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Review

Toward Resilience in Broadacre Agriculture: A Methodological Review of Remote Sensing in Crop Productivity, Phenology, and Environmental Stress Detection

Jianxiu Shen [1,*], Hai Wang [2] and Hasnein Tareque [1]

[1] Department of Primary Industries and Regional Development, Western Australia, Perth 6000, Australia; hasnein.tareque@dpird.wa.gov.au
[2] School of Engineering and Energy, Murdoch University, Murdoch 6150, Australia; hai.wang@murdoch.edu.au
* Correspondence: jenny.shen@dpird.wa.gov.au

Highlights

What are the main findings?

- Remote sensing methodologies for crop performance monitoring were systematically reviewed across the themes of productivity, phenology, and environmental stress.
- Advances and challenges were identified within individual themes and in their integration toward holistic monitoring.

What are the implications of the main findings?

- Emerging integration approaches offer pathways beyond monitoring toward decision-support systems for broadacre agriculture.
- Future directions of advancing resilience-focused applications of remote sensing are proposed.

Abstract

Large-scale rainfed cropping systems (broadacre agriculture) face intensifying climate and resource stresses that undermine yield stability and farm livelihoods. Remote sensing (RS) offers critical tools for improving resilience by monitoring crop performance—productivity, phenology, and environmental stress—across large areas and timeframes. This review aims to synthesize methodological advances over the past two decades in applying RS for broadacre crop monitoring and to identify key challenges and integration opportunities. Peer-reviewed studies across diverse crops and regions were systematically examined to evaluate the strengths, limitations, and emerging trends across the three RS application themes. The review finds that (1) RS enables spatially explicit yield estimation from regional to paddock scales, with vegetation indices (VIs) and phenology-adjusted metrics closely correlated with yield. (2) Time-series analyses of RS data effectively capture phenological transitions critical for forecasting, supported by advances in curve fitting, sensor fusion, and machine learning. (3) Thermal and multispectral indices support the early detection of abiotic (drought, heat, salinity) and biotic (pests, disease) stresses, though specificity remains limited. Across themes, methodological silos and sensor integration barriers hinder holistic application. Emerging approaches, such as multi-sensor/scale fusion, RS–crop model data assimilation, and operational and big data integration, provide promising pathways toward resilience-focused decision support. Future research should define quantifiable resilience metrics, cross-theme predictive integration, and accessible tools to guide climate adaptation.

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Keywords: remote sensing; broadacre agriculture; crop productivity; phenology; environmental stress

1. Introduction

Broadacre farming systems—especially large-scale, rainfed cropping systems, which account for nearly three-quarters of the world's cropland extent [1]—are under increasing pressure due to climate variability and resource stresses [2,3]. Rising temperatures, shifting rainfall patterns, and more frequent extreme weather events are already undermining crop yields and farm profits [2,4,5]. For example, in Australia's grain belt, climate change since 2000 has cut average broadacre farm profitability by about 22% [6,7]. Recent record-breaking droughts (e.g., the driest early-season period on record in 2024) across the south-west region of Western Australia delayed crop sowing and emergence, highlighting the vulnerability of current practices to climate extremes [6]. Global studies likewise confirm that climate variability, especially heatwaves and drought, is a dominant driver of year-to-year yield fluctuations, accounting for roughly 20–49% of global crop yield variability [2,5,8]. Concurrent hot-and-dry extremes have consistently negative impacts on major crops, and their occurrence is increasing. For example, the frequency of extreme hot/dry conditions during wheat seasons has risen several-fold in recent decades [9]. These trends threaten the reliability of crop production, making resilience a critical goal for broadacre agriculture [9,10]. In this context, resilience is defined as the capacity of the agricultural system to withstand, recover from, and adapt after disturbances [10]. Achieving resilience in broadacre cropping means maintaining productivity under variable climate and resource conditions and quickly rebounding from stress events. However, developing truly resilient farming systems is challenging because multiple stressors (such as drought, heat, pests and disease) often occur in combination [6]. There is a need for improved monitoring and management strategies that can handle this complexity and safeguard yield stability and farm incomes under a changing climate.

Remote sensing (RS) technologies—encompassing spaceborne, airborne, unmanned aerial vehicles (UAVs/drones), and proximal sensors—have revolutionized crop monitoring by providing multi-scale, non-destructive observations throughout the growing season [11]. These technologies are invaluable for tracking three key aspects of crop performance: productivity—yield (quantity and quality), phenology—development timing, and environmental stress. Modern RS platforms can continuously survey entire fields and regions, detecting plant traits and symptoms that are often invisible to the human eye [12]. This enables an accurate, early, and spatially detailed view of crop status, supporting timely management interventions.

Crop productivity, phenology, and stress metrics are complementary facets of crop performance. Phenological anomalies often foreshadow yield impacts, and early stress detection enables interventions to safeguard yields. However, studies in the literature using RS for agriculture tend to focus on either yield estimation, phenology mapping, or stress detection and assessment, without combining these aspects into a unified framework for proactive resilience. In addition, a recent comprehensive review of optical remote sensing for crop stress noted that most studies relied on single-sensor data and single-indicator stress proxies, rather than exploiting multi-sensor, multi-factor synergies [13]. In that review, most of the research designs were constrained by available sensors and tended to examine one stress factor at a time [13]. The authors identified a clear path forward: integrating data across multiple sensors and spectral domains to monitor multiple stress responses simultaneously (a more holistic view) and assimilating those observations into crop

models [13]. This points to a gap in current research—the need for integration. Similarly, while yield prediction studies and phenology studies exist separately, combining phenological metrics with yield models has proven beneficial yet is not universally practiced. Few studies explicitly link shifts in crop phenology due to climate stress with consequent yield outcomes and stress mitigation strategies [14].

In the context of resilience, this gap is even more pronounced. Resilience, by definition, spans multiple dimensions (stable yields, adaptive phenology, and stress resistance), but many investigations tackle these components independently. A farm-systems resilience review found that assessments often examine only a subset of performance metrics (e.g., economic yield or average productivity) and ignore others like temporal variability or environmental factors [10]. Therefore, there is a recognized need for integrating crop productivity, phenology, and stress monitoring approaches into a single framework—especially using remote sensing—as a non-destructive and cost-effective enabler. Without such integration, we risk missing important interactions, such as how phenological shifts might buffer yield losses under drought, or how early stress detection might save a season if coupled with adaptive management [3].

While existing reviews on remote sensing applications have summarized available sensor platforms and their usage [13] or explained the physiological relevance of spectral bands [12,13], this review narrows the focus to synthesize recent methodological advances in applying remote sensing to enhance resilience in rainfed broadacre cropping systems (e.g., cereal, maize, rice, soybean). Specifically, the review addresses three principal themes: (1) crop productivity monitoring (production and yield gaps estimation); (2) crop phenology monitoring and modeling (growth stages and development shifts); and (3) crop stress detection and assessment (abiotic and biotic stress). By integrating insights across these domains, this review highlights how RS technologies are evolving from monitoring tools toward comprehensive decision-support systems that can inform adaptive management and strengthen resilience under climate change. This paper is structured to first review thematic advances and limitations in RS applications, then examine integration trends and challenges toward resilience, and finally outline future directions.

2. Materials and Methods

To ensure comprehensive yet focused coverage of relevant research, a semi-structured literature search strategy was employed (Table 1). Google Scholar served as the primary search engine, with the Web of Science and Scopus considered for cross-referencing, to capture studies spanning multi-disciplinary agriculture, including remote sensing, agronomy, and climate adaptation.

Keyword combinations were designed to align with the principal themes of this review. Searches were conducted using Boolean operators (AND, OR) with string combinations: [“remote sensing” OR “UAV” OR “UAS” OR “drones”] AND [“crop produc*” OR “yield” OR “crop phenology” OR “crop stress” OR “resilience”].

This inclusive search approach aimed to accommodate terminology differences across disciplines and to capture studies addressing the intersection of remote sensing applications and agricultural resilience.

Following the initial search, studies were screened based on title and abstract review to identify potential relevance, with full-text assessments conducted where necessary.

The inclusion criteria focused on peer-reviewed journal articles reporting the application of remote sensing techniques to broadacre cropping systems, addressing at least one of the principal themes—crop productivity estimation, phenological monitoring, or environmental stress detection—and demonstrating clear agronomic relevance. Studies

were excluded if they focused solely on non-cropping systems, were purely methodological without direct agricultural application, or were not peer-reviewed.

Table 1. The stages and details of the literature selection process.

Stages	Description
Define review scope and objectives	Focus on remote sensing applications for: • Crop productivity; • Crop phenology; • Crop stress detection.
Initial database search	Searched Google Scholar [1], Web of Science [2], and Scopus [2] using keyword combinations: • ["remote sensing" OR "UAV" OR "UAS" OR "drones"] AND ["crop produc *" OR "yield" OR "crop phenology" OR "crop stress" OR "resilience"]; Each core theme—productivity, phenology, and crop stress—was searched separately for broader inclusion
Title and abstract screening	Selected studies relevant to broadacre cropping systems and at least one core theme.
Applying inclusion/exclusion criteria	Inclusion criteria: • Peer-reviewed journal articles; • Studies applying RS technologies to broadacre crops (e.g., wheat, maize, barley, and soybean); • Addressing at least one core theme; • Demonstrating agronomic relevance for resilience management. Exclusion criteria: • Non-cropping systems unless methodologies were transferable; • Purely methodological RS studies without agronomic application; • Non-peer-reviewed materials (e.g., conference abstracts and, technical reports).
Full-text assessment	• Conducted thematic review of full texts; • Removed papers not directly addressing crop monitoring (e.g., human health-focused studies).
Snowballing and expert recommendations	Added relevant studies identified through reference lists and expert consultation to ensure completeness.
Final dataset assembly	• Finalized 70 peer-reviewed articles; • Representing diverse geographic, climatic, and management contexts.

