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Review

Spatiotemporal Variability of Late-Ripening Citrus in Sichuan, China: A Review of Zoned Management Strategies

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Abstract

Late-ripening citrus exhibits considerable spatiotemporal variation in fruit quality, and implementing zoned management is further complicated by the unique biological and ecological characteristics of the Sichuan Basin. This review provides the first integrated climate–purple soil–terrain synthesis of zoned management for late-ripening citrus in the Sichuan Basin, examined across four dimensions: driving mechanisms, technical approaches, methodological evolution, and limitations. First, the causes of spatiotemporal quality variation are clarified by considering three factors: climate, soil, and topography. Secondly, current monitoring, analysis, and zoned management technologies are assessed for suitability in the frequently cloudy and foggy environment, hilly topography, and scattered orchard plots of the Sichuan Basin. Additionally, the methodological evolution from "general fruit tree methods" to "citrus-specific methods" to "Sichuan scenario-adapted methods" is delineated, and five major research gaps are identified: spatiotemporal data fusion, universality of dynamic zoning, multi-factor interactive modeling, economic feasibility evaluation, and technology dissemination. Based on these findings, future research directions are proposed, including multi-source data fusion, dynamic modeling, cross-regional transferability, economic optimization, and lightweight inclusive solutions, to provide systematic research frameworks and methodological references for zoned management of late-ripening citrus in the Sichuan Basin.

Keywords: late-ripening citrus; spatiotemporal differences; zoned management; Sichuan basin; flower–fruit coexistence; remote sensing

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1. Introduction and Background

1.1. Introduction

Citrus is the largest fruit crop worldwide. Late-ripening citrus represents an important sector of the citrus industry, reaching peak maturity from February to June of the following year, during the winter and spring slack season for fresh citrus markets, and it therefore holds considerable economic value [1]. Late-ripening citrus fruits remain on the tree for 12–14 months, experiencing a full annual environmental cycle and multiple phenological cycles, and are highly sensitive to spatiotemporal environmental conditions [1–3]. The fruit quality variability between years and among trees at different topographic positions has been recognized as a serious issue for late-ripening citrus production, with major quality traits reported to vary considerably by cultivar, topographic position, and year [3,4]. Because

these traits are quantified on different bases and reported under different study conditions, no single, uniformly defined coefficient of variation can be reliably assigned across the literature; the variation is therefore described qualitatively rather than as a fixed numerical range. Traditional water, fertilizer, and harvest management strategies are inadequate for addressing the multidimensional spatiotemporal heterogeneity [3,5–7].

In this review, the terms "late-ripening citrus" and "late-maturing citrus" are treated as synonymous, and "late-ripening citrus" is adopted consistently throughout. Late-ripening citrus is defined here as cultivars that reach commercial maturity from February to June of the year following flowering and remain on the tree for approximately 12–14 months, thereby experiencing a complete annual environmental cycle and multiple phenological stages. This review concerns late-ripening cultivars grown in the Sichuan Basin rather than late-ripening citrus in general. Among the diverse late-ripening cultivars, Buzhihuo (Shiranui/Dekopon), Chunjian, and Qingjian are used as representative examples because they are widely planted in the basin and their fruit quality is strongly influenced by regional climatic conditions; they are illustrative rather than exhaustive. Because the proposed zoned management framework depends closely on cultivar-specific phenology and on-tree retention time, this phenological definition and cultivar scope are stated explicitly at the outset.

Terminology. To ensure clarity and consistency, we establish the following terminology convention for this review: A management zone (MZ) is a spatially contiguous subregion of an orchard that exhibits relative homogeneity in soil properties, topography, microclimate, or crop performance and can be managed with a uniform set of practices. Management zone delineation (or zoning) refers to the process of identifying and mapping such zones using data analysis, spatial modeling, or field surveys. Zoned management denotes the practice of applying differentiated agronomic interventions—such as irrigation, fertilization, or frost protection—according to the characteristics of each zone. Precision zoned management is a technology-enhanced form of zoned management that integrates high-resolution spatial data (e.g., UAV multispectral imagery, satellite time series) and advanced quantitative methods (e.g., machine learning, geostatistics) to achieve finer spatial resolution and more accurate zone boundaries. Throughout this manuscript, management zone or MZ refers to the spatial unit itself, delineation or zoning refers to the mapping process, zoned management refers to the differentiated management strategy, and precision zoned management refers specifically to its data-intensive, model-driven implementation.

The region from 28°00′ N to 32°00′ N and 102°30′ E to 108°00′ E is one of China's most significant areas for late-ripening citrus cultivation [1,8,9]. This production system exhibits six typical biological and ecological traits in response to regional environmental factors, including climate, hilly topography, and parent material, that distinguish it from other systems: First, flower–fruit coexistence occurs on the same tree: flowers from the current spring and the fruit set from the previous spring coexist within the canopy. Competition for water and nutrients is evident between floral organs and overwintered fruit with an on-tree retention time of 12–14 months, particularly during the first two flowering cycles [1,10]. Second, overwintering occurs on-tree: fruit is left on the tree until the next winter (December–March), during which it is subjected to regular cold waves, frost events, and low temperatures but limited sunlight. In extreme years, ambient minimum temperatures in the region have been reported to fall below −3 °C, and natural fruit drop rates during the overwintering period can reach 20–40% [1,2,11]. Third, a temperature inversion phenomenon often occurs in the hilly area of the Sichuan Basin in winter. The downslope drainage of cold, dense air is assisted by nocturnal radiative cooling, and this cold air will form in the lowest points such as valley bottoms. Under this "cold-lake" effect, lower topographic positions are colder than upper and mid-slope positions, especially when there is no weather front to dissipate

inversions and the air is clear and calm with light winds. Topographically related differences in temperature amplify the spatial variation of orchard frost exposure due to frequent and relatively strong inversions in the Sichuan Basin during the winter season. Therefore, the risk of freeze damage to fruit can change considerably over short distances within the same orchard, and valley bottom areas and other cold air accumulation areas may be higher-risk than areas with good ventilation [12,13]. Furthermore, purple soils in the Sichuan Basin are formed from purple sedimentary parent materials, mainly Jurassic and Cretaceous strata, and retain a strong parent rock inheritance in their color, mineral composition, and physico-chemical properties. Because they are characterized by short formation times, rapid physical pedogenesis, and relatively weak chemical weathering, they are best described as weakly developed soils with a pronounced lithologic signature. Their fertility appears to depend largely on mineral-derived nutrient supply, especially potassium and phosphorus inherited from or released by the parent material, rather than on specific thresholds of organic matter or exchangeable calcium [14–16]. After temperatures recover in spring, on-tree fruit may face an increased risk of regreening and short-term declines in soluble solids, although the exact magnitude and rate of TSS (total soluble solids) loss should be derived from a study that directly reports °Brix changes under March–April field conditions [17,18]. Sichuan's citrus industry is dominated by late-ripening cultivars, including important hybrid types such as Buzhihuo, Chunjian, and Qingjian, and their fruit quality shows strong sensitivity to regional climatic conditions in the basin. Taken together, the evidence supports a close cultivar–climate–quality relationship in which temperature-related resource endowment is a key determinant of adaptation and quality formation [1,8,19]. Figure 1 summarizes the spatial aspects of the six distinct characteristics of late-ripening citrus in the Sichuan Basin and their relationships with quality variation.

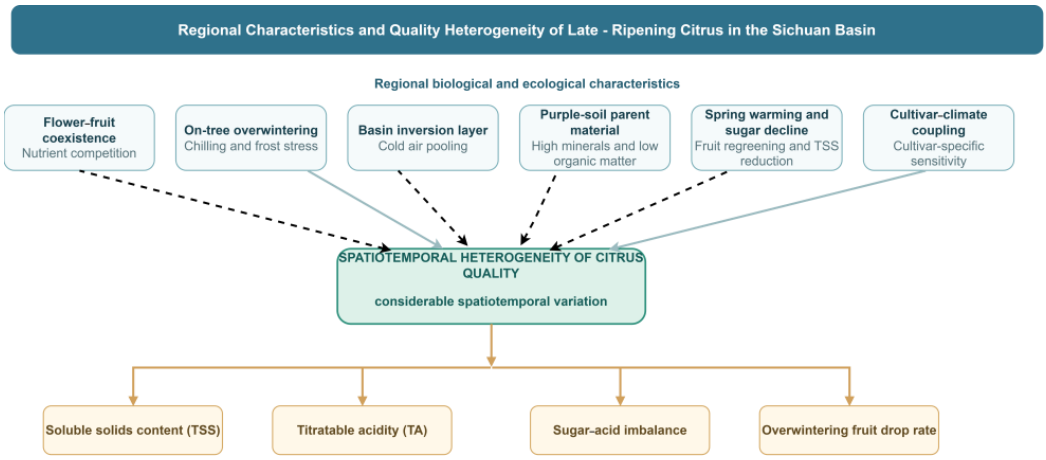


Figure 1. Conceptual synthesis of the relationships between the six biological/ecological characteristics of late-ripening citrus in the Sichuan Basin and the spatiotemporal heterogeneity of fruit quality (TSS, TA (titratable acidity), sugar–acid balance, and overwintering fruit drop rate). Solid arrows denote relationships directly supported by cited experimental studies; dashed arrows denote conceptual linkages synthesized by the authors that are plausible but not yet directly quantified for Sichuan late-ripening citrus. This figure is a conceptual schematic and does not represent a quantitative causal model. Major quality traits have been reported to show the considerable variation between years and among topographic positions. The magnitude differs by cultivar, trait, and conditions, and no single uniformly defined variation statistic is available across studies.

