wheat emerged as the most studied one across both CGPE and CYP contexts, reflecting its economic

Table 8
Limitation of studies, research gaps and future scopes.

Category	Limitations	Research gaps	Future scopes
Spatial and temporal generalizability	Most studies remain confined to specific regions, crops, or single growing seasons, restricting their applicability across diverse Mediterranean agroecosystem and temporal scales	Absence of multi-season, multi-crop, and cross-regional datasets that capture the variability in climate, soil, and management practices across the MED-rim	Develop scalable and transferable models validated across multiple regions, crops, and years; apply domain adaptation and transfer learning approaches to strengthen robustness and generalizability
Data availability for validation	High-resolution datasets are scarce, unevenly distributed, or fragmented; critical inputs such as phenological observations, in-situ ground truth, weather data, and UAV imagery remain particularly limited in North Africa and parts of the Middle East	Limited integration of diverse data sources, including phenology records, in-situ yield and soil measurements, high-frequency meteorological data, and high-resolution UAV imagery, with satellite-based RS products	Advance data fusion frameworks by integrating RS with IoT sensor networks, UAV platforms, and crowdsourced or citizen science contributions; establish open-access repositories of phenological and ground-truth data tailored to Mediterranean agroecosystems
Sensor constraints	Cloud cover and coarse temporal/spatial resolution reduce the reliability of optical datasets; advanced sources such as thermal, radar coherence, and hyperspectral imagery remain underutilized	Limited efforts to explore multi-sensor fusion (e.g., SAR, optical, thermal, hyperspectral), and UAV-based observations are rarely scaled beyond small pilot projects	Promote systematic multi-sensor integration (Sentinel, Landsat, MODIS, PRISMA, etc.) and scale up UAV technologies to improve spatial coverage, measurement precision, and temporal continuity
Phenology sensitivity	Model performance is highly stage dependent, with accuracy declining during early emergence and late senescence phases	Lack of dynamic modeling approaches capable of capturing continuous phenological transitions across growth stages	Incorporate phenology-aware, time-series driven modeling frameworks that explicitly account for crop developmental stages and seasonal variability
Validation challenges	Field validation remains constrained by labour-intensive protocols, limited spatial coverage, and fragmented efforts across studies.	Absence of standardized ground-truthing protocols and inconsistent quality control hinder comparability and reproducibility across the Mediterranean context	Establish harmonized, open-access validation frameworks with agreed protocols; create benchmarking platforms that allow systematic cross-comparison of AI and RS models at regional and transnational scales
Environmental variability	Soil heterogeneity, weather extremes, and diverse management practices (e.g., irrigation regimes, fertilization intensity) are often underrepresented in training datasets, limiting model robustness	Current models poorly capture the complexity of diverse farming systems and local practices, reducing their adaptability across MED-rim agroecosystems	Develop adaptive learning approaches calibrated with heterogeneous datasets; integrate biophysical, management, and socio-economic variables to improve model resilience under diverse and changing Mediterranean conditions

and dietary significance in the region. Perennial crops such as olives and vineyards are also highly represented, especially in CGPE studies, given their commercial importance. These crops are particularly sensitive to phenological stages and environmental stressors, making them ideal candidates for the application of AI-RS integration frameworks.

The data acquisition methods analysed in the review show a strong reliance on satellite-based RS, which accounted for nearly 70 % of the reviewed studies. Satellite platforms offer broad spatial coverage and open-access data, making them ideal for regional-scale applications. UAVs, while used less frequently, are emerging as key tools for field-scale, high-resolution monitoring, particularly for assessing biotic and abiotic stressors. Hybrid approaches that combine satellite, UAVs, and ground-based sensors show great promise in improving model performance through multi-source data fusion.

Despite these advances, the review highlights several critical limitations and research gaps. Firstly, there is an uneven geographical distribution of studies, with a strong concentration in Southern Europe particularly Italy, Spain, and Greece, while countries in North Africa (e.g., Algeria, Tunisia, Morocco) and the Middle East (e.g., Lebanon, Syria) are underrepresented. This disparity stems from limited access to infrastructures, fundings, and ground-truth data in those regions, resulting in knowledge gaps where precision agriculture tools are arguably most needed.

A further major limitation lies in the generalizability and transferability of models. Many studies are restricted to single locations, specific crop types, or short timeframes, which limits their scalability and broader applicability. Then, model robustness is challenged by sensor-related issues such as data noise, varying spatial resolutions, and spectral limitations, particularly in optical sensors under cloud-prone conditions. While radar and thermal imaging have been successfully employed in some cases, their use remains sporadic due to data availability and processing complexity.

The limited integration of crop phenology into modeling frameworks is also a notable gap. Given the seasonal variability and sensitivity of Mediterranean crops, prediction models must consider the specific timing of growth stages to improve accuracy. Studies that incorporated phenological transitions or adjusted model parameters seasonally reported higher performance, underscoring the importance of phenology-aware modelling.

The lack of standardized validation datasets and benchmarking methods impedes the comparability of results across studies. Ground-truthing remains essential for model training and evaluation but is often constrained by logistical and resource challenges. This shortfall is particularly pronounced in underrepresented MED-rim subregions, further widening the data and performance gap between research-intensive and data-scarce areas.

To overcome these challenges, future research should focus on four key areas. Boosting cross-border and regional collaborations can help bridging data and capacity gaps, especially in North Africa and the Middle East. An opportunity to increase research in NA-MED and ME-MED may come from innovation and research programmes of the European Union such as Horizon Europe and the PRIMA programme.

Second, expanding the use of hybrid AI frameworks and multi-source RS platforms may improve model robustness and accuracy across varied environmental contexts. Developing phenology-aware models with high generalizability will support more adaptive and scalable solutions. Lastly, establishing open-access validation datasets and leveraging cloud computing platforms may favour access to high-quality data and reduce computational barriers.

These result underscore the capability of AI models to manage complex temporal dynamics and spatial variability more effectively than the traditional empirical methods. These findings underscore the strength of AI models in managing temporal dynamics and spatial variability in operational crop monitoring.

Overall, these studies affirm that AI models, particularly those leveraging multi-temporal data, are well suited for agricultural applications. The ability to learn from multi-temporal patterns make AI highly effective for CGPE and CYP. Selecting the appropriate model architecture should balance data sequence length**,** desired accuracy, and available computational resources**.** These advancements pave the way for scalable, precise, and timely decision support systems in modern agriculture.

CRediT authorship contribution statement

Wondimagegn Abebe Demissie: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Luca Sebastiani:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Rudy Rossetto:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2025.127894.

Data availability

Data are available in the Supplementary Material file mmc2.xls.

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