[1] Primary search; [2] cross-referencing; "*" in the search strings is used to capture multiple word endings.

Following title and abstract screening, full-text evaluation, and the application of defined inclusion criteria, a final dataset of 70 peer-reviewed articles was assembled. Figure 1 presents a bibliometric overview of these studies.

Figure 1a shows the count of articles by year and geographic focus, with review-type articles—those not tied to specific regions—displayed in gray. Geographically, the studies span a wide range of production zones, including the North America (e.g., Midwest United States), South America (e.g., Brazil), Australia (e.g., Wheatbelt), Asia (e.g., China and

South Asia), Europe (e.g., Danube River Basin and Italy), and Africa (e.g., Nigeria). This global distribution enhances the applicability of the findings and underscores the need for integrated research approaches across regions and disciplines. The majority of publications appeared between 2018 and 2024, reflecting growing interest in applying remote sensing to crop monitoring. The selected articles span 22 journals, with *Remote Sensing*, the *Remote Sensing of Environment*, *Agricultural and Forest Meteorology*, *International Journal of Applied Earth Observation and Geoinformation* and *Agricultural Water Management* among the most represented (Figure 1b). Thematic coverage shows an emphasis on productivity (n = 29), phenology (n = 38), and stress detection (n = 31), though few studies (n = 7) addressed all three simultaneously (Figure 1c). A total of 29 review-type articles were included, many of which concentrated on single or double themes (Figure 1d). In addition, four studies in the dataset did not fall neatly into the three principal themes of productivity, phenology, or stress, but instead focused on broader methodological innovations and cross-cutting applications of remote sensing in agriculture. The following sections synthesize key developments across each thematic focus area.

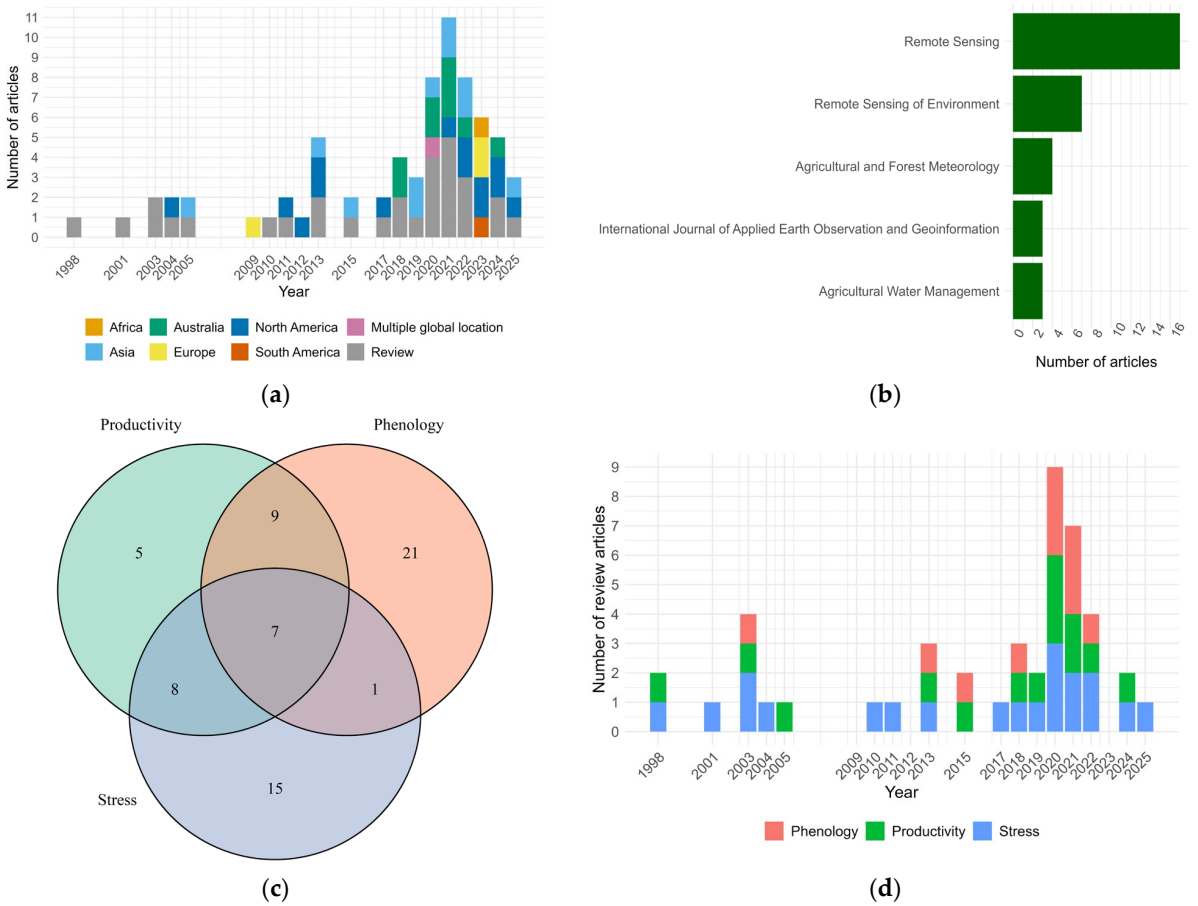


Figure 1. A bibliometric overview of the 70 selected peer-reviewed articles. (**a**) Count of articles by year and location. Note: "*Gray*" bars represent review-type articles not associated with specific geographic regions. (**b**) Top five out of twenty-two journals represented in the dataset. (**c**) Number of articles associated with each thematic focus—productivity, phenology, and environmental stress. (**d**) Count of review-type articles by year and theme. Note: Articles addressing multiple themes were counted once for each relevant theme.

The list of selected articles is provided in the Supplementary Materials. Bibliometric analyses were conducted in R-4.4.1 [15,16] using the '*ggplot2*' [17] and '*VennDiagram*' [18] packages. ChatGPT (model GPT-4o) [19] was used to assist with the initial structure of the manuscript and for grammar checking during later stages.

3. Thematic Review

This section reviews the development of remote sensing methods for (1) crop productivity monitoring, (2) crop phenology monitoring and modeling, and (3) crop stress detection and assessment, highlighting common methodologies, crop- or region- specific findings, and how these advances and remaining challenges to inform resilience-focused agricultural monitoring. A case study from the authors' ongoing projects is provided to support the discussion.

3.1. Remote Sensing for Crop Productivity Monitoring

Over the past few decades, research has evolved from simple empirical relationships between satellite indices and yield towards integrated approaches that combine multispectral imagery, crop phenology, weather data, and modeling frameworks.

3.1.1. Foundational Developments in Remote Sensing for Crop Productivity

In the 1990s, precision agriculture concepts emerged, integrating remote sensing with GPS and GIS to map within-field variability and guide inputs [20]. By the early 2000s, studies had established empirical yield models based on satellite-derived indices and thermal imagery [21]. For example, reflectance-based vegetation indices (such as the NDVI) and thermal-based estimates of crop water use were identified as two distinct approaches for predicting yields and detecting stress [21]. Concurrently, remote sensing was being incorporated into agricultural statistics for large-scale crop area and yield estimation, improving the design of survey sampling frames and accuracy of national yield forecasts [22]. These foundational efforts confirmed that spectral measurements from aircraft or satellites can capture crop health and biomass signals correlated with final yields, setting the stage for more advanced techniques [23].

3.1.2. Vegetation Indices and Phenological Metrics for Yield Estimation

A core method in the remote sensing of productivity is the use of vegetation indices (VIs) as proxies for crop health and yield. Decades of research show that metrics such as the Normalized Difference Vegetation Index (NDVI) [24] or Enhanced Vegetation Index (EVI) [25] correlate strongly with final yields in many crops, enabling pre-harvest yield forecasting [26,27]. In practice, simple models using seasonal NDVI or EVI metrics can capture a large fraction of yield variability (often with R^2 in the 0.6–0.7 range), although the most predictive index may depend on environmental context. For example, an EVI-based metric achieved an R^2 of approximately 0.67 for maize yield prediction in humid regions of the U.S., whereas a water-sensitive index (NDWI) performed better in semiarid areas (R^2 = 0.69) [27]. It is worth noting that broadacre field cereals and grains that achieve full ground cover provide a more continuous signal, making standard VIs more directly interpretable. Nonetheless, the methodologies can be adapted for row crops with appropriate adjustments, for example, masking inter-row soil or using higher-resolution UAV imagery.