The six biological and ecological attributes identified for late-ripening citrus in the purple-soil hilly region of the Sichuan Basin are consistent with a broader pattern seen across major citrus-producing regions, including Mediterranean calcareous-soil orchards, Brazilian sandy and Oxisol-based systems, and Florida's sandy-soil groves, where climate, soil, and

topographic conditions interact in region-specific ways to shape fruit quality, soil function, and production sustainability, thereby informing monitoring, orchard management, and land suitability or forecasting approaches [7,20–23]. Current management zone delineation methods typically combine kriging or other geostatistical interpolation, unsupervised data clustering, and remote sensing covariates. Most of the traditional methods, however, require more uniform field variability and need to be modified for structurally complex perennial fruiting orchards [24–26]. The use and reliability of these trees under the unique environmental factors of the Sichuan Basin (such as the frequent cloud and fog, purple soil, hilly landscape, and small orchard blocks), however, still need systematic verification.

This study establishes an analytical framework (driving mechanisms, technical approaches, methodological evolution, and research limitations) and systematically summarizes research findings on zoned management strategies for spatiotemporal variation in late-ripening citrus. This review focuses on three objectives: (1) clarifying the driving mechanisms of climate, soil, and topography in quality variation; (2) comparing the applicability of monitoring technologies, spatial analysis methods, and decision-making management technologies in typical Sichuan Basin production scenarios; and (3) summarizing the evolution of these technologies from general fruit tree methods to citrus-specific methods and then to Sichuan scenario-adapted methods. Existing reviews on citrus zoning have largely focused on general fruit tree precision agriculture or on citrus nutrition under climate change [22,23,26] and have not systematically addressed the coupled climate–soil–terrain mechanisms that operate in the Sichuan Basin. Specifically, no previous evaluation has incorporated (i) basin-level winter temperature inversions, (ii) the buffering capacity of purple-soil nutrients, and (iii) a cultivar-specific climatic sensitivity into a single zoning system. This is important because the zoning rules that are validated in flat and uniform orchards may not work in sloping and broken orchards or in cloudy areas of Sichuan [27,28]. The present review is designed to fill this gap by compiling 165 primary sources in a scenario-specific analytical framework. The main contributions of this review are as follows:

- Zoning synthesis of late-ripening citrus in the Sichuan Basin combined with the climate, purple soil, and hilly terrain.
- Comparative evaluations of monitoring, spatial analysis, and decision support technologies in the face of frequent clouds/fog and small, fragmented farmland.
- A methodological evolution map outlining the evolution of the methods employed within fruit tree, citrus, and Sichuan-adapted methods and explicitly identifying five research gaps.

1.2. Study Area

This review focuses on the late-ripening citrus production region of the Sichuan Basin, located between 28°00′ N–32°00′ N and 102°30′ E–108°00′ E. The 15 counties most important for citrus production are concentrated in the eastern and south-eastern part of the basin, where elevations (approximately 180–800 m on the basin floor and surrounding hills) and climate are most conducive to late-ripening citrus [29,30]. Late-ripening cultivars such as Buzhihuo (Shiranui/Dekopon), Chunjian, and Qingjian dominate this region, each with distinct climatic sensitivities [1,5,31]. As shown in Figure 2, the Sichuan citrus industry is organized into three industrial belts: the Western Sichuan Plain Belt (Pujiang, Danleng, Dongpo), the Southern Sichuan Belt (Renshou, Yibin, Luzhou, Rongxian, Leshan, Jingyan, Zigong), and the Central Sichuan Hilly Belt (Anyue, Ziyang, Zizhong, Nanchong, Guang'an) [29,30,32]. These belts also produce other citrus types (e.g., blood oranges, Ponkan, and lemons); the present review, however, specifically concerns the late-ripening hybrid cultivars grown within them. For cartographic context, the map in Figure 2 displays a larger extent of the region (approximately 25°00′ N–35°00′ N, 97°00′ E–109°00′ E) so that

the full provincial boundary and surrounding terrain, including the western mountain regions, rising above 5000 m, are visible. This map extent should not be interpreted as the boundary of the study area, which is confined to the citrus-producing region defined above.

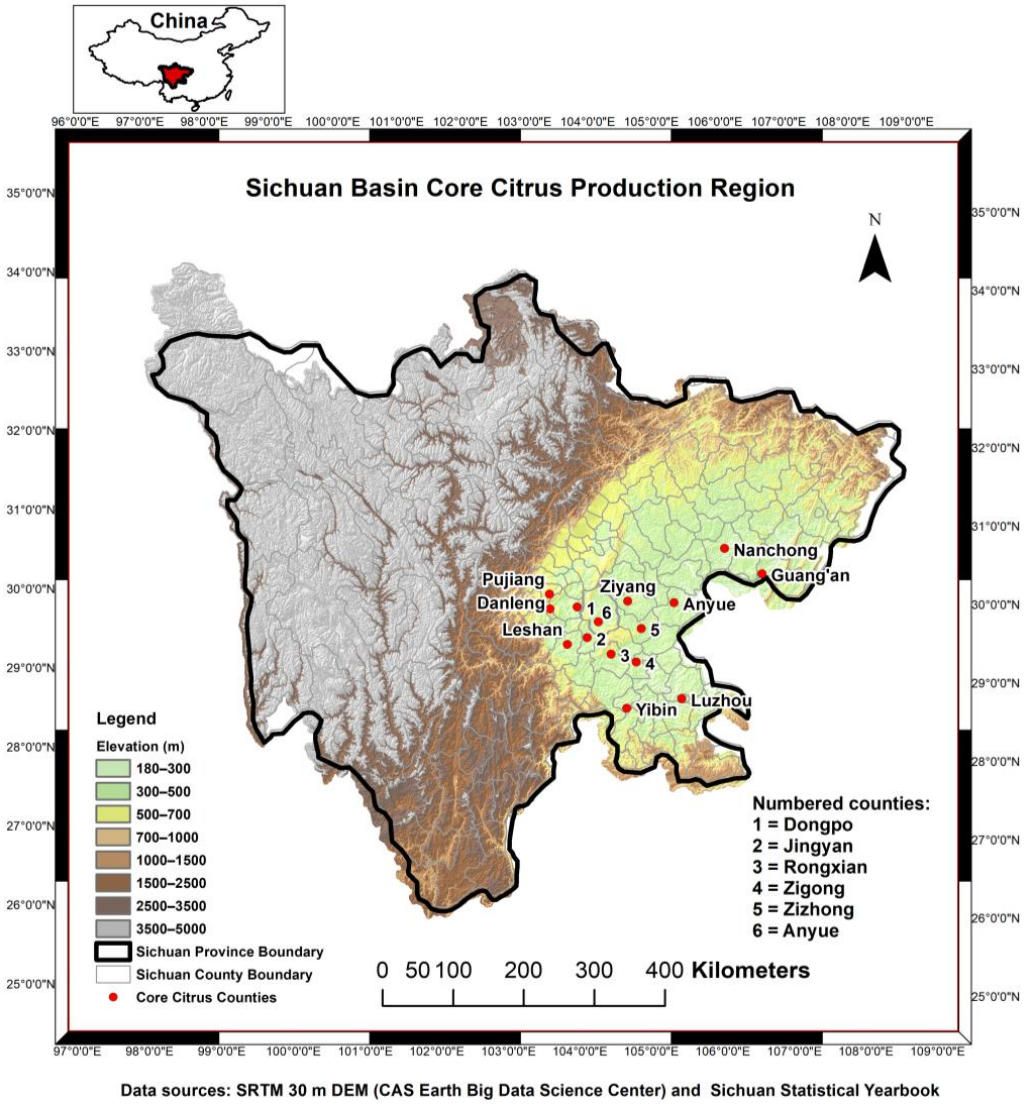


Figure 2. Study area map of the Sichuan citrus production region. Three industrial belts are shown: the Western Sichuan Plain Belt (Pujiang, Danleng, Dongpo), the Southern Sichuan Belt (Renshou, Yibin, Luzhou, Rongxian, Leshan, Jingyan, Zigong), and the Central Sichuan Hilly Belt (Anyue, Ziyang, Zizhong, Nanchong, Guang'an). Although these belts also produce other citrus types (e.g., blood oranges, Ponkan, and lemons), this review focuses on the late-ripening hybrid cultivars (Buzhihuo, Chunjian, Qingjian) grown within them. The map graticule (approximately 25°00′ N–35°00′ N, 97°00′ E–109°00′ E) indicates the map extent shown for provincial context and is larger than the study area; the late-ripening citrus study region lies within 28°00′ N–32°00′ N, 102°30′ E–108°00′ E.

1.3. Literature Search and Screening

The aim was to carry out a systematic and reproducible synthesis; thus, a structured literature search was performed in Web of Science Core Collection, Scopus, and CNKI databases for the period of January 2000 to June 2026. The search combined three concept blocks—crop, management/zoning, and methods—using database-specific field tags and Boolean operators. The exact search strings are provided in the Supplementary Material (Tables S2–S4). In brief, the Web of Science Core Collection search used TS = and ALL = fields; the Scopus search used TITLE-ABS-KEY; and the CNKI search used

SU% = with within-field + operators. Eligibility criteria for the search and screening are described in detail in the Supplementary Material (Table S1). Only peer-reviewed journal articles and official reports were included. Language restrictions were applied as follows: English only for the Web of Science Core Collection; English and Chinese for Scopus; Chinese–English expansion enabled for CNKI; and English or Chinese for backward snowballing. For all sources, the time restriction was 2000 to 2026 (June). The search was conducted on 14 July 2026.

Screening was conducted in two phases (titles and abstracts, then full texts), and two independent reviewers resolved any discrepancies. Retained full texts were then evaluated to determine whether they included the following six required quality criteria: a well-specified research design, validated methods, a large enough sample size and spatial extent, a replicable workflow, statistical rigor, and regional relevance.

The search retrieved 129 records from the Web of Science Core Collection, 174 from Scopus, and 105 from CNKI. An additional 213 records were found by backward snowballing of reference lists, bringing the total number of records to 621. Following the removal of duplicates (n = 180), 441 records were screened by title and abstract and 121 records excluded. The remaining 320 full-text articles were assessed for eligibility, and 155 were excluded for the following reasons: comprising a conference abstract, dissertation, or preprint; being written in a language other than English or Chinese; not being about citrus and having no methodological transferability; or the full text being unavailable. After screening and backward snowballing, 165 primary sources were included. The full flow is presented in Figure 3, and the individual counts and thematic distribution are shown in detail in the Supplementary Material (Tables S4–S6).

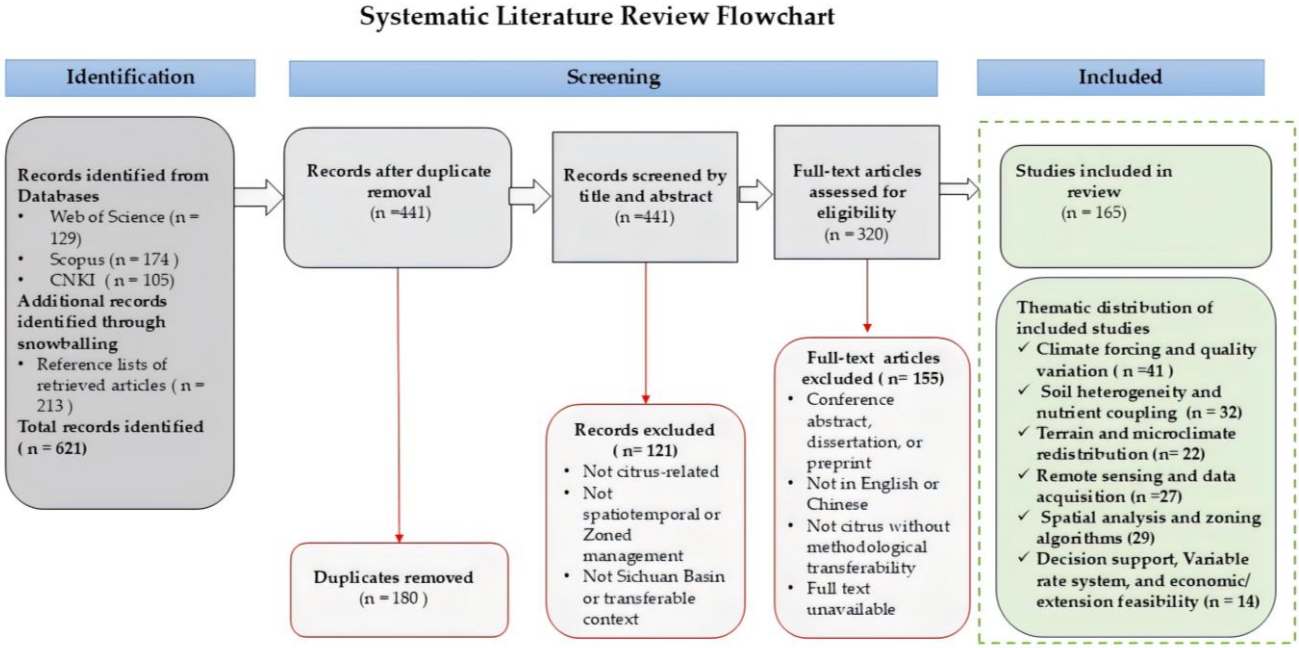


Figure 3. Systematic literature search and screening flowchart for studies on spatiotemporal variability and zoned management of late-ripening citrus in the Sichuan Basin (2000–2026).

2. Formation Mechanism and Driving Factors of Spatiotemporal Differences

Fruit quality formation in late-ripening citrus follows a multi-scale chain of interactions in the Sichuan Basin, where the regional climate determines thermal and moisture regimes, soil nutrient and water heterogeneity drives fruit development, and topography shapes the local microclimate and soil redistribution within orchards [1,8,33,34]. Quality formation

in late-ripening citrus in the Sichuan Basin differs from that in many other citrus-growing regions for several reasons: fruit remains on the tree through winter, and low winter temperatures alter sugar–acid metabolism; with a limited buffering capacity, purple soils are sensitive to acidification; the hilly topography causes many microclimatic and soil differences, leading to considerable spatial variability in fruit quality [1,2,7,35,36]. This section analyzes the impacts of climatic factors on interannual and spatial variations in fruit quality, the coupling relationship between spatial differences in soil nutrient and water conditions and fruit quality, and the regulatory effects of topographic factors on micro-domain differences in fruit quality. The mechanisms are illustrated in Figure 4.

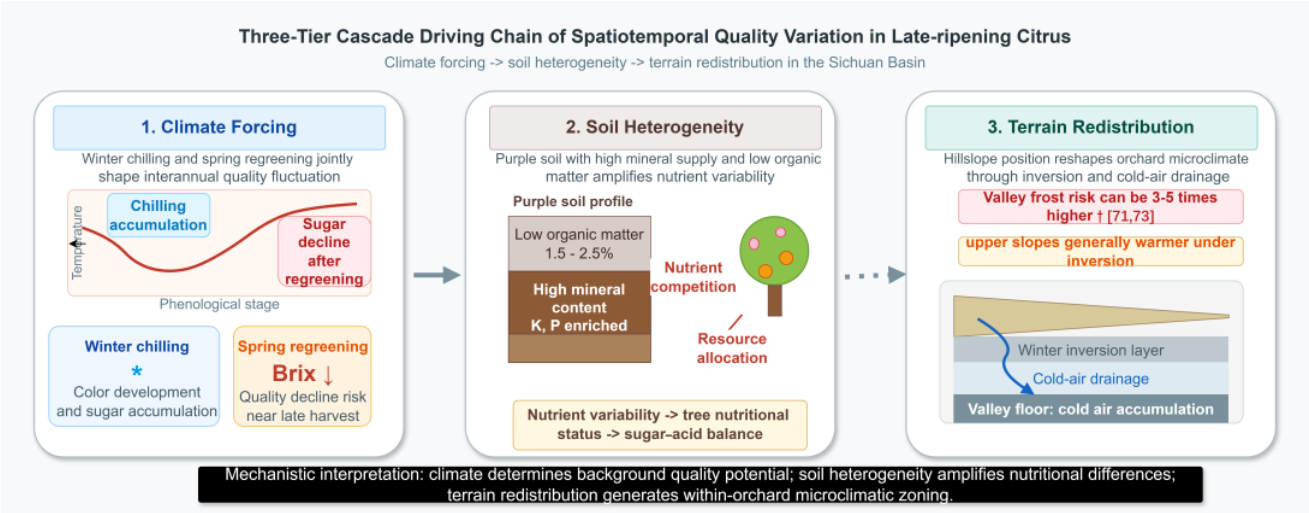


Figure 4. Conceptual three-tier driving chain (climate, soil, terrain) of spatiotemporal quality variation in late-ripening citrusin the Sichuan Basin. Solid arrows: mechanisms supported by cited studies; dashed arrows: author-proposed, unquantified links. This is a conceptual schematic, not a causal model. † Values (e.g., valley frost risk ~3–5 times) are compiled across studies/scales and are indicative only. Soil parameters are described in the following text.

2.1. Interannual and Spatial Driving Effects of Climatic Factors

Macro-scale variation in late-ripening citrus fruit quality is primarily controlled by climate at both interannual and spatial scales; however, the dominant factors differ substantially among climatic zones. Fruit quality in Mediterranean climate zones such as those in Spain and Italy is chiefly influenced by summer drought stress, experiencing differences in TSS and TA associated with the extent of drought stress during the growing season [31,37]. In the Sichuan Basin (which has a subtropical monsoon climate), by contrast, fruit quality is affected both by winter low-temperature stress and by the degree of sugar degradation during spring recovery from low temperatures, a process that is relatively unimportant in Mediterranean climate zones.

In the Sichuan Basin, late-ripening citrus fruit quality is associated with winter chilling accumulation, frost and freeze damage, and reduced winter light. These factors are described in the literature by distinct quantities that should not be interpreted as a single threshold: an ambient extreme minimum temperature below −3 °C was reported at the regional scale; and, under controlled conditions, a freeze-damage temperature of approximately −2.3 °C was reported, and cold-exposure treatments in the range of −1 to −7 °C were applied for 6–15 h, which affected soluble solids content, acidity, firmness, color, and antioxidant profiles [1,11]. As these values were derived from different studies and experimental conditions, they represent a regional climatic extreme, a reported damage threshold, and experimental treatment conditions, respectively. Light also has a measurable

effect: total soluble sugars in light-treated sweet oranges are higher than in dark-shaded oranges, and short-day shading (12% light transmittance for 18 days) increased soluble sugars through starch degradation and sugar storage [38–40].