Figure 2 demonstrates the use of MODIS NDVI monthly composites (MOD13C2, ~500 m resolution) from 2000 to 2023 to track wheat productivity across the Western Australian (WA) rainfed wheatbelt (from the authors' ongoing study). This multi-year integrated NDVI (iNDVI—April to November) record enables the retrospective assessment of landscape-scale yield variability, revealing the spatiotemporal patterns of crop productivity in response to poor seasons over two decades. For a location, positive values in the iNDVI anomalies (green color) correspond to known high-yield years with favorable growing season rainfall and a mild range of temperatures, whereas negative iNDVI anomaly values (orange/red colors) denote moderate to severe drought seasons that depressed wheat yields

(Figure 2a). The statistically significant correlations ($p < 0.001$) between iNDVI and historical climate derivatives (Figure 2b,c) or statewide yield records (Figure 2d) highlight the value of remote sensing for capturing climate-driven yield fluctuations. A case study examined within-field variation in the WA wheatbelt using Landsat NDVI sequences and showed that seasonal NDVI time-series metrics (iNDVI) can explain much of the inter-annual wheat yield variation (R^2 ~0.64) [28]. Likewise, a further study successfully hindcasted past wheat yields for 44 WA paddocks using archival satellite data with derived phenological metrics (such as timing, duration, and growth extent) (R^2 ~0.68) [29], underscoring the utility of retrospective remote-sensing analysis for agronomic insights.

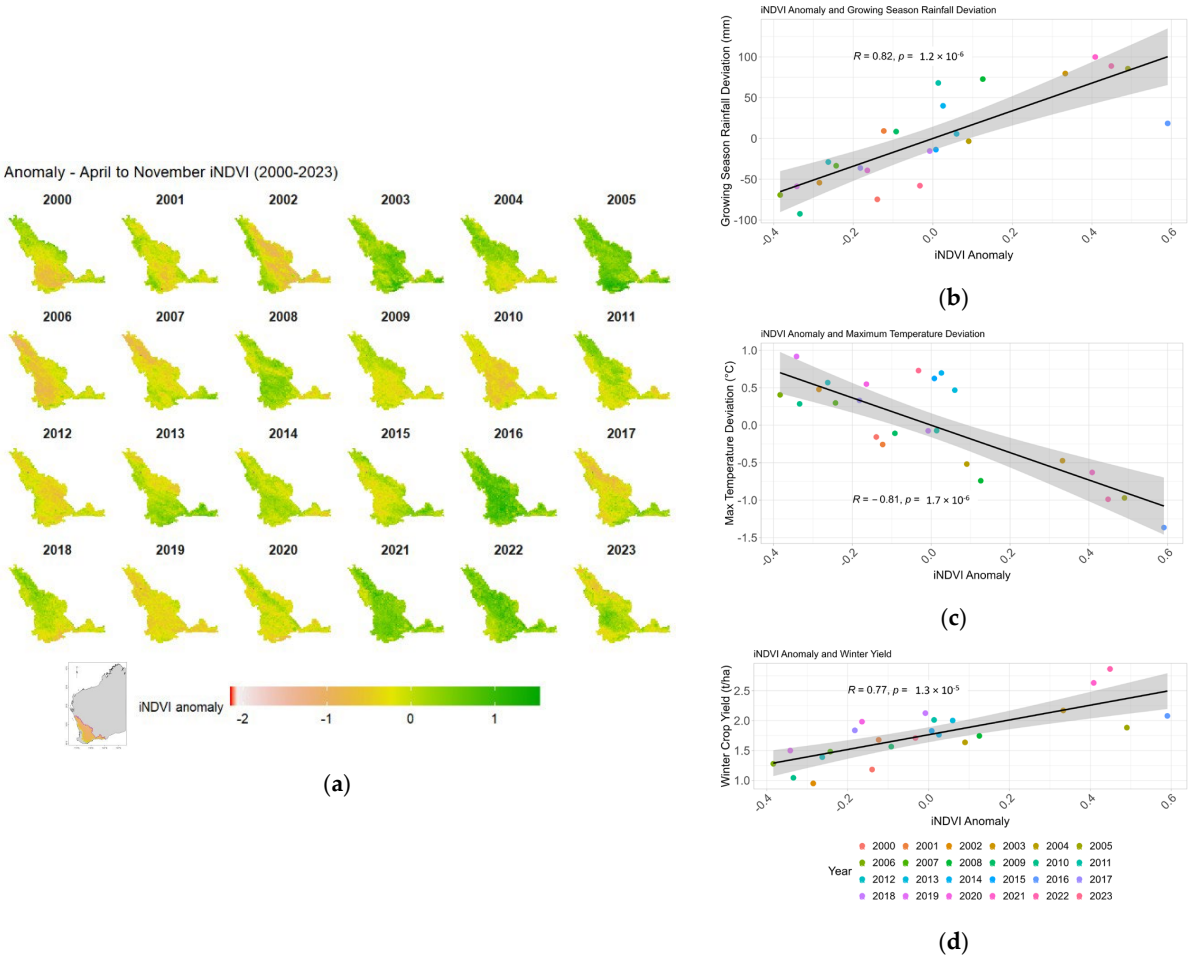


Figure 2. Time-series composite of MODIS Terra integrated NDVI (iNDVI) anomalies and climate factors from April to November (growing season) across Western Australia's rainfed wheatbelt during 2000–2023. (**a**) spatial iNDVI anomalies per year, with *"green"* colors indicating above-average vegetation activity and *"orange/red"* colors indicating below-normal productivity. (**b**) Growing season rainfall deviation (mm) in correlation to iNDVI anomaly changes. (**c**) Growing season maximum temperature deviation (°C) in correlation to iNDVI anomaly changes. (**d**) State-wide winter crops yield (t/ha) in correlation to iNDVI anomaly changes during 2000 to 2023. The Shadows in panels (**b**–**d**) indicate the 95% confidence interval. The figure highlights statistically significant correlations ($p < 0.001$) between remote sensing signals, climatic anomalies, and observed productivity. Note: This figure is derived from the authors' ongoing study. The monthly NDVI composites (MOD13C2) were generated post-season, which limits their utility for in-season forecasting. The gridded Climate data were obtained from the Australian Scientific Information for Land Owners (SILO) database (https://www.longpaddock.qld.gov.au/silo/, accessed on 26 November 2025), and historical winter crop yield data were sourced from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (https://www.agriculture.gov.au/abares/data, accessed on 26 November 2025).

However, Figure 2 also illustrates key limitations of NDVI-based monitoring. First, the complete seasonal NDVI composite becomes available only after crop harvest, limiting its usefulness for in-season yield forecasting or early drought warning. In other words, detailed phenological curves and productivity metrics can only be confirmed post-season, an approach often termed retrospective or hindcasting, rather than being amenable to near-real-time prediction [30]. A second limitation is the impact of cloud cover on optical NDVI observations. In some growing seasons, heavy or persistent cloud cover leads to data gaps or noisy composites; this cloud contamination disrupts the continuity of the NDVI time series, complicating year-to-year comparisons and trend analysis [28]. Studies in the WA wheatbelt have noted that missing NDVI data due to clouds are "unavoidable" and must be handled carefully [28]. Recent approaches attempt to mitigate this issue by gap-filling or blending data from multiple sensors—for instance, applying spatially weighted interpolation to fill Landsat NDVI gaps in WA croplands [31].

3.1.3. Integrating Remote Sensing with Climate and Crop Models

While VIs alone capture general productivity trends, they often cannot fully account for factors such as weather extremes, soil conditions, and management practices that affect yield. To address this, researchers have increasingly integrated remote sensing data with climate information and process-based crop models. By combining these data sources, models can distinguish weather-driven yield fluctuations from the crop's spectral signals. For example, one study used satellite thermal infrared imagery to infer root-zone soil moisture via an energy balance model and fed that output into a crop simulation model (DSSAT) for rain-fed maize fields [32]. This integration of remotely sensed drought stress enabled accurate yield estimates in regions with sparse rain gauges by capturing moisture deficits that vegetation indices alone might miss [32]. In another case, scientists in South Asia assimilated satellite observations into the DSSAT to constrain the leaf area index (LAI) and biomass, greatly improving the representation of crop growth in data-sparse farming areas [33]. Such approaches are especially valuable under compound climate extremes. In the Danube River Basin, a novel copula-based framework was used to analyze maize yield losses due to back-to-back drought years using a suite of remote sensing indices including the two-band enhanced vegetation index (EVI2), evaporative stress index (ESI), and relative soil water availability [34]. That study underscored the disproportionate impact of consecutive droughts on productivity, especially in countries like Romania, Bulgaria, and Slovakia.

High-resolution remote sensing has likewise been employed to improve yield predictions under variable climate conditions. In northeastern Australia, for instance, assimilating Sentinel-2 data (eight different spectral indices) into a field-scale wheat model significantly enhanced yield prediction accuracy. Single spectral metrics alone explained over 70% of the yield variability (for example, a red-edge chlorophyll index achieved an R^2 of 0.76 with observed yields), and combining those indices with a modeled water stress factor increased the R^2 to about 0.91 in training (and ~0.93 upon independent validation) [35].