Interannual climate variation appears to affect citrus internal quality: higher cumulative temperature tends to promote soluble solids accumulation, whereas lower cumulative temperature and cooler early-season conditions tend to maintain higher acidity and thereby shift the sugar–acid balance [5]. Limited sunlight may further exacerbate interannual quality variation relative to that in Mediterranean production areas with more abundant sunlight. There are also significant differences in climatic sensitivity among cultivars (Table 1). Buzhihuo is most sensitive to winter low-temperature accumulation, showing pronounced differences in soluble solids content between high- and low-temperature years. Chunjian is sensitive to the rate of spring temperature rebound, which promotes sugar degradation and shifts the sugar–acid balance. Qingjian is sensitive to the duration of on-tree fruit retention (approximately 14 months) and shows the most severe cumulative effect of interannual temperature variation on soluble solids content, together with a high natural fruit drop rate [5,31]. These cultivar-level differences in climatic sensitivity indicate that zoned management approaches in the Sichuan Basin will not be accurate unless the cultivar dimension is taken into consideration.

Table 1. Climatic sensitivity and fruit drop characteristics of major fruit-bearing late-ripening cultivars of citrus in Sichuan.

Cultivar	Sensitive Climatic Factor	Quality Response (Qualitative)	References
Buzhihuo	Temperature and thermal accumulation	Marked variation in soluble solids content between warm and cold years	[1,5,41–43]
Chunjian	Winter low temperature and subsequent spring warmth	Variation in sugars and acidity driven by spring sugar degradation	[44]
Qingjian	Climatic variability during growth and ripening	Strong cumulative effect on soluble solids content and a high natural fruit drop rate	[44,45]

2.2. Soil Nutrient Heterogeneity and Its Spatial Coupling with Fruit Quality

An important driver of fruit quality differences within orchards is spatial heterogeneity in soil nutrients. In the Sichuan Basin, purple soils are distinguished by their nutrient properties, which are transferred partly from their parent rocks, and their relatively low organic matter or organic carbon levels and comparatively high levels of mineral nutrients, particularly potassium and phosphorus [46,47]. Studies in Southwest China and other agricultural systems indicate that these soil characteristics are spatially variable due to parent material, topography, land use, erosion, and fertilization, resulting in significant within-site and between-site variation that allows for site-specific nutrient management [16,36,47–50]. Low organic matter content is generally associated with lower cation exchange capacity (CEC) and reduced nutrient buffering capacity. Where buffering capacity is low, spatial heterogeneity in mineral nutrients may translate comparatively directly into spatial differences in tree nutrition, although CEC, nutrient availability, and plant response are also governed by soil texture, mineralogy, pH, exchangeable bases, moisture, rooting depth, fertilization, and landscape position. Because the cited studies largely derive from general soil science and other cropping systems, this mechanism is inferred rather than demonstrated directly in Sichuan citrus orchards, and it therefore requires local verification. The effect of minor nutrient supply differences on quality is intensified by nutrient competition during the flower–fruit coexistence period (an on-tree fruit retention period of up to 12–14 months). Reflecting this lower buffering capacity, the correlation between soil nitrogen and fruit

quality is generally reported to be more pronounced in purple soil than in red soil or Oxisol [51–57]. This contrast is qualitative and is inferred from the buffering-related soil properties summarized in Table 2 rather than from a measured coupling coefficient; accordingly, Table 2 compares soil nutrient characteristics across soil types rather than a quantified nutrient–quality coupling.

Under low sampling intensity, ordinary kriging may be constrained by reduced interpolation accuracy and unstable variogram fitting, while co-kriging and regression kriging approaches can improve orchard soil mapping by incorporating correlated ancillary variables, at the cost of greater data requirements that may reduce field applicability where sampling and auxiliary information are limited [58–60].

Table 2. Comparison of soil nutrient characteristics among orchard soil types relevant to nutrient–quality relationships.

Soil Type	Nutrient Buffering Capacity (Qualitative)	Typical Implication for Nutrient Management	Reference
Sichuan purple soil	Low	Mineral nutrient heterogeneity maps relatively directly onto tree nutrition	[46,61]
Jiangxi red soil	Moderate	Intermediate buffering of spatial nutrient variation	[62,63]
Brazilian Oxisol	Relatively strong	Stronger buffering attenuates spatial nutrient variation	[64,65]

2.3. Regulatory Effect of Topographic Factors on Micro-Domain Differentiation of Fruit Quality

Micro-scale hydrothermal redistribution among topographic positions appears to be the finest link in this three-level framework, and, in the hilly Sichuan Basin, it likely operates against a background of frequent winter temperature inversions and strong terrain-controlled climatic heterogeneity that can amplify frost exposure in low-lying orchard sites and, in turn, amplify spatial variation in fruit quality [12,66,67]. The representation of fine-scale temperature fields in hilly terrain depends strongly on DEM resolution. As DEM resolution becomes coarser, terrain smoothing weakens slope- and aspect-related temperature contrasts and reduces spatial heterogeneity, which can degrade the representation of local cold air accumulation and other topographic thermal effects [68,69]. In complex terrain, models with spatially constant coefficients are often inadequate, whereas geographically weighted and random forest-based approaches better capture nonlinear and spatially heterogeneous temperature relationships when fine-resolution terrain and environmental covariates are available [70–72]. However, these methods are black-box in nature, which can conflict with the interpretability required for zoned management [73–75].

Table 3 contrasts the dominant topography–quality effects across producing regions. The comparison is qualitative: the reported metrics differ in physical nature and spatial scale and are used to characterize the dominant topographic effect in each region rather than as directly comparable values. Winter temperature inversion in the Sichuan Basin is described by a vertical lapse/inversion rate and occurs predominantly in winter; in the California Central Valley, nocturnal inversions are reported as an absolute temperature difference over a stated elevation range on frost nights; São Paulo uses an altitude-based agroclimatic mapping approach rather than a single temperature value; and Mediterranean regions are characterized by an absolute heat stress threshold in summer. Because these regions rest on different topographic assumptions, methodologies established elsewhere encounter adaptability limitations when transferred to the Sichuan Basin context.

Table 3. Comparison of dominant factors of topography–quality effects in different producing areas (reported metrics differ in type and are not directly comparable; see note).

Producing Area	Dominant Topographic Factor	Spatial Scale	Reported Metric (Type)	Reported Value	Seasonality	References
Sichuan Basin hilly area	Frequent winter temperature inversion associated with deep basin topography	Basin to sub-basin scale; local hilly areas likely add finer cold air pooling	Vertical temperature lapse/inversion rate	~1.6 °C per 100 m in winter; complex terrain increases local cold-damage risk	Winter	[76,77]
California fruit districts/ Central Valley	Nocturnal temperature inversion for frost protection	Hillslope to local orchard scale	Absolute temperature difference over an elevation range	>15 °C over 70 m elevation on frost nights	Winter	[78]
São Paulo, Brazil	Altitude-linked agroclimatic zoning	Regional scale	Qualitative mapping approach (no single temperature value)	Altitude used with latitude/longitude for disease–climate risk mapping	Year-round	[79]
Mediterranean citrus regions	Dry-climate heat exposure and microclimate variation	Macroclimate to microclimate scale	Absolute heat stress temperature threshold	Fruit quality shifts when temperatures exceed ~35 °C	Summer	[31,80,81]

Note: The reported metrics differ in physical nature, comprising a vertical temperature lapse/inversion rate (°C per 100 m), an absolute temperature difference over a stated elevation range (°C), a qualitative altitude-based mapping approach, and an absolute heat stress threshold (°C). They are therefore not directly comparable and are presented to characterize the dominant topographic effect in each region rather than as a common quantitative index.

3. Key Technical Approaches for Zoned Management

Data acquisition, spatial analysis, zoning delineation, and decision implementation constitute the four steps of the closed-loop technical chain for zoned management of late-ripening citrus [24,82]. Based on the unique characteristics of the Sichuan Basin—including frequent winter cloud and fog, significant gradients in soil nutrients, and small hilly orchard fields—we propose a multi-source collaborative acquisition system integrating satellite remote sensing, unmanned aerial vehicle (UAV) monitoring, and ground sensor calibration. Although satellite–UAV synergy and citrus thermal resource assessment have been reported in general or non-Sichuan contexts, such an integrated framework has not been operationally implemented for Sichuan citrus zoning [1,83,84]. In sloping orchards, image errors can be minimized through terrain-following flight planning, accurate DEM support, and oblique image acquisition, as demonstrated for general high-relief topographic surveys rather than in citrus orchards specifically [85–87]. UAV-derived soil, topographic, and crop indicators have been used to delineate citrus management zones in orchards outside Sichuan—for Israeli, Iranian, and Spanish citrus—and fruit quality maps can support localized decisions, but none of these studies was conducted under Sichuan Basin conditions, so the approach has been demonstrated in principle yet requires regional adaptation [7,24–26,88]. Citrus zoning is well suited to fuzzy clustering, although the optimal number of management units remains context-dependent [24–26,89]. The results are validated for interannual stability and intra-zone homogeneity [89–91]. For decision implementation, row-scale prescription maps and lightweight decision support systems (DSS) specifically designed for small, sloping orchards remain to be developed. Variable-rate irrigation and fertilization technologies have been demonstrated in other crops and general contexts, but their calibration for Sichuan purple-soil citrus orchards under cloud and fog conditions requires site-specific validation [90,92,93].

3.1. Data Acquisition: Comparison Between Remote Sensing Monitoring Methods

The accuracy and timeliness of data acquisition are foundational requirements of the zoning management technology chain, as high-quality data are prerequisite for subsequent spatial analysis and zoning delineation. Table 4 systematically compares the six data acquisition techniques studied across five dimensions: spatial resolution, temporal resolution, spectral range, cost, and operational complexity. The reported resolutions are typical val-

ues under standard acquisition conditions and vary with sensor model, flight altitude, and atmospheric conditions, while the cost and operational complexity ratings follow the qualitative criteria defined in the table note.

Table 4. Multidimensional comparison of data acquisition methods.

Method	Spatial Resolution	Temporal Resolution	Spectral Range	Single-Coverage Cost †	Operational Complexity †	Reference
UAV multispectral	0.05–0.1 m (altitude-dependent)	On-demand flight	5–10 bands (VIS-NIR, red-edge)	Medium	Medium	[94–96]
UAV hyperspectral	0.1–0.3 m (altitude-dependent)	On-demand flight	Hundreds of contiguous bands	High	High	[97,98]
Sentinel-2	10/20/60 m (band-dependent)	5-day revisit (twin-satellite)	13 bands at 3 resolutions	Low	Low	[99–101]
Landsat-8/9	15/30/100 m (band-dependent)	16-day revisit (8-day combined)	11 bands at 3 resolutions	Low	Low	[99,101,102]
Ground-based sensor	Point scale	Continuous	Sensor-specific bands	Medium	Low	[97,103]
Ground-based manual sampling	Point scale	On-demand	Laboratory analysis	High	High	[94,104]

Note: † Cost and complexity are qualitative ratings assigned by the authors. Single-coverage cost denotes the relative expenditure to obtain one full-orchard dataset (equipment, acquisition, and processing): Low = freely available satellite imagery requiring only processing; Medium = consumer/professional UAV operation or fixed in-field sensors; High = hyperspectral instrumentation or laboratory chemical analysis. Operational complexity reflects the skill, calibration, and post-processing burden: Low = largely automated acquisition with minimal calibration (satellite download, fixed sensors); Medium = trained operator with standard photogrammetric processing (UAV multispectral); High = specialized expertise for sensor calibration, radiometric correction, or wet chemistry analysis (UAV hyperspectral, manual sampling). Ratings are relative comparisons among the six methods rather than absolute values, and actual costs depend on local labor, equipment, and orchard scale. Spatial and temporal resolutions are typical values under standard acquisition conditions and vary with sensor configuration, flight altitude, and cloud cover.

Beyond these tabulated dimensions, the number of spectral bands should not be equated with usable information for citrus monitoring. Although Sentinel-2 and Landsat provide 13 and 11 bands, respectively, these are distributed across several spatial resolutions, and only a subset is directly useful at the orchard scale—principally, the 10 m visible and near-infrared bands and the red-edge bands relevant to canopy chlorophyll and nutrient status. Several coarse-resolution bands (e.g., the 60 m atmospheric correction bands of Sentinel-2 and the 100 m thermal band of Landsat) contribute little to fruit quality or fine-scale canopy assessment in fragmented hilly orchards.

One of the main difficulties for data acquisition is frequent cloud and fog in winter. This is particularly true for the Sichuan Basin, where frequent cloud cover over the winter period of overwintering (December–February) results in limited optical satellite acquisitions, and other hilly areas in southwestern China have faced similar challenges [105,106]. With on-demand flight capability, UAVs can operate beneath low cloud ceilings or during breaks in cloud cover, providing a scheduling advantage over optical satellites during the critical winter monitoring season. This advantage is not unconditional: flying above a cloud layer does not remove cloud obstruction along the sun–target–sensor path, and low-illumination, overcast conditions reduce and destabilize incoming radiation, compromising radiometric consistency across flights. Reliable winter UAV monitoring therefore requires radiometric calibration (e.g., reference panels or irradiance sensors) to ensure comparability between acquisitions, together with terrain-following flight to maintain a consistent canopy distance over sloping orchards. Due to the complex topography of the Sichuan Basin's hilly region, there are two challenges for data quality and flight safety. In sloping orchards, the relative height of the UAV above the canopy varies, causing spatial resolution to be higher on lower slopes and lower on upper slopes. These systematic errors are magnified, generating spatial

errors in quality prediction when retrieving canopy parameters [107]. This issue is not fully addressed by existing commercial UAV flight planning software but can be partially resolved by flying along contour lines or using terrain-following mode.

3.2. Spatial Analysis: Geostatistics and Fuzzy Clustering Algorithms

Spatial analysis serves as the primary link between data collection and zoning demarcation. Table 5 summarizes the reported characteristics of geostatistical and fuzzy clustering algorithms used in agricultural management zone delineation, including partition boundary flexibility, zone differentiation capacity (assessed variously by ANOVA F-tests for hard clustering or fuzzy validity indices such as the FPI (fuzziness performance index), MPE (modified partition entropy), and NCE (number of extragrades) for probabilistic methods), and computational efficiency. These characteristics are drawn from studies that differ in crop, spatial scale, input variables, and validation approach; the table is therefore descriptive rather than a controlled quantitative comparison.

Table 5. Comparison of zoning performance between geostatistical and fuzzy clustering methods.

Method	Reported Inter-Zone Differentiation Capacity †	Zone Boundary Flexibility	Computational Efficiency	References
Ordinary kriging + k-means	Medium	Rigid	High	[108,109]
Co-kriging + k-means	Medium	Rigid	Medium	[109,110]
Regression kriging + k-means	Medium-high	Rigid	Medium-low	[111]
FCM (Fuzzy C-Means)	Medium-high	Flexible	High	[24,26,90]
FKM (Fuzzy K-Means)	Medium-high	Flexible	High	[25,108,112]
Gustafson-Kessel	High	Flexible	Medium	[113]
Mixture model	High	Flexible	Low	[114]

Note: † Ratings are qualitative summaries of the general tendencies reported across the cited studies and are relative comparisons among the listed methods rather than standardized quantitative results. "Zone boundary flexibility" distinguishes hard-clustering methods that assign each location to a single zone (rigid) from fuzzy or probabilistic methods that allow graded membership and transition zones (flexible). "Reported inter-zone differentiation capacity" reflects the extent to which each method has been reported to produce zones with statistically distinguishable properties, assessed in the original studies by ANOVA F-tests (for hard-boundary methods) or fuzzy validity indices such as FPI, MPE, and NCE (for fuzzy methods). An F-test indicates whether zone means differ significantly but does not itself quantify the magnitude of heterogeneity. "Computational efficiency" is a relative ranking based on algorithmic complexity (e.g., the mixture model's EM optimization is more costly than k-means). Because the cited studies differ in crop, spatial scale, number and type of input variables, and validation design, the table is descriptive and does not constitute a controlled comparison; readers should consult the original references for quantitative results in context.

Fuzzy clustering algorithms and geostatistics-coupled k-means two-stage methods differ in zone boundary flexibility and multi-factor fusion capacities. The mixture model delivers variance reduction effects yet imposes high computational costs, restricting its applicability for independent zoning within fragmented orchards. The Gustafson–Kessel algorithm adopts an adaptive distance metric, which enables it to cope with the broad magnitude ranges of mineral nutrients and organic matter present in purple soil.

Based on cluster number sensitivity analysis, the optimal number of management zones in hilly fields in Sichuan and central China was found to be three, as indicated by minima in fuzzy performance metrics such as FPI, MPE, and NCE. A separate commercial citrus plantation study found six optimal zones, showing that optimal zone number varies by orchard context rather than supporting a general flat-orchard benchmark of 5–8 zones [24,27,115]. This aligns with the study of Zeraatpisheh et al. (2020) [24], who reported that six optimal management zones were delineated for a heterogeneous citrus plantation using principal component analysis and fuzzy c-mean clustering, supporting the finding that hilly terrains with smaller, fragmented fields require fewer management zones than large-scale flat or-

chards. Field parcels within such hilly settings are generally limited in individual plot size. Excessive zoning subdivisions produce overly small individual management units, which hinder the practical implementation of variable-rate field operations. Such a limitation constitutes a key distinguishing feature between the Sichuan study region and plain-based production zones.

3.3. Decision Support System and Variable-Rate Operation Execution

The implementability of zoning management in orchards depends not only on the delineation method but also on the adaptability of downstream execution components, especially DSS and mechanized operation technologies. In the Sichuan Basin, this adaptability is constrained by the predominance of sloping and fragmented farmland, as more than 90% of cultivated land is on slopes and the relative share of 10–25° sloping farmland has increased [28]. Under these conditions, three limitations become prominent: terrain mismatch between zoning prescriptions and fragmented hillside plots, reduced execution reliability of mechanized operations as slope and fragmentation increase, and higher integration and usability requirements for orchard DSS due to the complexity of perennial orchard management [116,117]. The quantitative indicators in Table 6 are drawn largely from studies of hilly agriculture in general rather than from Sichuan citrus orchards specifically, and their exact magnitudes for late-ripening citrus remain to be validated.

Table 6. Reported adaptability constraints relevant to orchard DSS and mechanization in hilly terrain.