Integration approaches are also being used to attribute yield losses to specific extreme weather events in near-real time. For instance, a recent study in South Australia paired high-frequency Sentinel-2 VI time series with concurrent weather data to detect and quantify crop damage from heatwaves and drought. The researchers developed a "crop damage index" (CDI) based on the deviations of observed greenness from expected phenological trends, which allowed the mapping of yield losses at sub-field resolution as the season progressed [14]. The CDI showed a high correlation with actual yield outcomes (R2 ~0.83 for wheat and ~0.91 for barley), enabling the early identification of areas suffering weather-induced yield deficits [14]. Overall, blending satellite observations with meteorological

and agronomic data produces more robust yield estimates and diagnostic insights than any single data source on its own [32,36].

3.1.4. Precision Agriculture and Yield Gaps Estimation

Remote sensing technologies have become indispensable tools for advancing precision agriculture, particularly in large-scale broadacre systems where within-field variability can significantly influence productivity.

In Australia, long-term Landsat NDVI time series have been employed to characterize persistent yield zones across broadacre cropping landscapes [28]. These records reveal stable patterns of productivity over time, allowing the identification of consistently low- or high-yielding patches. For example, integrating multi-season NDVI-based metrics achieved correlations of up to r = 0.8 with observed wheat yields (with RMSEs in the range of 0.5–0.6 t/ha) [28]. This information enables growers to pinpoint underperforming areas and tailor management interventions, such as adjusting fertilizer or seeding rates, to address localized constraints. A large-scale application of this approach was recently demonstrated across 20 million hectares in WA's wheatbelt, where satellite-derived crop rotation histories were combined with the agricultural production systems simulator (APSIM) crop modeling and machine learning to quantify the benefits of different rotations on wheat yield [37]. The results challenge conventional assumptions from field trials and highlight how landscape-level management insights can be derived from remote sensing–model fusion.

In the context of increasing climatic uncertainty, one of the most critical applications of remote sensing is in evaluating yield gaps and monitoring resilience. Yield gaps—defined as the difference between actual and attainable yields under optimal conditions —are pervasive across both high- and low-input systems [38,39]. Satellite-derived VIs offer a scalable method for assessing these gaps across large spatial extents, especially where ground data are sparse [39]. In smallholder systems, for example, the remote sensing of crop phenology has been proposed as a promising approach for identifying chronically underperforming fields by capturing intra-seasonal variability in crop development stages. However, spatial mismatches between satellite-derived phenology and the fine-scale yield variability in smallholder landscapes remain a key limitation [40]. This underscores the need for higher-resolution data and data fusion techniques to enable the practical application of phenology-based yield gap detection at smallholder scales [40].

In regions vulnerable to food insecurity, such as South Asia, operational drought monitoring systems now incorporate remote sensing-based indices such as the ESI and the Vegetation Health Index (VHI), offering early indicators of drought onset and duration [41]. These tools enable more proactive responses to agricultural stress and contribute to regional food security efforts.

Unmanned aerial vehicles (UAVs) have enhanced the spatial resolution of crop monitoring, offering centimeter-level imagery on demand [42,43]. Equipped with multispectral or thermal sensors, UAVs can detect subtle early indicators of stress—ranging from nutrient deficiencies to pest and disease outbreaks—often before visual symptoms emerge [42,44,45]. This early detection capability supports targeted interventions, potentially reducing yield losses and minimizing input waste. While operational limitations remain, the utility of UAVs has been demonstrated in research contexts [42]. For example, one study combined multi-temporal UAV imagery with machine learning to predict cotton yields, using deep learning to quantify opened bolls from RGB images and multispectral indices (R^2 = 0.85) [46]. In rice, researchers introduced a phenology-adaptive vegetation index approach to continuously estimate plant area index (PAI) from UAV multispectral data. This method outperformed traditional single-stage models and showed strong agreement with ground measurements (R^2 ~0.80 in controlled plots) [47].

Looking forward, emerging frameworks, described as "Agriculture 5.0" envision the integration of satellite and UAV data with internet of things (IoT) sensor networks, automated machinery, and AI-driven decision support systems that can provide growers with dynamic tools for adaptive management [48,49].

3.2. Remote Sensing for Crop Phenology Monitoring and Modeling

Crop phenology—the timing of developmental stages such as emergence, flowering, and maturity—is a critical indicator of crop performance and adaptation. Accurate phenological information aids yield forecasting, crop management, and climate adaptation assessments. Remote sensing offers a practical means for monitoring phenology over large areas, complementing or replacing sparse ground observations. This section reviews recent advances in remote sensing–based methods for extracting, integrating, and evaluating crop phenology information for broadacre agriculture.

3.2.1. Crop Phenology Information from Remote Sensing

Early satellite-based attempts in the 2000s demonstrated that time-series VIs (like the NDVI) can be used to infer key phenological transition dates (e.g., planting or harvest) at regional scales [50,51]. In fact, the potential of remote sensing for tracking crop phenology in precision agriculture was already recognized in early reviews [52]. Subsequent research has greatly improved the precision of phenology retrievals by refining algorithms, leveraging new sensors, and integrating ancillary data. Notably, numerous recent reviews highlighted the rapid advances in remote-sensing phenology and their importance for sustainable agricultural practices [23,43,48,49,53]. The methods for extracting crop phenology information from remote sensing data include the following:

- Threshold-based approaches—simple rules (e.g., NDVI exceeding a fixed threshold value) to mark the start or end of a season [50,51]. These methods are straightforward but may require calibration and can be sensitive to noise.
- Curve fitting and smoothing—fitting functions (e.g., logistic, spline, or sigmoid models) to VI time-series to identify inflection points corresponding to phenological events [54,55]. For instance, double-sigmoid fits to Sentinel-2 NDVI have been used to detect crop green-up and senescence, aligning well with field observations [54]. Similarly, wavelet transforms and harmonic analysis have been applied to MODIS time-series to smooth out noise and better capture seasonality [55,56].
- Time-series derivatives—computing the first or second derivative of smoothed VI curves to pinpoint the dates of rapid change. This technique was shown to improve the detection of sowing and harvest dates in soybean when compared across algorithms. It was stated that smoothing-based methods (e.g., TIMESAT, phenex) yielded lower timing errors than simple derivative or threshold methods [57]. Open-source toolkits now facilitate such analyses: for example, the CropPhenology R package can calculate ~15 phenological metrics (such as the start of season and end of season) from NDVI time-series [58].
- Multi-sensor data fusion—combining observations from multiple satellites to achieve high revisit frequency and all-weather monitoring. For example, blending optical and radar data has helped overcome cloud-related gaps: a recent framework fused Sentinel-1 SAR with Sentinel-2 optical imagery to track wheat phenology, improving agreement with ground camera (PhenoCam) observations of growth stages [59]. Likewise, merging Landsat and Sentinel-2 in a harmonized time-series enables within-season phenology mapping rather than only post-season analysis [30]. Additionally, Zhao et al. [59] demonstrated a deep learning approach to fuse Sentinel-1 and -2 time-series, which further improved the accuracy of detecting the crop season start and

end by leveraging spatial–temporal features. Emerging data sources are also being explored. For instance, satellite solar-induced fluorescence (SIF) measurements combined with the NDVI have been used to monitor cropland photosynthetic phenology, capturing seasonal peaks and early stress signals in rainfed crops [60]. One study in WA filled cloud gaps in Landsat NDVI sequences via spatial interpolation, reduced the reconstruction error by ~75% [31].

- High-resolution and proximal sensing—utilizing fine-scale imagery and ground-based sensors to refine satellite phenology estimates. Near-surface digital cameras (PhenoCams) and drone imagery have been used to validate and calibrate satellite-derived phenology [61]. For instance, PlanetScope cubesat data (3–5 m resolution) in combination with PhenoCam observations allowed the detection of crop canopy cover change and senescence with high temporal detail [61]. Even low-cost tools like smartphone cameras have been tested: in India, plot-level wheat phenology (e.g., dates of canopy closure and heading) was captured using RGB images, offering an inexpensive alternative for smallholder farms [62]. In addition to supporting satellite observations, a recent deep learning approach detected rice growth stages from UAV imagery with a classification accuracy of ~84%, enabling near real-time mapping of key phenological events and harvest dates for field plots [63].
- Machine learning and hybrid models—advanced algorithms that learn phenological patterns from multi-source data. Recurrent neural networks (long short-term memory method) guided by crop growth model outputs have enabled near-real-time phenology estimates that assimilate weather, soil, and MODIS satellite data [64]. These hybrid approaches can predict phenological stages on a daily basis, which is a leap beyond traditional end-of-season phenology metrics. Additionally, machine-learning models using remotely sensed pheno-metrics have been applied to related tasks like early yield forecasting. In one case, an XGBoost model using MODIS-derived phenology indicators could predict U.S. corn yields as early as the mid-season growth stage with only slight loss of accuracy compared to using detailed ground-observed stages [65]. More broadly, the fusion of satellite observations, machine learning, and crop modeling is expected to further enhance phenology prediction and crop classification in operational farming systems [66].