Adaptability Issue	Specific Manifestation	Quantitative Indicator	References
Mismatch Between DSS Assumptions and Plot Scale	DSS designed for larger, flatter, regular plots; Sichuan dominated by sloping, fragmented land	Sloping farmland 10–25° increasing; hilly plots ≤ 0.05 ha; mainstream machinery turning radius ≥ 5 m	[28,117,118] ([112] Sichuan sloping cropland; [114,115] general hilly agriculture/DSS, not citrus-specific)
Terrain-Induced Limits on Operational Accuracy and Access	Slopes and fragmentation reduce machinery continuity and accessibility	Slope > 15°: wheel slip rises steeply; fragmentation F > 0.6: empty travel > 30%; poor terrain adaptability linked to 42% higher operating cost and 63% efficiency loss	[117] (general hilly/mountainous agricultural machinery; not obtained in citrus orchards)
Limited Suitability of Existing Orchard Platforms	Platforms validated within modest slope and spacing envelopes; steeper/irregular Sichuan orchards less covered	Platform optimized for ≤15° slopes and ≤6 m spacing; in Chongqing, 53% of orchards lie on 8–25° slopes, 4.4% exceed 35°	[119,120] (orchard operation platforms); [116] (Chongqing citrus orchard survey)

Note: Values are reported from the cited studies, which differ in agricultural system, crop, machinery type, and operational task. The quantitative indicators for terrain-induced operational limits (slope, fragmentation index F, operating cost, and efficiency loss) derive from general studies of hilly and mountainous agricultural machinery [114] rather than from citrus orchards. The fragmentation index F, machinery types, operational tasks, and sample conditions follow the definitions and settings reported in that source, which readers should consult for details. The Chongqing slope distribution statistics refer to citrus orchards [116]. These figures indicate the general scale of operational challenges in hilly terrain; their exact magnitudes for Sichuan late-ripening citrus remain to be validated.

Regarding the applicability of variable-rate irrigation strategies, the three approaches, which are soil moisture sensor-based, evapotranspiration model-based, and canopy temperature-based, respectively, differ in their applicability given the weak water-holding capacity of purple soil (Table 7). The soil moisture sensor-based approach is directly related to the water dynamic of the citrus root zone but requires soil-specific calibration and proper installation as the sensor readings can vary from place to place and depth to depth within

the drip zone [121]. Irrigation scheduling based on evapotranspiration (ET) models in the Sichuan Basin seems possible with limited input data, but the resulting model accuracy depends on regional climate conditions, particularly solar radiation and cloudiness, and requires field testing and calibration of the models [122]. The canopy temperature-based approach is physiologically based on crop water stress, which causes stomatal closure and an increase in leaf temperature [123]. However, the canopy temperature–water stress relationship for evergreen citrus canopies differs from that for deciduous crops due to iso-hydric behavior, in which rapid stomatal closure in response to a high vapor pressure deficit (VPD) occurs even under well-watered conditions, as reported in thermography studies of citrus [124–126]. In a cross-species comparison of CWSI measurement errors, citrus was reported to have the shallowest non-water stress baseline slope (-0.5 °C kPa^{-1}) among the crops examined [123], rendering CWSI calculations particularly sensitive to measurement errors and requiring species-specific recalibration. These findings come from citrus grown outside the Sichuan Basin, and their applicability under the basin's humid, frequently overcast conditions has not been established.

Table 7. Comparison of the applicability of three variable-rate irrigation strategies in purple-soil orchards.

Strategy	Response Mode	Water-Saving Potential	Inherent Spatial Representativeness Limitation of Point-Scale Measurements	Reference
Evapotranspiration model	Model prediction	Medium	Applicability under low sunlight and overcast conditions unverified	[127–129]
Canopy temperature	Physiological stress indicator	Medium-high	Stress relationship for evergreen canopies requires recalibration	[130–132]
Soil moisture sensor	Real-time direct response	Relatively high	Difficult shallow installation and calibration, insufficient point-scale representativeness	[103,133,134]

Note: Water-saving potential is a qualitative, relative ranking synthesized by the authors from tendencies reported in the cited studies, not a standardized quantitative measure; no direct head-to-head comparison under identical conditions is available, and actual performance depends on soil type, climate, calibration, and crop.

4. Methodological Evolution Pathways and Cross-Scale Comparison

Through systematic synthesis of the existing literature, a gradual evolution from general fruit tree methods to citrus-specific methods and then to Sichuan scenario-adapted methods is revealed. This evolutionary process shows that the approach to zone management has shifted from being crop-centric to being scenario-centric.

4.1. Management Zone Delineation Methods for General Fruit Trees

General fruit tree management zoning methods have developed a relatively unified methodological paradigm across four aspects: sampling strategy, core variables, zoning algorithm, and validation methods. Regarding sampling methods, regular grid sampling (30 m × 30 m) is more commonly used in apple orchards and vineyards, whereas stratified random sampling is preferred in olive orchards due to terrain complexity [135]. As shown in Table 8, soil characteristics like nitrogen, organic matter, and pH are generally used as the major variables, and yield data are included, with fruit quality data included if the zoning classification needs to reflect variation in product quality in addition to production for fruit orchards [136]. Although the k-means method is a still common method for determining management zones, recent zoning studies have increasingly incorporated dimensionality reduction with fuzzy clustering to improve the ability to partition a heterogeneous landscape and to minimize within-zone variability [137]. Zone validation is frequently performed using ANOVA to see if agronomic variables vary significantly between zones, but this

test is sensitive to independent observations and can yield false-positive results if there is high spatial autocorrelation [138]. Other validation methods are complementary, such as multivariate tests like MANOVA and classification-based tests like linear discriminant analysis with leave-one-out cross-validation (LOOCV), which, in one study, classified the cultivation zones perfectly both internally and externally.

Table 8. Comparison of the core frameworks of management zone delineation methods for different fruit trees.

Crop	Biological Characteristics	Core Zoning Variables	Dominant Algorithm	Validation Method	References
Apple	Deciduous, single harvest	Soil + yield + fruit quality	Multivariate geostatistics + non-parametric clustering	Spatial variability mapping over 3 years	[136]
Grape	Deciduous, single harvest	Soil (ECa, depth, topography) + canopy (NDVI) + quality	Fuzzy k-means (FKM)	FPI, NCE, pixel-by-pixel degree of agreement	[92,139]
Peach	Deciduous, single harvest	Soil + tree attributes (yield, fruit weight, firmness, soluble solids)	Principal component analysis + fuzzy c-means (FCM)	FPI, modified participation entropy	[140]
Olive	Evergreen, single harvest	Soil + leaf nutrient contents	Fuzzy k-means (FKM)	PCA, weighted overlay, fuzzy performance index	[141]
Citrus	Evergreen, multiple harvests	Soil + biological + terrain attributes	PCA + fuzzy c-means (FCM)	Significant heterogeneity variation among MZs, relative cost analysis	[24]

However, the transferability of the general management zone framework to the purple-soil hilly region of the Sichuan Basin is limited by differences in terrain and soil heterogeneity rather than by crop type alone. Sichuan Basin farmland is dominated by hilly landscapes and strong within-field soil variability, and uniform regional recommendations can lead to both under- and over-application of inputs [27]. In the Jianyang hilly field in Sichuan, soil properties showed variation that ranged from low to moderate-to-high and differing spatial dependence, and management zones were delineated using principal component analysis with fuzzy clustering rather than a simple fixed soil–yield template [27]. More broadly, studies in hilly agroecosystems show that yield patterns vary with hillslope position, curvature, wetness, drainage, soil depth, and nutrient redistribution, so the relationship between soil indicators and yield is spatially heterogeneous rather than uniform across the landscape [142]. Accordingly, applying a general framework in Sichuan requires adding locally relevant terrain, nutrient, and, where available, multi-year yield or remote sensing covariates and validating zoning performance with spatial metrics or yield-based criteria rather than assuming that soil organic matter alone is the dominant driver [30,114].

4.2. Applicability Limitations in Citrus Scenarios

The general fruit tree zoning methods serve as a methodological basis, but they are not directly applicable to late-ripening citrus in the Sichuan Basin due to its different canopy structures, phenology, stress, and temporal needs. The contrasts can be presented in four dimensions: remote-sensing retrieval, quality prediction, stress response, and timeliness (Table 9). The comparison is to be interpreted as a contrast to traditional one-season orchard designs or as a general orchard description for all fruit crops.

It is more difficult to retrieve evergreen citrus using remote sensing as the persistent canopy cover makes it harder to see the direct soil areas and increases the canopy–background interaction. The integration of the spectral, structural, soil, and terrain data has been commonly integrated in citrus studies in recent years. Leaf nutrient status estimation has been performed using multispectral imagery from UAVs, and the retrieval of the leaf area index and soil moisture has been achieved using multimodal UAV observa-

tions [94,143,144]. In the Sichuan Basin, the cloudy, hilly environment can further reduce the temporal continuity of optical satellite data [105].

Table 9. Four-dimensional differences between general fruit tree methods and the Sichuan late-ripening citrus scenario.