Remote sensing-based phenology monitoring has now been demonstrated across diverse cropping systems and regions (Table 2). Studies have mapped crop calendars in complex smallholder landscapes [40], identified cropping pattern shifts [56], and tracked long-term phenology trends under climate variability [67]. Notably, satellite phenology metrics have been used to diagnose yield gaps [39] (also mentioned in Section 3.1.4): for example, reviews concluded that aligning planting dates with optimal climate windows (as inferred from phenology maps) could help close yield gaps, though caution is needed in heterogeneous smallholder fields [34,40]. Similarly, phenological shifts detected via remote sensing offer insight into climate change impacts. In Australia, variations in NDVI green-up and senescence timing have been linked to temperature and rainfall anomalies, revealing stage-specific climate sensitivities of winter crops [67]. In a similar framework, Duan et al. [14] showed that integrating satellite phenology with weather data can detect and attribute cereal yield losses to specific drought and heat events, illustrating how phenological deviations reflect the impact of climate extremes. This highlights phenology as a key resilience indicator—crops that maintain or adjust their development timing under stress tend to perform better.

Table 2. Case studies of remote sensing approaches for crop phenology monitoring, with their reported accuracy in capturing phenological timing.

Study (Crop/Region)	Remote Sensing Approach	Phenological Outcomes and Accuracy
Sakamoto et al. [55] (rice/Japan)	MODIS EVI time-series; Wavelet based filter	Planting date, heading date, harvesting date, and growing period; detected ~10-day error on average
Rodigheri et al. [57] (soybean/Brazil)	MODIS and Sentinel-2; NDVI/EVI2 time-series; six algorithms compared (e.g., TIMESAT and phenex)	Sowing date and harvest date; RMSE ~ 16–17 days for the best methods; smoothing-based algorithms outperformed simple threshold/derivative approaches in timing accuracy
Gobin et al. [54] (mixed crops: winter wheat, silage maize, and late potato/Belgium)	fAPAR time series from proximal (DHP [1] photos) and satellites (DMC [2] constellation, Sentinel-2); double sigmoid model fitting	Key growth stages (stem elongation, senescence, canopy closure, flowering and fruit development); captured within ~6–10 days of actual timing (field observations)
Boschetti et al. [68] (rice/Italy)	Five-year MODIS NDVI time series; local polynomial function + Savitzky–Golay filter, calibrated with thermal time (growing degree days)	Start of season, peak, end of season; high agreement with ground thermal units (R^2 ~0.92 between satellite-derived and observed phenological timing)
Pei et al. [65] (maize/the U.S.)	MODIS-derived land surface phenology metrics (MCD12Q2) used in an XGBoost yield prediction model	Yield prediction possible by mid-season using satellite phenology metrics, with <5% error increase compared to using observed phenology
Zhao et al. [59] (winter wheat/China)	Sentinel-1 + Sentinel-2 time-series; deep learning integration (CNN-LSTM [3])	Start of season and end of season; ~5-day detection error (vs. field-observed dates)
Yang et al. [63] (rice crop/China)	mono-temporal UAV RGB imagery; deep learning architecture (CNN-SPP [4])	Harvested date; ~84% agreement with ground observations
Duan et al. [14] (cereal/Australia)	Sentinel-2 EVI2 time-series fused with climate data; anomaly detection approach	In-season yield loss events identified via phenology anomalies; extreme-weather impacts detected with high precision (R^2 ~0.8 for yield loss attribution)
Ji et al. [26] (corn/U.S.)	MODIS NDVI (8-day) time-series; Savitzky–Golay smoothing + second-derivative phenology detection	Start and end of growing season per pixel; phenologically adjusted NDVI improved yield prediction accuracy (explained ~85% of yield variance)
Shen and Evans [28] (wheat/Australia)	Multi-year Landsat NDVI sequences; multi-polynomial fitting	Within-field phenology and productivity anomalies; NDVI seasonal patterns explained yield deviations (R^2 ~0.6–0.7) across years
Viña et al. [51] (maize/U.S.)	Visible atmospherically resistant indices (VIS bands) from field spectroradiometer	Onset of reproductive stage and senescence; detected earlier than conventional NDVI (improved timeliness of phenology detection)
Bolton and Friedl [27] (maize and soybean/U.S.)	MODIS EVI2 and NDWI [5]; phenology-integrated regression models	Peak greenness ~65–75 days after green-up correlated strongly with final yields; adding phenology metrics reduced crop yield forecast error by ~10–15%
Zhao et al. [69] (corn and soybean/U.S.)	MODIS NDVI time-series at varying temporal resolutions (daily vs. 16-day)	Phenology detection timing under different revisit intervals; coarse 16-day data caused ~10–14-day shifts in estimated stage dates compared to daily observations

[1] DHP—digital hemispherical photography; [2] DMC—Disaster Monitoring Constellation; [3] CNN-LSTM—convolutional neural network-long short-term memory; [4] CNN-SPP—convolutional neural network incorporated spatial pyramid pooling; [5] NDWI—normalized difference water index.

3.2.2. Integrating Phenology with Crop Growth Models

Another important integration is of phenology information into crop growth models and decision support tools. By assimilating remote sensing-derived phenological dates

or leaf area dynamics, crop models can be continually adjusted to real field conditions. For example, satellite-observed LAI and biomass were fed into the DSSAT crop model for maize, markedly improving the simulation of crop development and yield under drought stress [33]. The fused model achieved high agreement with field measurements (LAI R^2 ~0.85 and biomass R^2 ~0.95), illustrating the value of using phenology-sensitive RS inputs to constrain model predictions [33]. Such approaches enable early in-season yield forecasts and proactive management. Indeed, phenology-driven yield forecasting has progressed to the point that by mid-season, one can predict final yields with reasonable confidence if key growth milestones (e.g., flowering time) have been remotely sensed [65]. Studies integrating satellite phenology metrics into yield models consistently report improved accuracy: for instance, adjusting NDVI time-series based on each pixel's observed green-up date significantly enhanced corn yield predictions in the U.S. Corn Belt [26]. Case studies in Australia [28,29] of using phenological patterns to explain historical yield anomalies have been discussed in Section 3.1.2.

3.2.3. Challenges for Remote Phenology Monitoring

Despite these advances, challenges remain in remote phenology monitoring. Dense time-series data are required to pinpoint short growth stages, yet frequent cloud cover or coarse revisit intervals can obscure critical transitions [54]. For example, using a 16-day satellite revisit interval instead of daily observations can introduce errors on the order of 10 days in detected phenology dates [69]. As noted earlier, missing observations in optical datasets can be interpolated or supplemented with radar to avoid bias [31]. Moreover, inconsistencies in defining phenological turning points (e.g., what NDVI level constitutes "onset of greenness") can lead to inter-study variation [70]. Double cropping is an added challenge [57], as overlapping growth cycles complicate the separation of distinct phenological phases within a single season. Wu et al. [11] similarly emphasize that multi-cropping systems and fine-scale field heterogeneity still pose substantial uncertainties for the remote sensing of phenology, even as new sensor fusion techniques begin to mitigate these issues. Standardizing phenology definitions and validation with ground truth (phenology networks, cameras, and field observations) is essential for comparing results.

Nevertheless, the overall trajectory is positive—with multi-sensor networks (satellites, UAVs, and in situ sensors) and improved algorithms, remote sensing is providing evermore reliable crop phenology information. This lays a foundation for resilience-building strategies, because phenological adaptation (the ability to adjust timing) is a major mechanism by which crops avoid damage from heat or drought. In the next section, we turn to remote sensing of the stresses themselves, and how early warnings can be derived before phenological or yield impacts fully manifest.

3.3. Remote Sensing for Crop Stress Detection and Assessment

Crop stress, whether due to environmental extremes or biological factors, has been a major focus of agricultural remote sensing research. Early work recognized that multispectral imagery and thermal infrared measurements could reveal crop health issues like moisture deficits and pest outbreaks before yield losses occurred [20]. Over the past two decades, a wide range of approaches have been developed to remotely assess crop stress at scales from individual plants (using drones or proximal sensors) to entire regions (via satellites) [13,52]. Notably, several comprehensive reviews highlight these advances in remote sensing for crop stress detection and assessment [23,39,43]. The choice of technique and its effectiveness depend on the stress type and the spatio-temporal scale of analysis [71]. Below, we review how remote sensing is being used for abiotic stress detection (focusing

on drought and heat) and biotic stress detection (pests, diseases, and weeds), highlighting key examples, methods and results from refined studies.

3.3.1. Drought and Water Stress

Drought and water accessibility are among the stresses most detrimental to crop production [41], especially in broadacre farming systems. Remote sensing has been extensively used to detect plant water stress [72], including high-resolution UAV surveys for the early detection of water deficits [73]. A common approach is to track VI anomalies and moisture-sensitive indices from optical satellite data [41,74]. For example, normalized difference indices derived from MODIS and Landsat (NDVI, NDWI, and NDMI) have been used to assess vegetation health and soil moisture status in croplands [74]. Declines in NDVI-based metrics often signal emerging water stress (as shown in Figure 2), and composite indices such as the Vegetation Condition Index (VCI) integrate the current NDVI with historical ranges to gauge drought severity [74].

At regional scales, drought indices that combine satellite NDVI and land surface temperature (LST) (the LST-NDVI trapezoid mechanism) can capture broad agricultural drought events [75]. Ali et al. [75] characterized spatio-temporal drought patterns across South Asia (2001–2017) using the Temperature-Vegetation Dryness Index (TVDI) from MODIS thermal and vegetation data alongside a satellite-based Drought Severity Index (DSI). They found that these indices successfully mapped major drought episodes, with a modified water supply index performing best in certain seasons [75]. Similarly, Shahzaman et al. [41] evaluated multiple MODIS-derived drought indices in South Asian croplands and identified the Evaporative Stress Index (ESI) as a particularly effective early indicator of agricultural drought [41]. These remote indicators have become part of operational drought monitoring systems, providing early warning of crop water stress and impending yield losses [41,44].

At the field scale, high-resolution imagery allows more nuanced assessment of crop water status. Sentinel-2 satellites (10–20 m resolution) in particular have enhanced stress monitoring at farm scales [76]. Beyond passive optical imagery, thermal infrared sensing is a powerful tool for detecting water stress via canopy temperature. Stressed plants under soil moisture deficits exhibit elevated leaf temperatures due to reduced evaporative cooling. Ground-based studies in irrigated maize fields showed that canopy temperature-derived indices closely track crop water status [36]. Kullberg et al. [36] evaluated thermal infrared indices (e.g., Degrees Above Non-Stressed, DANS) using stationary IR thermometers in Colorado corn and found that they could reliably estimate crop evapotranspiration (ET) coefficients, enabling real-time irrigation scheduling [36]. Gu et al. [77] used UAV thermal imagery to compute the CWSI—which compare canopy and air temperature—in cotton trials, distinguishing drought-tolerant cultivars by their lower canopy temperatures under stress [77]. Such applications illustrate the value of remote sensing for plant breeding and management, identifying genotypes or field zones that withstand water stress.

Multi-sensor approaches and modeling can further improve drought assessment. Remotely sensed ET models combined with crop growth simulations have been used to infer root-zone moisture and yield impacts. Mishra et al. [32] developed a stress estimation tool that fuses satellite-derived ET (using the ALEXI thermal model) with DSSAT crop model to map soil moisture stress and predict yields (discussed in Section 3.1.3) in North Alabama [32]. Likewise, Zhao et al. [35] showed that assimilating multi-spectral Sentinel-2 indices into a wheat crop model improved field-scale yield prediction in Australia, implicitly capturing the effects of in-season water stress [35]. Another novel strategy is to use statistical frameworks to link stress indicators with yield losses. Potopová et al. [78] combined multiple dimensional feature space—including the two-band enhanced vegetation

index (EVI2), the evaporative stress index (ESI from thermal/ET data), and relative soil water availability—in a copula modeling approach to quantify maize yield loss probabilities under drought in the Danube basin [78]. By integrating these indicators, they could probabilistically estimate drought-induced yield reductions, offering a risk assessment tool for climate extremes [78]. Table 3 summarizes case studies of remote sensing techniques used to detect water stress and drought impacts in crops.

Importantly, remote sensing can detect not only pure drought stress but also compound and related stresses. Salinity stress, for example, often co-occurs with water deficits and produces similar spectral symptoms (e.g., reduced canopy moisture and greenness). Using satellite indicators, Wen et al. [79] evaluated crop responses under combined salinity and drought stress in the U.S. Their analysis of Sentinel-2 derived biophysical variables (LAI, fractional cover, canopy water and chlorophyll content) revealed that crops experienced far greater impacts under combined salinity-drought stress than under either stress alone [79]. Notably, leaf area declined earlier and more severely when both stresses were present, indicating a compounding effect [79]. This highlights that remote sensing metrics can sensitively capture the exacerbated plant responses to multiple simultaneous stressors. In general, water-related stresses (drought and, salinity) tend to manifest clearly in remote measurements—plants under water stress exhibit lower reflectance in NIR and often higher thermal emission—making them relatively well-monitored via current satellites [21,80]. Nonetheless, accurately estimating available soil moisture from space remains challenging. Research into microwave and thermal-infrared techniques for direct soil moisture retrieval continues [81], as does research for the better integration of optical drought indices with hydrological models to improve crop stress forecasts.

Table 3. Case studies of remote sensing techniques for detecting water stress and drought impacts in crops.

Study (Crop/Region)	Stress Type	Remote Sensing Method	Key Metrics/Results
Mishra et al. [32] (corn/North Alabama, U.S.)	Soil moisture stress (drought)	Thermal IR evapotranspiration model (ALEXI) + crop model (DSSAT)	Integrated satellite ET and crop growth modeling to map root-zone moisture and predict yield under drought; demonstrated improved early warning of stress-related yield loss (validated against field data) [32].
Kullberg et al. [36] (corn/Colorado, U.S.)	Canopy water stress (irrigation)	Canopy temperature indices (stationary thermal sensors)	Thermal indices (e.g., DANS/DACT [1]) closely estimated crop ET coefficients; enabled real-time irrigation scheduling by indicating developing water stress in the canopy [36].
Ali et al. [75] (eight countries in South Asia)	Drought (agricultural)	MODIS NDVI and LST indices (DSI [2], TVDI [3]) + TRMM rainfall	Retrospective drought mapping from 2001 to 2017; identified major drought events. Indicated that a combined vegetation–soil water index performed best for seasonal drought monitoring in this region [75].
Zhao et al. [35] (wheat/Northeastern Australia)	Climate stress impacts on yield	Sentinel-2 multispectral indices + crop model assimilation	Improved field-scale yield prediction by ~15–20% by incorporating in-season vegetation index data. The RS-model fusion captured yield losses due to drought/heat stress that a standalone model would miss [35].
Shahzaman et al. [41] (South Asian croplands)	Drought (index evaluation)	MODIS-derived drought indices (ESI [4], VHI [5], EVI [6], SAI [7])	Comparative study of drought indicators; identified the Evaporative Stress Index (ESI) as the most reliable indicator of agricultural drought severity in this region [41].

Table 3. *Cont.*

Study (Crop/Region)	Stress Type	Remote Sensing Method	Key Metrics/Results
Wen et al. [79] (multiple crops/U.S.)	Salinity and drought (combined)	Sentinel-2 biophysical variables (LAI [8], FVC [9], FAPAR [10], etc.)	Different crops showed distinct spectral responses under combined stress. Combined salinity–drought stress led to earlier and larger drops in LAI and canopy water content than single-factor stress [79].
Taiwo et al. [74] (cropland/Nigeria)	Drought and land use change	Landsat NDVI, NDWI [11], NDMI [12], VCI [13] time-series analysis	Monitored effects of land use change on vegetation health and drought severity. Noted declining NDVI and moisture indices in areas of cultivation expansion, indicating heightened drought stress on croplands [74].
Potopová et al. [78] (maize/Danube River basin, EU)	Drought (compound events)	Multi-index (EVI2 [14], ESI, relative soil saturation) + copula modeling	Probabilistic modeling of yield losses under drought. Multi-sensor indices fed into a copula model accurately quantified maize yield loss risk from drought events (e.g., capturing nonlinear yield decline probabilities) [78]
Gu et al. [77] (cotton/Texas, U.S.)	Water stress (breeding trials)	UAV thermal imaging (CWSI [15])	High-resolution CWSI maps identified spatial and genetic differences in crop water stress. Enabled selection of drought-resistant cotton lines by pinpointing cultivars with lower canopy temperatures under water deficit [77].
Duan et al. [14] (wheat and barley/South Australia)	Heat vs. drought (yield loss attribution)	Sentinel-2 EVI2 anomaly (Crop Damage Index) + thermal time integration	Near-real-time detection of heat- and drought-related yield losses ~60 days before harvest. Achieved R^2 of 0.83 (wheat) and 0.91 (barley) in predicting yield reduction by separating heat stress effects from drought via thermal-time analysis [14].

[1] DANS/DACT—degree above non-stressed/degrees above canopy threshold; [2] DSI— drought severity index; [3] TVDI—temperature vegetation drought index; [4] ESI—evaporative stress index; [5] VHI—vegetation health index; [6] EVI—enhanced vegetation index; [7] SAI—standardized anomaly index; [8] LAI—leaf area index; [9] FVC—fraction of vegetation cover; [10] FAPAR—fraction of absorbed photosynthetically active radiation; [11] NDWI—normalized difference water index; [12] NDMI—normalized difference moisture index; [13] VCI—vegetation condition index; [14] EVI2—two-band enhanced vegetation index; [15] CWSI—crop water stress index.

3.3.2. Heat and Thermal Stress

Extreme heat events can stress crops independently of soil moisture, accelerating development, impairing pollination, and shortening grain fill. Detecting heat stress via remote sensing is less straightforward, as many spectral changes (leaf wilting and premature senescence) overlap with drought signals. A promising approach is to incorporate meteorological data (temperature records or thermal time) alongside vegetation indices to isolate heat impacts. Duan et al. [14] presented a novel yield-loss detection method using Sentinel-2 time series in South Australian cereal crops, where they introduced a thermal time (growing degree day) dimension to the vegetation index analysis [14]. By comparing expected and observed EVI2 trajectories on a thermal time axis, they could attribute yield reductions to either moisture stress or heat stress anomalies.