Dimension	Conventional Fruit Tree Framework	Sichuan Late-Ripening Citrus Characteristics
Remote sensing retrieval	Seasonal canopy development may provide periods with greater soil/background visibility	Evergreen canopy reduces direct soil visibility; canopy, soil, and terrain signals are coupled
Quality prediction	Often based on one production season and a defined harvest period	Extended on-tree period and multiple phenological stages require multi-temporal information
Stress response	Often emphasizes one dominant environmental constraint	Water, low temperature, nutrient status, and terrain-related microclimate may vary simultaneously
Timeliness	Zones may be recalculated between production seasons	Requires cross-year stability together with capacity for within-season updating

Therefore, satellite products must not be considered as a primary zoning data source, but rather must be complemented by targeted UAV surveys and ground measurements. There also is a need for an increased temporal element in quality prediction. As late-ripening citrus is exposed to environmental conditions over an extended production cycle, a single-date observation is not sufficient to capture quality formation. China has seen that interannual climatic variation has an impact on internal quality of citrus [5], and time-series remote sensing has been found to enhance characterization of the seasonal variations in yield [145]. Stress response is also multidimensional: the suitability of citrus varieties in Sichuan is determined by the interacting heat, moisture, and radiation conditions [1], and basin temperature inversions and spatially variable purple-soil properties add further stress dimensions [12,36]. Lastly, there should be some stability through time in perennial management. Operational zones need to be maintained long enough and consistently over time to allow for year-on-year management, as dynamic citrus zoning shows that canopies can be changed during the season. The proper framework should thus be a combination of stable terrain and soil layers and dynamic canopy, moisture, and temperature data.

4.3. Research Progress on Citrus-Specific Modeling Methods

Citrus-specific modeling can be considered as three methodological steps which can be seen as overlapping: static sensing and prediction, multi-temporal dynamic zoning, and multi-source or digital-twin integration. In this review, a digital twin denotes a virtual representation of an individual orchard that is continuously updated with multi-source observations and used for prediction and management, which is distinguished from a process-based digital model or simulation that is mechanistic and parameterized but not necessarily linked to continuous observation of a specific orchard. This is conceptual and not a solid historical taxonomy, as there is overlap among the approaches and performance is highly dependent on the prediction target and study context. The first stage is aimed at the extraction of the canopy or production characteristics from single- or few-period remote sensing data. In the citrus sector, UAV multispectral imagery has been used successfully for the estimation of the nutrients of citrus leaves [94], and UAV multimodal imaging has been applied to the retrieval of the leaf area index [143]. Other newer yield models are based on a combination of vegetation indices and texture features and machine learning techniques. Onwude et al. (2024) [146] reported R^2 values around 0.79–0.85 for fruit number prediction using XGBoost and CPSO-optimized XGBoost. These methods are effective in

mapping spatial heterogeneity; however, most do not reflect the entire process of fruit quality development, but rather predict other fruit parameters, such as canopy status, nutrition, water condition, or yield. The second stage involves repeated observations and introduces temporal variability explicitly in zone delineation. Termin et al. (2023) [26] combined constant terrain variables with canopy nitrogen and tree height in a spatiotemporal fuzzy C-means scheme, using a support vector regression model for canopy nitrogen (reported $R^2 = 0.771$) before applying the estimates in dynamic management zone analysis. This is a positive step from a static zoning approach to one that is time responsive, but it is for nitrogen management and not for the coupled quality processes that are typical of late-ripening citrus. In the third stage, it is integrated into digital representations of orchard systems, where observations are from different sources. Lin (2022) [147] built a Mandarin digital twin integrating weather, soil, management, and fruit data, reporting $R^2 = 0.43$ for sugar content and $R^2 = 0.84$ for fruit size, illustrating that predictive accuracy differs markedly between traits within a single study, with sugar content being inherently harder to predict than fruit size. Avioz al. (2025) [148] developed a digital model of Valencia orange growth, reporting harvest quality predictions within 5% error (as defined in that study). The accuracy metrics cited above (R^2, RMSE, and percentage error) are study-specific values obtained for different response variables (fruit number, canopy nitrogen, sugar content, fruit size, and overall harvest quality) with different units, sample sizes, validation strategies, and spatial and temporal scopes. They therefore cannot be compared directly and should not be interpreted as evidence that any one methodological stage is intrinsically more accurate than another; a lower R^2 for sugar content, for example, reflects the inherent difficulty of predicting that trait rather than a deficiency of the modeling stage. These values indicate that each approach can perform well for its specific target under its own conditions, not that the stages form an ascending scale of accuracy. Sichuan needs regional adaptation of application. Even in hilly fields, there is a significant soil variability and management zone heterogeneity [27], and field-scale variation in the acidity of the purple soil can be increased by citrus culture [36]. In addition, there is considerable evidence of basin-scale temperature inversions [12], but little is known about orchard-scale cold air patterns and their direct effects on late-ripened fruit quality. A regionally adapted framework should therefore combine the persistent variables that are intrinsic to the landscape (such as relative elevation, slope, aspect, terrain position, and stable soil properties) with the dynamic variables that are part of the environment (canopy condition, soil moisture, soil temperature, and measured fruit quality). Validation should be performed not only to check the model fit, but also to check cross-year stability, cross-orchard and cross-cultivar transferability, and within-zone homogeneity and economic operability. Multi-year field datasets linking terrain, microclimate, purple-soil properties, canopy dynamics, management, and fruit quality in the same spatial scale are thus the most pressing research need for management.

5. Current Challenges and Existing Issues

Zoned management of citrus is still limited in Sichuan due to the lack of winter observation, zone changing from year to year and by cultivar, and inadequate economic and extension capacity in hilly orchards with limited planting areas [1,29]. The five research gaps identified in the Abstract are each addressed in the following subsections and are linked here to the reviewed evidence, the current limitation, and the corresponding future direction. First, spatiotemporal data fusion (Section 5.1) is constrained by the 2–3-month winter gap in optical satellite coverage and by the resolution and geometry mismatch between UAV and satellite data [148]. A multi-source fusion framework that treats UAV data as a distinct, radiometrically and temporally harmonized observation phase is required, and it must be validated for continuity through the overwintering period and for consis-

tency across sensors and years. Second, the universality of dynamic zoning (Section 5.2) is limited because static zones lose reliability under interannual climate and inversion variability [149–151]. Incremental updating and time-series clustering, together with a consistently defined interannual overlap metric, are needed for cross-year stability. Third, multi-factor interactive modeling (Section 5.3) remains weak because climate, soil, topography, and cultivar sensitivity are typically modeled individually or by simple superposition, while nonlinear methods that capture their interactions are largely black-box [149–151]. Interpretable machine learning and structural or process-based coupling are required, with validation extending to the interpretability of the estimated interactions and their generalization across orchards and cultivars. Fourth, economic feasibility evaluation (Section 5.4) is critical because equipment-intensive precision systems show low smallholder adoption in fragmented hilly orchards [149–151]. Lightweight, cooperative-based precision schemes are needed and should be assessed for viability across operating scales [149–151]. Fifth, technology dissemination (Section 5.5) is hampered by reliance on single-channel, informal extension. A combined model of cooperative training, local demonstration, and multi-stakeholder platforms is required, validated by adoption rate and willingness across farmer groups [149–151]. Table 10 provides a structured synthesis of the five research gaps identified in this review, linking each gap to the reviewed evidence, the current limitation, the required data or method, and the validation requirement. The table is intended to be read alongside Sections 5.1–5.5, which discuss each gap in detail.

Table 10. Synthesis of research gaps, reviewed evidence, current limitations, required data or methods, and validation requirements for zoned management of late-ripening citrus in the Sichuan Basin.

Research Gap	Evidence	Limitation	Data/Method	How to Validate
Spatiotemporal data fusion	Winter cloud and fog cause a 2–3-month gap in satellite data. Fusion accuracy drops 30–50% when the time gap exceeds 30 days [152].	No continuous winter observations. UAV and satellite data are not harmonized in resolution, geometry, or timing.	Multi-source fusion framework. Treat UAV data as a separate observation phase. Apply radiometric correction, spatial registration, and temporal matching.	Test continuity through the overwintering period. Check cross-sensor and cross-year consistency.
Dynamic zoning universality	Complete re-zoning gives 40–55% interannual overlap. Incremental updating gives 70–80%. Time-series clustering is most stable [149–151,153].	Static zones become unreliable under year-to-year climate variability and winter temperature inversions.	Incremental updating. Time-series clustering. A consistent metric to measure interannual overlap.	Assess cross-year stability, within-zone homogeneity, and interannual overlap.
Multi-factor interactive modeling	Fruit quality is driven by coupled climate, soil, topography, and cultivar effects [1,8,33,34]. Most models treat factors separately or use black-box methods [70–77].	Interactions among factors are rarely disentangled. Model interpretability is too low for management decisions.	Interpretable machine learning. Structural equation models or Bayesian networks. Digital-twin coupling of process and observation.	Check interpretability of estimated interactions. Test generalization across orchards and cultivars.
Economic feasibility	Total factor productivity gains are 0.123–0.130% [32]. The average farm has ≈6.16 plots and 6.06 mu. Costs decline only above ≈47 mu [154].	Smallholders cannot adopt equipment-intensive precision systems in fragmented hilly orchards.	Lightweight precision tools. Mobile phone-based instruments. Low-cost remote sensing. Cooperative or service provider access to UAVs. Targeted technical support.	Evaluate viability across operating scales. Assess cost–benefit, adoption and willingness to pay.
Technology dissemination	Informal extension dominates. Farmer field schools, Science and Technology Backyard, and cooperative training improve adoption [155–159].	Reliance on single-channel, informal extension. Weak last-mile delivery.	Cooperative-based technical training. Local demonstration. Multi-stakeholder service platforms.	Measure adoption rate and farmer willingness across different farmer groups.