Meanwhile, the use of thermal remote sensing in agriculture has predominantly targeted plant water status, given the tight coupling between heat and transpiration. Comprehensive reviews of thermal imaging applications in precision agriculture note that canopy temperature mapping is invaluable for early stress detection and irrigation management [11,82]. Khanal et al. [82], for example, surveyed current and potential uses of thermal sensors and highlighted their effectiveness in spotting water deficits before visible symptoms occur. As discussed above, thermal indices can serve as proxies for crop stress, but they generally signal a physiological response (stomatal closure) that could result from

either drought or acute heat. One emerging indicator that responds to both water and heat stress is solar-induced fluorescence (SIF). SIF is an optical radiation (peaks near 685 nm and 740 nm) emitted by chlorophyll during photosynthesis: it tends to drop sharply when photosynthesis is inhibited by stress. A recent study reviewed UAV-based SIF sensing for crop water stress detection [83], noting that fluorescence signals are highly sensitive to the onset of stress [83]. Because heat and drought both constrain photosynthesis, SIF measurements (often combined with traditional reflectance indices) are being explored to flag heat-stressed crops that may still appear green but have reduced carbon uptake. Going forward, an integration of thermal imagery (for canopy temperature) with optical and fluorescence data could provide a more specific diagnosis of heat stress versus water stress in crops [13]. This multi-sensor strategy is expected to improve the discrimination of stress causes—for instance, separating a heatwave's impact from a soil moisture deficit—which is critical for guiding the appropriate management response.

3.3.3. Biotic Stress

Biotic stresses from pathogens, insect pests, and weeds also leave signatures that remote sensing can exploit. Stressed crops often exhibit localized discoloration, defoliation, or growth suppression that can be detected with high-resolution spectral imagery. Weed infestations were among the earliest targets of remote sensing in precision agriculture [84]. In fact, Lamb and Brown [84], over twenty years ago, demonstrated that mapping weed patches via aerial multispectral imagery could guide site-specific herbicide applications in Australian fields. Subsequent work expanded on weed detection algorithms: Thorp and Tian [85] reviewed techniques for distinguishing weeds from crops using spectral and textural features, laying a foundation for automated weed mapping. Today, UAVs equipped with multispectral or hyperspectral cameras can capture detailed physiological and structural information at sub-meter resolution, enabling real-time intervention [44].

Plant diseases and insect attacks can be more subtle, but they too induce physiological changes observable from above. Foliar diseases often reduce chlorophyll content in infected areas, causing spectral reflectance changes (e.g., higher red reflectance and lower NIR) similar to nutrient deficiencies [13]. Pest damage (e.g., defoliation or sap sucking) can create patchy canopy thinning or premature senescence, again altering vegetation index values. Critically, these biotic stress signals might be confused with other stresses if only a single sensor is used. However, research shows that multi-temporal and multi-spectral observations can improve detection. For instance, UAV surveys have caught early-stage disease outbreaks by detecting abnormal temporal trends in crop greenness before widespread symptoms appear [42]. Thermal imaging can also aid disease scouting: infected plants often have warmer canopies due to reduced transpiration, a phenomenon that a remote thermal camera can pick up in precision agriculture trials [13]. Hunt Jr and Daughtry [44] emphasize that UAVs add significant value here: by flying low and slow, they can capture fine-grained variability in crop temperature and color, helping to spot incipient pest or disease foci that satellites might overlook. In practice, this means that an integrated approach (combining optical, thermal, and perhaps even fluorescence sensors on UAVs) can provide an early warning of biotic stress. As an example of integration, Maes and Steppe [42] outline how drone-based hyperspectral imaging, in combine with machine learning, has identified nutrient deficiencies and pathogen-infected plants in experimental settings. However, to date these technologies have seen limited deployment in broadacre settings due to their cost and data complexity [13]. Overall, while biotic stress detection via remote sensing is inherently complex, the literature shows steady progress. Comprehensive frameworks now exist that catalog spectral disease markers and recommend sensor combinations for improved pest/disease monitoring [13,34].

Across the literature, remote sensing has proven to be a versatile means of assessing crop stress from the leaf to the regional scale. Optical vegetation indices, thermal measurements, and even advanced fluorescence and radar techniques each capture different facets of plant stress responses [13]. Still, a clear message from recent studies is that no single sensor or index can unravel the full complexity of stress physiology. Most practical scenarios involve multiple concurrent stressors—drought, heat, and biotic attacks overlapping—which can confound spectral signals [13,14]. This has spurred a shift toward multi-sensor data fusion and integrative analysis. As noted in a comprehensive review by Berger et al. [13], combining data across the visible, infrared, and thermal domains (and at multiple time points) greatly improves the ability to detect and differentiate stress factors. Likewise, multi-factor modeling approaches are emerging to attribute crop losses to specific stress events [14] or to capture interactions (like salinity exacerbating drought) [79].

However, challenges remain in scaling these methods from experimental studies to operational farm management [11]. Limitations, such as data volume, processing complexity, and the need for ground calibration still hinder the wide adoption of real-time stress monitoring.

4. Toward Resilience-Based Remote Sensing Applications

Remote sensing enables spatially explicit yield estimation at scales ranging from paddocks to entire regions. Vegetation indices (e.g., NDVI and EVI) and phenology-adjusted metrics provide strong correlations with yield outcomes [34,39]. RS-derived productivity maps help to assess yield gaps and optimize input use. However, productivity estimates remain indirect, sensitive to confounding factors such as soil background and climate variability [23]. While climate drivers are often well quantified, the spatial heterogeneity of soil properties—such as texture, organic matter, and fertility—also strongly influences remotely sensed productivity signals but remains underrepresented in most studies. Furthermore, the accuracy of productivity monitoring continues to be limited by the availability of timely, cloud-free imagery.

Phenological monitoring through time-series imagery captures growth transitions such as green-up, flowering, and senescence, critical for forecasting and management [38,66,77]. Advances in curve fitting, multi-sensor fusion, and machine learning now deliver improved accuracy. However, coarse revisit intervals and cloud contamination introduce errors of ~7–15 days [79,86], limiting precise scheduling. Double-cropping systems further complicate interpretation [57].

RS allows the early detection of abiotic stress (drought, salinity, and heat) and biotic pressures (diseases, pest, and weeds) before visible yield loss [14,23,34]. Thermal and multispectral data are especially useful, and indices such as the Evaporative Stress Index (ESI) perform well operationally [44]. Still, stress signals are often non-specific, making it difficult to distinguish overlapping causes without ancillary data [36,82]. Adoption is also constrained by limited validation datasets.

The recent literature suggests that combining the perspectives on crop productivity, phenology, and stress metrics offers a more complete understanding of crop health and stability than analyzing each in isolation [50]. With climate extremes becoming more frequent and drought-related yield losses increasingly documented [5,87], key integration approaches—multi-sensor/scale data fusion, RS-crop model data assimilation, and big data integration—are being developed to bridge the three themes, as summarized in Table 4.

Table 4. Integration cases for remote sensing in broadacre agriculture.

Approach	Data Types	Example Applications	Strengths	Limitations	Case Studies
Multi-sensor fusion	Optical (NDVI, EVI), radar (SAR backscatter), thermal (LST [1], canopy temperature)	Combining Sentinel-1 SAR with Sentinel-2 optical to improve phenology tracking; thermal + multispectral for drought stress	All-weather coverage; captures structural + physiological signals; reduces noise from clouds	Requires advanced fusion algorithms; differing spatial/temporal resolution complicates analysis	Zhao et al. [59]
Multi-scale synergy	UAV multispectral/thermal, proximal sensors, satellite imagery (10–500 m)	UAVs mapping crop water stress and pests, validated against Sentinel time series	High spatial resolution; UAV data calibrates/validates satellite metrics; bridges farm and regional scales	UAV operations limited by cost, logistics, regulations; difficult to scale across regions	Sharma et al. [73]
RS–crop model data assimilation	Satellite indices (LAI, NDVI), climate data, crop model parameters (APSIM [2], DSSAT [3])	Assimilation of Sentinel-2 into wheat model for in-season yield prediction; RS + APSIM across the Australian wheatbelt	Improves model accuracy; links mechanistic understanding with real-time observations; enables scenario testing	Requires ground calibration; model complexity; transferability across regions may be limited for rotation analysis	Zhao et al. [35] Lawes et al. [37]
Operational and big data integration	Multi-source RS (optical, radar, thermal), IoT sensor streams, climate forecasts	AI-driven Agriculture 5.0 platforms integrating RS + IoT [4] for yield prediction and risk alerts	Handles diverse, high-volume data; near real-time decision support; adaptable to multiple crops	Data-hungry; risk of overfitting; requires large training datasets and validation	Peña-Barragán et al. [88] Martos et al. [48] Waldner and Diakogiannis [89]

[1] LST—land surface temperature; [2] APSIM—agricultural production systems simulator; [3] DSSAT—decision support system for agrotechnology transfer; [4] IoT—internet of things.

- Multi-sensor/scale data fusion—One key integration pathway is multi-sensor/scale fusion, which merges observations from different platforms or spectral domains to overcome the limitations of a single data source. Different sensors capture unique aspects of crop condition, so fusing their data provides a more robust picture of the system. For example, combining Sentinel-1 radar (which penetrates clouds) with Sentinel-2 optical imagery (rich spectral information) enabled the accurate mapping of crop phenology even in persistently cloudy regions [59]. Multi-sensor fusion improves temporal coverage and diagnostic power: studies show that blending visible, infrared, and microwave indicators enhances stress detection [36]. The trade-off is the requirement for advanced fusion algorithms and the challenge of reconciling differing spatial and temporal resolutions, handling big data volume (the digital footprint issue) [53], while UAV-based applications are further constrained by costs, logistical demands, regulatory restrictions, and limited scalability across regions [43,53,73].
- RS-crop model data assimilation—Rather than treating remote sensing outputs as standalone products, a resilience approach feeds these data into crop growth models to continually adjust simulations to reality. Upon updating model parameters with observed indices (e.g., greenness or leaf area), the model's predictions become more accurate and responsive to that season's conditions. For instance, blending high-resolution Sentinel-2 imagery with a wheat model enhanced field-scale yield prediction in Australia compared to either input alone [35]. At regional scales, integrating remote sensing with climate data and crop models has been used to assess yield gaps and

test management scenarios [37]. The key benefit of model-data assimilation is better prediction: it can provide early warning of potential yield losses and evaluate "what-if" strategies, aiding proactive management. On the downside, these approaches demand careful calibration and significant computing resources, because models must be tuned to local conditions and continuously supplied with quality weather and soil data.

- Operational and big data integration—A resilience-based approach also demands that remote sensing insights be translated into actionable intelligence for farmers, agronomists, and policymakers. This is driving the development of operational decision-support systems that integrate multi-source data and deliver user-friendly outputs (such as drought alerts, yield forecasts, or advisories on sowing and irrigation). Under the scope of "Agriculture 5.0" concept [48], RS is being linked with on-farm sensors and AI analytics to enable smart farming solutions [90,91]. For example, object-based image analysis has been used to integrate vegetation indices, textural metrics, and phenology for accurate crop identification and soil management assessments at the field scale [88]. Similarly, advances in deep learning now allow robust extraction of field boundaries directly from satellite images, reducing the need for manual inputs [89]. However, these systems are highly data-hungry, risk overfitting without sufficient training and validation datasets, and often require large, curated data streams that are not readily available across all regions. This raise concerns over scalability and generalizability, especially in data-poor farming systems.

In practice, emerging national programs have been established to integrate RS tools for crop monitoring. For example, the group on earth observations global agricultural monitoring (GEOGLAM) initiative (https://www.cropmonitor.org/, accessed on 26 November 2025) fuse satellite indicators with ground reports to flag emerging crop failures; the Australian Plant Phenomics Network (APPN) (https://www.plantphenomics.org.au/, accessed on 26 November 2025) integrates controlled-environment, field, and mobile phenotyping platforms across diverse cropping zones, providing data-driven phenotyping to accelerate the development of climate-resilient crops.

Looking ahead, advancing RS for broadacre agriculture resilience requires moving beyond monitoring individual crop performance themes toward integrated frameworks that define and quantify resilience itself (Figure 3). A resilient cropping system maintains yield (productivity) by possibly adjusting phenology (e.g., drought-escaping or frost-avoiding) and by tolerating stress (via physiological or management means). Thus, a resilience monitoring system should ideally capture all these dimensions. for example, a composite "RS-resilience index" might include the coefficient of variation in NDVI or yield over years (lower = more stable), the extent of phenology shift under heat (smaller shift = more resilient variety), and the greenness retention during stress (higher = tolerant). These metrics could also incorporate soil-related indicators such as top-soil moisture retention, salinity dynamics, erosion risks, and agricultural drought thresholds, which strongly influence crop responses to climatic stress [79], and are crop- and region-specific [75,78] yet remain underrepresented in current remote sensing frameworks. By defining such metrics, we can directly measure how well management interventions or new technologies bolster crop resilience. Decades of satellite archives [92] (e.g., the Landsat record) make it possible to compute these indicators by analyzing long-term patterns of productivity and recovery under varying conditions.

Another direction is integrating predictive capabilities with remote sensing. This includes coupling climate forecasts with current crop conditions to anticipate stresses before they fully develop, enabling truly proactive responses. For instance, seasonal rainfall forecasts combined with early-season vegetation health maps could identify fields/patches likely to suffer drought impact, allowing for targeted intervention. Initial demonstra-

tions of deep learning in agriculture show that it can handle complex data integration tasks [86,88,89], paving the way for more autonomous monitoring systems.

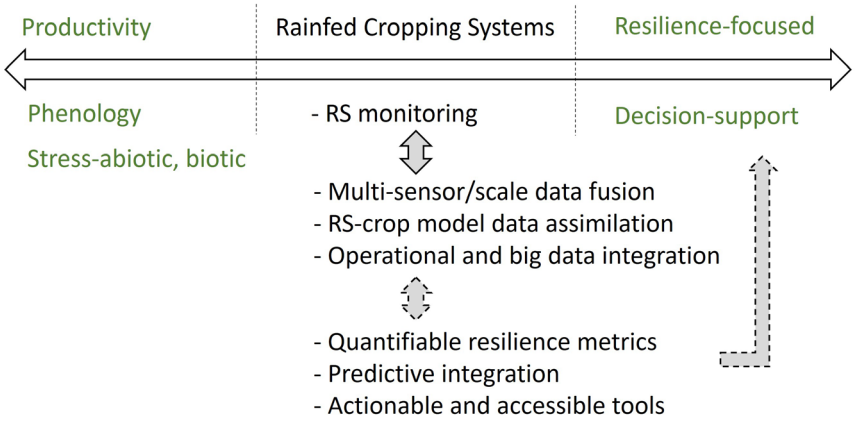


Figure 3. Conceptual pathway for transitioning remote sensing (RS) applications in rainfed cropping systems from productivity, phenology, and stress monitoring (left side, in green) toward resilience-focused and decision-support outcomes (right side, in green). Note: Double-headed arrows represent interactive feedback loops; Black solid arrows indicate the emerging approaches along this pathway; Dashed arrows and lines denote the proposed directions toward resilience.

Continued advances in machine learning and artificial intelligence (AI) [93] will greatly facilitate these efforts. Emerging AI-driven platforms promise to ingest multi-modal data (satellite, drone, ground sensors, and historical yields) and automatically flag risks or recommend optimal interventions. A critical challenge, however, is ensuring that these integrated tools are accessible and trusted by end-users [62]. Many farmers still struggle to access or interpret raw satellite data, highlighting the need for user-friendly interfaces and the co-design of information services. Moreover, information must be delivered in a timely and reliable manner to be actionable. Developing intuitive farm dashboards, mobile apps, and training programs [43] will be essential to boost adoption and realize the resilience benefits of these technologies.

5. Conclusions

This review synthesized methodological advancements in remote sensing (RS) for broadacre agriculture across three interrelated themes: crop productivity, phenology, and environmental stress. Yield (productivity) monitoring via vegetation indices (VIs) and RS–crop model integration provides robust estimates of yield and yield gaps across scales. Phenology detection has advanced through refined time-series analysis and multi-sensor fusion. Stress detection—especially for drought and heat—has improved to attribute yield losses to specific extreme events, with early identification of anomalies on crop health.

However, limitations remain within each theme: (1) Productivity estimates from RS are often indirect, sensitive to soil background and climatic variability, and constrained by cloud-free optical imagery. (2) Phenology monitoring remains challenged by coarse revisit intervals, cloud-related gaps, inconsistent stage definitions, and overlapping cycles in multi-cropping systems. (3) Stress detection methods are hindered by the non-specificity of spectral responses, the difficulty of identifying overlapping stressors, and the limited availability of ground-truth data for validation.

A notable recent trend is a shift toward integration across themes. Multi-sensor and multi-scale fusion merges optical, thermal, and multispectral signals, improving temporal coverage for applications such as phenology mapping in cloudy regions or stress detection across environments. RS–crop model data assimilation strengthens predictive capacity by continually updating growth simulations with observed indices, improving

yield forecasts and enabling scenario testing at multiple scales. Operational and big data frameworks extend these advances to decision-support systems. Yet integration introduces significant challenges: (1) fusion algorithms must reconcile spatial-temporal mismatches and handle the digitization footprint issue; (2) assimilation requires careful calibration and quality ancillary data; (3) UAVs applications remain costly and difficult to scale; and (4) AI platforms are prone to overfitting and reliant on large training datasets. These limitations underscore the need for rigorous validation and scalable design to ensure operational impact.

Looking ahead, advancing remote sensing for broadacre agriculture resilience entails moving beyond monitoring toward integrated frameworks that directly inform adaptive management. One key future direction is to develop integrated resilience metrics that remote sensing can quantify and incorporate with soil-related indicators, and future research should focus on defining and validating them. Another direction lies in embedding predictive capabilities—such as aligning remote sensing signals with seasonal climate forecasts—to proactively identify and mitigate stress impacts before they fully emerge. Equally crucial is the translation of data into farmer-facing tools, emphasizing intuitive dashboards and decision support systems that convert complex observations into timely, actionable guidance.

Supplementary Materials: A list of the selected articles, including their complete bibliographic information, reviewed in this study can be downloaded at https://www.mdpi.com/article/10.3390/rs17233886/s1.

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