Note: The table maps directly to Sections 5.1–5.5. Each row corresponds to one subsection. Abbreviations: TFP = total factor productivity; UAV = unmanned aerial vehicle.

5.1. Spatiotemporal Data Fusion and Multi-Source Information Standardization

Frequent winter cloud and fog in the Sichuan Basin can create a 2–3-month gap in optical satellite observations during the critical on-tree overwintering period. When the time difference is over 30 days, the manuscript synthesis reports that the accuracy of the representative spatiotemporal fusion approaches can drop by 30–50% [152]. This is significant for evergreen citrus trees because of the lack of direct soil visibility and the presence of

canopy–background mixing. When satellite data are not available, UAV observations can contribute centimeter-scale data; however, fusion is challenging because of the difference in spatial resolution, geometry, illumination, and timeliness of the two observation platforms. Such mismatches may cause errors in scale transformation between canopy-level UAV features and satellite pixels. Therefore, within this framework, UAV data should be considered as a separate observation phase and made consistent with satellite and ground data by using appropriate radiometric correction, spatial registration, variable definitions, and temporal matching. A Sichuan-oriented approach should aim to maintain continuity during the overwintering period and maintain comparability between sensors and years.

5.2. Dynamic Zoning and Cross-Variety Transferability

Interannual variations in climate and temperature inversion conditions may cause static zones to become unreliable. The manuscript presents interannual overlap rates of whole-area re-zoning ranging between 40% and 55%, and summarizes three strategies for updating (Table 11). These reported rates derive from different studies, and definitions and are not directly comparable; they are cited to illustrate the relative behavior of each updating strategy rather than to rank their performance.

Table 11. Comparison of three dynamic zoning update strategies.

Update Strategy	Method Characteristics	Interannual Overlap Rate	Data Requirements	References
Complete re-zoning	Independent zoning each year, without relying on historical information	40–55%	Annual full-factor sampling	[149]
Incremental updating	Bayesian recursion/Kalman filter updating boundaries	70–80%	Annual micro-scale temperature measurement	[151]
Time-series clustering	Merging multi-year data into a single zoning	Most temporally stable zones	One-time multi-year data collection	[150]

Note: "Interannual overlap rate" refers to the proportion of the study area assigned to the same management zone in consecutive years; the exact definition (e.g., area overlap ratio, intersection over union, or pixel agreement) follows the respective source. Because these values originate from studies conducted on different crops, spatial scales, and definitions, they are not directly comparable and are indicative of method characteristics rather than a controlled quantitative comparison [149–151].

Another limitation is the cross-variety transferability. However, as mentioned in Section 2, the temperature accumulation, spring warming, and long on-tree retention have different effects on Buzhihuo, Chunjian, and Qingjian. A model calibrated to one cultivar can thus be misleading for another cultivar as regards its climatic sensitivity. In cases where enough observations exist, cultivar-specific calibration is recommended, but when the labeled data are limited, transfer learning or domain adaptation can be more efficient. Both methods need to be validated independently before use in operation.

5.3. Multi-Factor Interactive Modeling

As established in Section 2, fruit quality variation in late-ripening citrus arises from the coupled action of climate, soil, and topography rather than from any single factor [149–151]. Within the Sichuan Basin, these factors are strongly interdependent: terrain governs cold air pooling during winter inversions [149–151] and the redistribution of soil water and nutrients across slope positions, so that the water status, low temperature, nutrient supply, and terrain-related microclimate may act on fruit development simultaneously rather than in isolation (Table 9). Their combined influence is therefore unlikely to be additive.

Most zoning studies reviewed here, however, treat the driving factors individually or through simple linear superposition. Geostatistical and fuzzy clustering workflows combine soil, canopy, and terrain covariates into a single feature space (Sections 3.2 and 4.1) without representing the interaction terms among them, and models with spatially constant coefficients are often inadequate in complex terrain [149–151]. Methods that capture nonlinear and spatially heterogeneous relationships, such as geographically weighted regression and random forests, improve predictive skill but are largely black-box, and their limited interpretability conflicts with the transparency required for management zone decisions [149–151]. As a result, the relative contribution of each factor and its interactions is rarely disentangled. This gap is especially consequential in the Sichuan Basin, where pronounced field-scale soil variability [149–151], citrus-induced purple-soil acidification [149–151], and cultivar-specific sensitivity (Table 1) add further interacting dimensions to well-documented basin-scale inversions whose orchard-scale expression remains largely unknown [149–151].

Future work should move from single-factor mapping toward explicit interactive modeling. Interpretable machine learning frameworks can quantify both the direction and magnitude of factor interactions while preserving decision transparency [149–151]; structural equation models or Bayesian networks can represent the causal pathways of the climate–soil–topography–cultivar chain and test interaction effects directly. Building on the digital-twin integration described in Section 4.3, multi-factor coupling within such representations can further embed these interactions in a process-aware model of the orchard, provided the constituent models are validated against independent observations [149–151]. In all cases, validation must extend beyond overall model fit to test the interpretability of the estimated interactions and their generalization across orchards and cultivars.

5.4. Economic Feasibility

In the case of Sichuan citrus production, the economic viability is the most important factor limiting the use of precision management, with the industry still exhibiting high levels of labor, land, and capital inputs in most production regions, suggesting that upgrading based on capital investment is not directly proportional to the total factor productivity benefits [32]. This constraint is further reinforced by the structure of the southwest hilly agriculture production area, which has an average of about 6.16 plots divided into an average of about 6.06 mu (≈0.4 ha) of cultivated land. The total minimum commuting time is about 45 min, while a one-standard-deviation increase in turnover will increase the operating cost by 7.1% for the number of plots, 15.1% for the Simpson index, and 12.2% for commuting time [154]. Costs only start to decline above an average farm size of 47 mu (≈3.13 ha), much higher than that observed, which might help to explain the limited adoption of such equipment-intensive precision systems by most smallholders [154].

A better way forward is to follow a lightweight precision scheme with the assistance of mobile phone-based instruments in conjunction with low-cost remote sensing, cooperative and service provider access to UAVs, and focused technical support, rather than massive hardware investment. This is the direction of the evidence that found that low cost, small scale, and services, subsidies, credit, and training support successful adoption [160–162]. It also fits the scale structure of hilly citrus entities nearby in Chongqing, where the estimated moderate operating scale differs by entity type—approximately 1.8–2.7 ha for smallholders, 5.02–7.53 ha for family farms, and 16.88–25.33 ha for cooperatives—and only 47.22% of entities reach their respective moderate scale [163]. For income effects, the most obvious citrus evidence from Sichuan is that one, two, and three green agricultural technologies led to citrus sales income rising by 7.1, 10.5, and 19.8 percentage points, respectively, due to higher yields and sale prices that more than covered the additional costs [164].

5.5. Field Extension and Translation

The majority of farmers in China continue to receive little formal extension but have access to neighbors or local contacts, a pattern similar to the intermediary models found at the village level [155]. Adoption benefits vary by age and farm size, and new media extension can facilitate the adoption process; however, the effects are different on various groups [156]. There is also evidence at the China-wide level of the importance of demonstration and multi-stakeholder platforms. Farmer field schools enhance cognition and adoption of new technologies in practice [165]. The Science and Technology Backyard model uses demonstrations, on-farm research, farmer groups, and extension agents, and its upgraded "one-stop" program involving government, enterprises, universities, and farmers was more effective than traditional extension [157]. Last-mile extension in citrus systems in Sichuan can be reinforced more effectively under a cooperative-based technical training model, a local demonstration model, and a multi-stakeholder service platform model than under a single-channel extension model, as the cooperative-based technical training model can significantly promote the adoption and willingness of the smallholders, and the evidence from China indicates that the model of extension relying on demonstration and integration is more effective than the model of extension solely relying on the top-down method [157–159,165].

6. Conclusions

This review provides the first integrated synthesis of climate, purple-soil, and terrain drivers for zoned management of late-ripening citrus in the Sichuan Basin, comparatively evaluates monitoring, spatial analysis, and decision support technologies in areas with frequent cloud and fog and fragmented hilly plots, and delineates the methodological evolution from general fruit tree methods to citrus-specific methods to Sichuan-adapted approaches while identifying five research gaps. Zoned management of late-ripening citrus in the Sichuan Basin must rely on methods that involve consideration of climatic variation as well as purple-soil variation, the hilly terrain, the extended on-tree life, and the varietal reactions. The current approaches have several shortcomings, including a lack of winter remote sensing data, incompleteness in spatial coverage across data sources, variability in zoning across years, uncertainty in cross-variety transferability, and the expense of implementation in a fragmented orchard. These constraints highlight the need to build regionalized, not directly transferred, frameworks of precision agriculture [1]. Future research should combine satellite, UAV, and ground observations, develop dynamic and cultivar-oriented zoning models, perform zone validation over years and orchards, and include technical performance and economic feasibility evaluation. Delivering lightweight and cooperative models could enhance practical adoption.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy16212088/s1, Table S1: Eligibility criteria applied during search and screening; Table S2: Web of Science Core Collection Search Strategies; Table S3: Scopus Search Strategies; Table S4: CNKI Search Strategies; Table S5: Time and language restrictions by database; Table S6: Record counts and screening flow; Table S7: Thematic distribution of included studies (n = 165).

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